Environment International 192 (2024) 109036

Contents lists available at ScienceDirect

Environment International

journal homepage: www.elsevier.com/locate/envint

Full length article

Socioeconomic deprivation modifies green space and mental health associations: A within person study

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ARTICLE INFO

Handling Editor: Adrian Covaci

Keywords:
Greenspace
Vegetation
Wellbeing
Ecosystem services
Health inequality
Epidemiology

ABSTRACT

Living in an area with good availability and accessibility of residential green spaces such as parks, woodlands, and residential gardens can improve mental health and reduce the global disease burden. Unlike for physical health, it is not well understood if mental health and green space associations might be modified by local area deprivation. Existing evidence for this association comes from cross-sectional studies, widely considered vulnerable to confounding and bias. Individual time-invariant mental health status, personality, and other factors may result in positive effect modification on green space and mental health associations in more deprived areas. We use fixed-effects models that remove time-invariant confounding by calculating differences within-persons to eliminate this bias and add to the existing evidence. We modelled changes in mental health status, green space, and deprivation (relative to the within-person mean) within 54,666 individuals with a combined total of 300,710 mental health scores from one of the world's largest panel surveys: "Understanding Society" in the UK. We found a positive effect of increasing residential green space on mental health and this was positively modified and intensified by area deprivation before and after adjusting for confounding. Our results support providing green space to protect against the negative impact of socioeconomic deprivation on health, particularly for those moving from a less deprived to a more deprived area.

1. Introduction

Mental health is an integral health component (Prince et al., 2007) and a major contributor to the global disease burden (Vigo et al., 2016). Understanding modifiable factors of the environment that can improve mental health, such as green space, is vital to reduce this burden (Collins et al., 2011) (Twohig-Bennett and Jones, 2018; WHO, 2017). Availability of green space near to people's homes creates more opportunities for nature contact to relieve stress and improve cognition, strengthen a person's health (build capacity) and reduce harmful environmental exposures (Markevych et al., 2014), which builds biopsychosocial resilience (White et al., 2023). The most cited restorative benefits of direct nature contact are reduction in stress and cognitive fatigue restoration, as outlined in Stress Reduction Theory (SRT) (Ulrich, 1983) and Attention Restoration Theory (ART), respectively (Kaplan and Berman, 2010) which consequently improve mental health (Houlden et al., 2018). Nature contact also builds capacity for social contact (Astell-Burt et al., 2013) and physical health, through improved physical activity, which is linked to mental health (Hunter et al., 2015). In addition, green space can provide many other ecosystem services, acting as a nature-based solution reducing risk of mental health harm (Marselle et al., 2021) from flooding, the urban heat island effect and potentially air pollution (Richards et al., 2022; Tan et al., 2020, 2021). The beneficial impact of nature contact, encourages use and further support for its protection (Soga and Gaston, 2016).

Different environmental, social, and individual factors can modify residential green space-mental health associations (Marselle et al., 2021), which may impact policy and practice. One example is

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https://doi.org/10.1016/j.envint.2024.109036
Received 16 April 2024; Received in revised form 16 August 2024; Accepted 24 September 2024
Available online 30 September 2024

neighborhood socioeconomic deprivation. Those living in less socio-economically deprived areas often have better health literacy (Svendsen et al., 2020) and better general health (Stringhini et al., 2010) and are likely to have the disposable income to substitute poor green space access, for example, via paid gym memberships to increase physical activity. Living in a greener area with better green space access might not necessarily further improve their already high health status. Whereas those living in more deprived areas often have poorer health (Pathirana and Jackson, 2018) and would conversely benefit from more green space (Rigolon et al., 2021). Green space may buffer the adverse impacts associated with living in a more deprived area (Bellis et al., 2008; Rees-Punia et al., 2018), including the deterioration of mental health (Wells, 2021).

The evidence for deprivation modifying green space-mental health associations is inconclusive, especially compared to green space-physical health associations. Deprivation positively modified physical health and green space association in most analyses across 122 recently systematically reviewed studies, supporting the theory that green space has an equigenic effect (Rigolon et al., 2021). However, there have been relatively fewer studies investigating effect modification by local area deprivation of green space and mental-health associations. These are mostly cross-sectional studies (Rigolon et al., 2021) which are vulnerable to confounding from time-stable factors (Bärnighausen et al., 2017) such as established aspects of a person's personality, their generation (i.e. age over 20–30 years) or long-standing health conditions that may correlate with a person's mental health and neighborhood green space. These studies found that green space-mental health associations have been positive in more deprived areas in some studies (Flouri et al., 2018; McEachan et al., 2016; Mitchell et al., 2015), while others have found no effect (Nichani et al., 2017; Sugiyama et al., 2016; Triguero-Mas et al., 2015).

Confounding bias in studies of deprivation as a green space-mental health effect modifier can be partially addressed by using approaches, that only uses within-person variation, such as fixed-effect models (Bärnighausen et al., 2017; Gunasekara et al., 2014). Conceptually fixed-effect models treat a person's mean health and exposures through multiple responses in time as a control for their outcome, exposures, and effect modifiers as recorded in each response (Quintana, 2021). This type of approach can be used to study deprivation as a green space and mental health effect modifier. Although, fixed-effects models are not longitudinal, by them only modelling within-person change, it addresses time-stable confounding, which is one of the cited reasons for needing more longitudinal green space and health research (Howard et al., 2017; Marselle et al., 2021; Nguyen et al., 2021). Some studies have used fixed-effects models to associate mental health and residential green space exposure, where exposure variation comes through moving their home address. Most of these found positive associations (Alcock et al., 2015; Cleary et al., 2019; Gubbels et al., 2016; Krekel et al., 2016; White et al., 2013), while one did not (Noordzij et al., 2020). The latter studies' authors consider that there may not have been enough within-person variation to detect significant effects of the same size as previous studies. It is important to note that while internal validity can be increased by this approach, by completely controlling for time-invariant confounding, it is often at the sacrifice of external validity. This is due to the people whose residential green space exposure changing being the only ones contributing to the estimated impact of residential green space (and socioeconomic deprivation). Therefore, this evidence can be seen as complementary to the cross-sectional evidence base.

We are unaware of studies investigating whether local area socio-economic deprivation change modifies associations between green space change and mental health. Should green space-mental health associations be stronger in more socioeconomically deprived areas, providing or protecting green space in these areas could reduce health inequalities, particularly in the UK, where health disparities amongst different socioeconomic groups are widening (Marmot, 2020). Here we present multiple fixed-effects analyses of participants in the Understanding Society cohort (Institute for Social and Economic Research, 2021) in Great Britain to address this knowledge gap. We hypothesise that: (i) higher levels of exposure to residential green space improves mental health. (ii) Increased local area deprivation positively modifies this green space-mental health association.

2. Materials and methods

2.1. Study area, population and data source

Our study population was all participants in Understanding Society (US) – The UK Household Longitudinal Study 2009–2019 (waves 1–9) living in Great Britian (GB). We excluded responses from Northern Ireland that were outside the domain of our effect modifier and any response that missing information on model variables due to survey non-response. We also excluded respondents that only participated in one wave as they would provide no within-person variation to model. US is one of the world's largest panel surveys (Turek et al., 2021), and an extension of the earlier British Household Panel Survey (BHPS) (Institute for Social and Economic Research, 2018). Our study area is highly urbanized, with 83 % of the population living in urban areas in 2019 (Government Office for Science, 2021). Inequality of disposable income in the UK is ranked fourth highest amongst OECD states with very high income (OECD, 2024).

Each US participant was interviewed approximately yearly for each wave, across a 24 months data collection window (Institute for Social and Economic Research, 2021). The US was initially designed in 2009 to be a representative sample of the UK population. The general population sample in Great Britain was identified through a two-step process. First, postcode sectors (and smaller aggregations) were classified based on government regions, population density, and the proportion of individuals from various ethnicities and socioeconomic statuses (Lynn, 2009). These classifications were used to stratify the sampling. A random selection of these postcode districts, weighted by the number of addresses they contained, was then identified as the primary sampling units from which respondents were recruited. A smaller number of individuals from the BHPS and a "boost sample" of target ethnic minorities are also included from the outset of US (Lynn et al., 2023). We managed this data using the R packages "data.table" and "dplyr" (Dowle et al., 2019; Wickham et al., 2022).

2.2. Health outcome

Our outcome of interest was the participant's score on the Mental Component Summary of the Short-Form 12 Health Survey. This mental health score is on a scale of 0–100, with higher scores representing better mental health. It is calculated from answers to six questions, some Likert, some binary, on participants' feelings in the past four weeks focusing on vitality, social functioning, role-emotional and mental health (Ware et al., 1996, 2002). The score is widely used to measure mental health in epidemiological research and has a high specificity and sensitivity when detecting the prevalence of medically diagnosed mental illness in the general population (Vilagut et al., 2013).

2.3. Residential green space exposure

We defined green space exposure as the percentage of land within 1,600 m (m) of each US participant's wave-specific household Lower Layer Super Output Area (LSOA) Population Weighted Centroid (PWC) covered in vegetation. A US participant's household wave specific LSOA was identified through postcodes that US interviewers record during each wave. A 1,600 m distance buffer is at the upper end of commonly used buffers in epidemiological studies (Kondo et al., 2018; van den Berg et al., 2015) and has been shown to be more sensitive to the modifying effect of deprivation in a previous systematic review (Rigolon et al., 2021). 1,600 m approximates a maximum 20-minute walk. We used buffers from the PWC rather than the proportional coverage of LSOAs to better represent a person's activity radius. LSOAs are census boundaries constructed to reflect relatively equal number of residents. This means that their area is very large in rural areas and potentially very small in urban areas and, therefore, not appropriate to assess green space exposure in a comparable way across US participants.

We defined green space as vegetated land (all classes of woodland, arable, grassland, fen, heather, and bog) according to the UK Centre for Ecology and Hydrology Land Use Map 2017 (UKCEH-LCM 2017) (Morton et al., 2020) (20 x 20 m resolution) or land with over 50 % tree cover according to Copernicus Land Monitoring service Very High-Resolution Layer – Tree Cover Density (Copernicus TCD) product (European Environment Agency, 2018) (20 x 20 m resolution). We used both products as tree cover outside woodland is a typical green space exposure in cities and can, for example, identify street trees (Salmond et al., 2016). We extracted the percentage coverage of the summed pixel fractions for each buffer, which we define as residential green space. As with earlier studies, we assumed green space to be static over time and that exposure change only occurred when a respondent moved to a different LSOA (White et al., 2013). Prior land cover products had a lower resolution which might lead to misclassification of smaller green space patches. We completed our exposure assessment using R's packages "raster", "exactextractr", and "sf" (Dowle et al., 2019; Hijmans et al., 2019; Pebesma, 2018; R Core Team, 2019).

2.4. Socioeconomic deprivation as effect modifier

We assessed effect modification by local area deprivation using the continuous Carstairs index of socioeconomic deprivation of each participant's wave-specific LSOA (Carstairs and Morris, 1990). The Carstairs index is frequently used in epidemiological analyses to represent socioeconomic deprivation across GB. The Carstairs index is a composite area-level measure of deprivation and is calculated from UK census variables related to the proportion of male unemployment, lack of car ownership, overcrowding, and low social class. We used the 2011 Carstairs index at it matched most closely the US waves (2009–2019). Rather than using a buffer around the PWC of an LSOA to identify nearby Carstairs index derived deprivation (as we did for residential green space), we used the Carstairs index of the LSOA a person resided in. This is due to LSOAs being created based on the socioeconomic similarity of their populations going back to the first census's (Dibben, 2016). Like green space, we assumed that an area's socioeconomic deprivation score stayed the same over time and that any change in local area deprivation was due to individuals moving to a different LSOA.

2.5. Covariates

We selected covariates a priori including time-varying factors that are plausibly corelated with within-person changes in residential green space exposure and have previously been shown to be strongly associated with health and/or directly linked to trade-offs when choosing a new area where to live.

2.5.1. Major health determinants

Older age, becoming unemployed and having less individual disposable income is associated with major negative mental health changes (Nagasu and Yamamoto, 2020). These factors may also plausibly correlate with within-person changes in green space exposure and local area deprivation after moving LSOA. We, therefore, included wave-specific age quintile, job status (categorized as employed, unemployed or outside workforce) and individual disposable income as possible confounders.

We created quintiles of age across all responses before excluding any incomplete cases from the data. Incomplete cases are those that lacked information on our outcome of interest, exposure, or potential confounding variables. The age groups were defined as: 15- years (reference group), 31–42 years, 43–52 years, 53–65 years, and 66–102 years.

We categorised individuals' employment status declared to US to aid interpretation as follows: employed (those declaring their wave specific status as "self-employed" or "employed"), unemployed (self-declared "unemployed") and outside workforce (self-declared "retired", "on maternity leave", "in family care of home", "full-time student", "LT sick or disabled", "inside government training scheme", "in unpaid work", "on apprenticeship", or "doing something else").

We followed the US-recommended approach to calculating individual disposable income (Institute for Social and Economic Research, 2021) as household income minus outgoings for rent or mortgage, divided by an OECD-equivalence factor based on the number of children and adults per household, deflated to a 2015 base year using the UK consumer price index.

2.5.2. Trade-offs with having more residential green space

Some participants may trade off the economic cost of moving to a greener neighbourhood (Belcher et al., 2019) against other home characteristics (Stevenson et al., 2016), which may impact their mental health. These factors may potentially confound green space-mental health associations and therefore we have included them in adjusted models.

2.5.2.1. Survey covariates. We, included the following wave-specific factors which are potentially correlated with a change in green cover caused by moving and also impact mental health:: (i) bedrooms per person (Pierse et al., 2016), and (ii) commute time (categorized as 0 – 15 min, 15 – 30 min, 30 – 60 min, >60 min or no commute information) (Feng and Boyle, 2014), We calculated the number of bedrooms per person by dividing the household bedrooms in each wave by the number of household residents.

2.5.2.2. Area level covariates. Population density is inversely correlated with green space (Fuller and Gaston, 2009) and correlated with many aspects of the urban environment that impact health (Beenackers et al., 2018). Areas of high population density, for example, often have better access to active transport facilities, encouraging physical activity and positively impacting health (Stevenson et al., 2016). We calculated the area-weighted mean population per pixel (100 x 100 m resolution) within 1,600 m of each individual's wave-specific LSOA from the 2011 WorldPop product (Lloyd et al., 2017), which is calculated from 2011 UK census data, using R's packages "raster", "exactextractr" and "sf" (Dowle et al., 2019; Hijmans et al., 2019; Pebesma, 2018; R Core Team, 2019).

We excluded other area level environmental factors that impact mental health but are also mediators between residential green space and mental health through the provision of ecosystem services, for example urban heat and air quality (Richards et al., 2022; Tan et al., 2020).

2.6. Statistical methods

We ran fixed-effects models to investigate whether a change in a person's residential green space exposure (from moving residence) was associated with changes in their mental health and whether changes in their local area deprivation (from moving residence) modified this. By design, fixed-effects models do not model differences between persons (or groups) but differences (changes) within persons, impacting the interpretation of coefficients (Quintana, 2021) We also only obtain variation in green space from home movers who may have different demographics than the general population, and or tendency to benefit from green space exposure, which may further impact coefficient interpretation.

2.6.1. Determining change using within-person differences

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

Changes in residential green space, local area deprivation, and population density in this analysis come from moving to an address in a different LSOA between responses. Other covariates, such as a person's income or marital status, may vary between waves.

Participants that only had one response were removed from our analysis because at least two waves per person were needed to model change from the within-person mean. We also excluded cases where health outcome, green space exposure, or effect modifier information was missing, because of question non-response or mistakes in survey administration or participants residing in Northern Ireland (outside our exposure and effect modifier data domain).

2.6.2. Modelling approach

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

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

Table 1
Variables used in statistical models.

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

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

3. Results

The final sample included 300,710 responses from 54,666 US participants, out of a possible 409,863 responses from 86,094 individuals. Individuals participated for an average of 4.8 waves across a potential 9 waves (Table 2). Less than one-quarter of respondents (12,385 or 23 %) moved LSOA at least once and therefore had variation in their green space or local area deprivation exposure (Table 3). There was a balance of US participants' mental health, green space and socioeconomic deprivation increasing or decreasing (Fig. 1). The change in mental health, residential green space, and local area deprivation was approximately normally distributed (Fig. 1). The standard deviation of change in mental health score, residential green space, and local area deprivation was 6.40, 5.98, and 0.75, respectively. Within-person increases in green space were moderately negatively correlated with within-person decreases in local area deprivation and population density (r = -0.41 and −0.72, respectively, see supplementary materials I).

The median value and Inter Quartile Range (IQR) of continuous model variables was broadly the same between all respondents, and those that moved LSOA at least once or twice (Table 4). The distribution of age moved towards younger age categories in the sub-sample of movers. For example, the percentage of people aged 15–30 jumped from 19.7 % for all respondents to 32.8 % and 46.5 % for those that moved once or twice respectively. Movers also tended to be less likely to be employed, but when they had available commute information, more likely to commute longer (Table 4).

There was a balance of US participants' mental health, green space and socioeconomic deprivation increasing or decreasing (Fig. 1). The change in mental health, residential green space, and local area deprivation was approximately normally distributed (Fig. 1). The standard deviation of change in mental health score, residential green space, and local area deprivation was 6.40, 5.98, and 0.75, respectively. Within-person increases in green space were moderately negatively correlated with within-person decreases in local area deprivation and population density (r = -0.41 and −0.72, respectively, see supplementary materials I).

In univariate analysis, we found no significant association between residential green space change and mental health score change (Model 1 in Table 5). However, after adjusting for potential confounders, the association between residential green space change and mental health

Table 2
The number of waves per participant in our final dataset. We removed individuals with less than two waves and missing information on explanatory variables and confounders.

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

Table 3
The number of times US participants moved their LSOA during the nine understanding society waves.

Number of times moved LSOA	Number of individuals	Percentage of individuals
0	42,281	77.34
1	9,271	16.96
2	2,246	4.11
3	630	1.15
4	194	0.35
5	36	0.07
6	8	0.01

score change was significant and positive (Model 2 in Table 5). Local area deprivation change had a significant ($p < 0.05$) positive modifying effect on the mental health score change – residential green space change association (Model 3 in Table 5). Johnson-Neyman intervals revealed that the slope of residential green space change significantly differed from zero when local area deprivation increased by more than −0.09 in Model 3. Potential socioeconomic confounders had the expected direction of association when statistically significant (Fig. 3).

4. Discussion

We found a significant positive association between changes in home movers residential green space and changes in mental health after adjusting for potential covariate confounders. This finding aligns with the majority of previous research investigating residential green space and mental health associations cross-sectionally (Kondo et al., 2018; Twohig-Bennett and Jones, 2018) and using within-person variation (Cleary et al., 2019; Gubbels et al., 2016, 2016; Krekel et al., 2016), including those conducted on home movers in the BHPS which Understanding Society is an extension of Alcock et al. (2015), White et al. (2013). Our finding adds to the evidence supporting creating and protecting green spaces for public health in the UK.

We also found a significant positive modifying effect of local area deprivation change on the green space change and mental health score change association. This finding aligns with the few previous cross-sectional studies (Rigolon et al., 2021). However, the slope of residential green space was only significant when deprivation stayed constant or increased, as revealed by Johnson-Neyman intervals (Fig. 2). This indicates that for residential green space to have an increased effect the area where a person moved to needs to be more deprived relative to their historical average local area deprivation exposure. Furthermore, decreasing a person's residential green space exposure (again, through moving) had a minor impact on their mental health unless local area deprivation also increased (effect size near zero, Fig. 3).

Our results, contingent on the direction of deprivation change and the amount of deprivation change, have a few possible explanations. If an individual's mental health is impacted from moving to a more deprived area, they may be more amenable to the restorative benefits of residential green space. This is something supported by experimental evidence grounded in ART and SRT whereby individuals are first given a stressor before the restorative benefits of green space can be detected (Kaplan and Berman, 2010; Ulrich, 1983). Furthermore, empirical studies have found nature to buffer stressful life events and adversity more generally (Wells, 2021). This is related to previous work that people in less socioeconomically deprived areas have a higher baseline mental health status, that is much harder to improve, for example by providing more residential green space (Rigolon et al., 2021). Secondly, an individual's mental health may be damaged if an individual feels forced to live in a particular geographic location that is both less green and more socioeconomically deprived to have access to work and/or family (Morris et al., 2018). These may be the only places where these individuals can buy/rent a property of the required size and within a travelling distance needed to be near work and family. Additionally, the probability of encountering the effects of local area deprivation (for example, crime and violence, lack of resources) may also be lower in a greener area due to there being fewer built-up surfaces that can show apparent signs of deprivations effects (Bellis et al., 2008; Rees-Punia et al., 2018). Lastly, those living in less deprived areas could have the

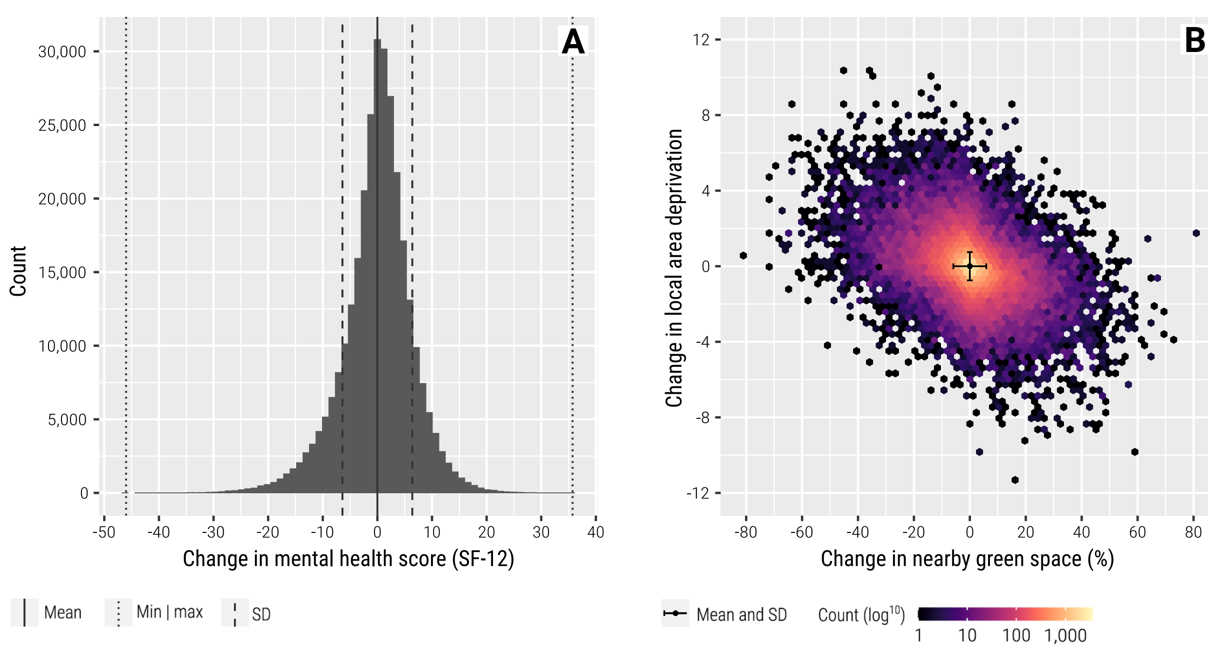

Fig. 1. Distribution of change in outcome (A) and exposure and effect modifier (B). Each n is one score (from one wave). (A) Histogram of change from within-person mean mental health score (the mental score component of the SF-12 survey) n = 300,710. (B) density plot of change in local area deprivation scores (Carstairs index) and residential green space from their respective within-person mean, n = 78,065. We removed 222,645 points (74 % of all responses) in (B) from individuals who did not change LSOA for display purposes only. The minimum and maximum deprivation score change was −11.2 and 10.3, respectively. The minimum and maximum green space change was −80.9 and 81.2, respectively. Density counts in plot B are on a log-10 scale. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 4
Difference in model continuous variable median and Inter Quartile Range (IQR) values and the categorical variable percentage in each category for: all responses (All) and responses where a participant moved at least once (1 +) or twice (2 +).

Explanatory variable	Median			IQR			Percent in categories		
	All	1+	2+	All	1+	2+	All	1+	2+
Mental health score (sf-12)	51.8	50.7	49.4	43.9–57.1	42.8–56	41.5–55			
Residential green space (%)	48.6	46.8	44.2	29.7–68.9	28.7–67.2	26.9–66.1			
Local area deprivation (Carstairs score)	−0.871	−0.879	−0.735	−2.53–1.88	−2.48–1.74	−2.4–1.66			
Population density (residents per ha)	11.6	12.3	13.2	5.4–20.1	5.91–20.8	6.42–22.2			
Residents per bedroom	1	1	1	0.75–1.5	0.75–1.5	0.75–1.5			
Disposable household income (£)	1,340	1,310	1,240	902–1,920	852–1,900	783–1820			
Age									
7 %							19.7	32.8	46.5
31 – 42 years							20.3	29.5	29.6
43 – 52 years							19	15.3	11.9
53 – 65 years							21.2	13.6	8.69
66 – 102 years							19.8	8.94	3.33
Employment status									
Unemployed							56.1	64.7	67.2
Employed							39.4	29.8	26.3
Outside workforce							4.55	5.45	6.45
Commute time									
0 – 15 min							20.2	22	22.2
15 – 30 min							15.3	18.5	20
30 – 60 min							10.1	13.3	15.3
>60 min							2.36	3.2	3.76
No commute information							52	43	38.7

Table 5
Coefficients and 95% Confidence Intervals (CI) from the fixed-effects models. Coefficients are predicted for each model explanatory variable's one-unit increase relative to each respective variable within-person mean.

Explanatory variable	Model 1			Model 2			Model 3		
	Est.	CI	*p*-value	Est.	CI	*p*-value	Est.	CI	*p*-value
Residential green space (%)	0.00418	−0.000119 – 0.00848	0.057	0.0069	0.000589 – 0.0132	0.032	0.0069	0.000209 – 0.0128	0.32
Local area deprivation (Carstairs score)				−0.0482	−0.0871 – -0.0117	0.01	−0.0481	−0.0857 – -0.0103	0.013
Residential green space*local area deprivation							0.00273	0.0000939 – 0.00537	0.04
Population density (residents per ha)				0.00695	−0.00523 – 0.0191	0.292	0.00735	−0.00483 – 0.0195	0.237
Residents per bedroom				−0.31	−0.393 – -0.231	<0.001	−0.309	−0.258 – -0.0886	<0.001
Disposable household income (£1,000′s)				0.0134	−0.00287 – 0.0297	0.138	0.0134	−0.00295 – 0.0297	0.108
Age									
15 – 30 years (reference)				—	—	—	—	—	—
31 – 42 years				−1.72	−1.91 – -1.52	<0.001	−1.72	−1.91 – -1.52	<0.001
43 – 52 years				−2.67	−2.93 – -2.42	<0.001	−2.67	−2.93 – -2.42	<0.001
53 – 65 years				−3.06	−3.36 – -2.75	<0.001	−3.06	−3.36 – -2.76	<0.001
66 – 102 year s				−3.16	−3.51 – -2.81	<0.001	−3.17	−3.52 – -2.81	<0.001
Employment status									
Unemployed (reference)				—	—	—	—	—	—
Employed				1.40	1.21 – 1.6	<0.001	1.4	1.21 – 1.60	<0.001
Outside workforce				1.29	1.11 – 1.46	<0.001	1.29	1.11 – 1.46	<0.001
Commute time									
0 – 15 min (reference)				—	—	—	—	—	—
15 – 30 min				−0.333	−0.456 – -0.209	<0.001	−0.333	−0.457 – -0.210	<0.001
30 – 60 min				−0.451	−0.602 – -0.299	<0.001	−0.451	−0.602 – -0.299	<0.001
>60 min				−0.475	−0.728 – -0.223	<0.001	−0.475	−0.728 – -0.223	<0.001
No commute information				−0.211	−0.354 – -0.0678	0.004	−0.211	−0.354 – -0.0676	0.004

disposable income to substitute poor green space access (and its health benefits) with paid gyms, for example. Therefore, the health benefits of having additional green space for them would be lower than in more deprived populations (Rigolon et al., 2021).

4.1. Strengths and limitations

Variation in green space and neighbourhood socioeconomic deprivation exposure was within respondents and came from individuals moving home. Only modelling within-person variation was the primary strength of this analysis, as it allowed us to control bias from between-person confounding. However, the act of moving itself could have an impact on health (Cheung and Wong, 2022). Future research should investigate the impact of changing levels of deprivation and residential green space on health within the same location.

Conducting a fixed-effects analysis by demeaning our model

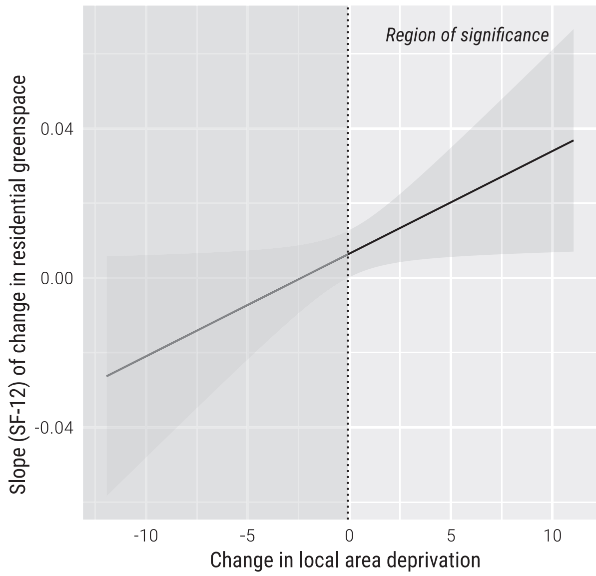

Fig. 2. Johnson-Neyman plot showing the effect modification by change in local area deprivation on change in residential green space and change in mental health associations with adjustment for potential confounders (Model 3). Johnson-Neyman intervals are used to indicate at what values of an effect modifier an associate has a significant association with an outcome. All values have been demeaned within persons, showing the effect of change of each wave response from the multi-wave within-person means. The region of significance indicates the levels of change in local area deprivation where the slope of residential green space is significantly different from zero.

variables with a simple linear regression allowed us a greater number of degrees of freedom with which to estimate associations than would be possible using, for example trends over time using a first difference estimator (Wooldridge, 2010). However, this assumed that each yearly exposure to residential green space and local area deprivation was an individual exposure–response event. However, there may be cumulative or adaptive effects from living in an environment for more than one year, although this has not been found in one study (Alcock et al., 2014). For example, a respondent's first year of exposure to more residential green space after moving may be associated with only temporary mental health improvements, but their mental health may return to pre-move levels in subsequent years. In this case, our model predicted associations might underestimate green space benefits in the first year after moving and overestimate them later.

We may not have identified all time-variant confounders and effect modifiers (such as ethnicity and urbanicity) which could potentially bias associations. Variation in respondent green space and socioeconomic deprivation was due to them moving home, and the characteristics of movers differed slightly to that of our overall sample which was more representative of the general population. Specifically, movers were more likely to be younger, not employed and when employed, commute longer times to work. As the underlying population of movers had a slightly different demographic profile, the mental health response to a change in green space on its own and under effect modification from deprivation may be different for a more representative general population sample. This could be investigated in the future as another effect modifier.

We may have potentially misclassified an individual's true exposure to green space, by using the percentage of all green space within 1,600 m of a respondents LSOA PWC as an approximation for their actual exposure. Many people do not use residential green spaces, so the expected mental health impact on those who do will likely be underestimated. However, this information was not available in Understanding Society. A buffer distance of 1,600 m assumes that these green spaces are the ones truly available to our sample, however, many people will lack the ability to travel that distance. Furthermore, we did not have the residential address of respondents, and had to use their LSOA PWC as a proxy for where they live. We chose the buffer distance based on it being sensitive to the modifying effect of socioeconomic deprivation in previous studies (Rigolon et al., 2021), it representing a 20-minute walk and it being at the upper end of previous studies (Kondo et al., 2018; van den Berg et al., 2015), which is relevant due to recent research finding people travel further to their nearest green space than previously thought (Schindler et al., 2022). Furthermore, using our LSOA PWC availability approach, avoided the modifiable areal unit problem presented in previous similar studies that use the percentage of green space within LSOAs (Alcock et al., 2014; Bu et al., 2022; Cummins

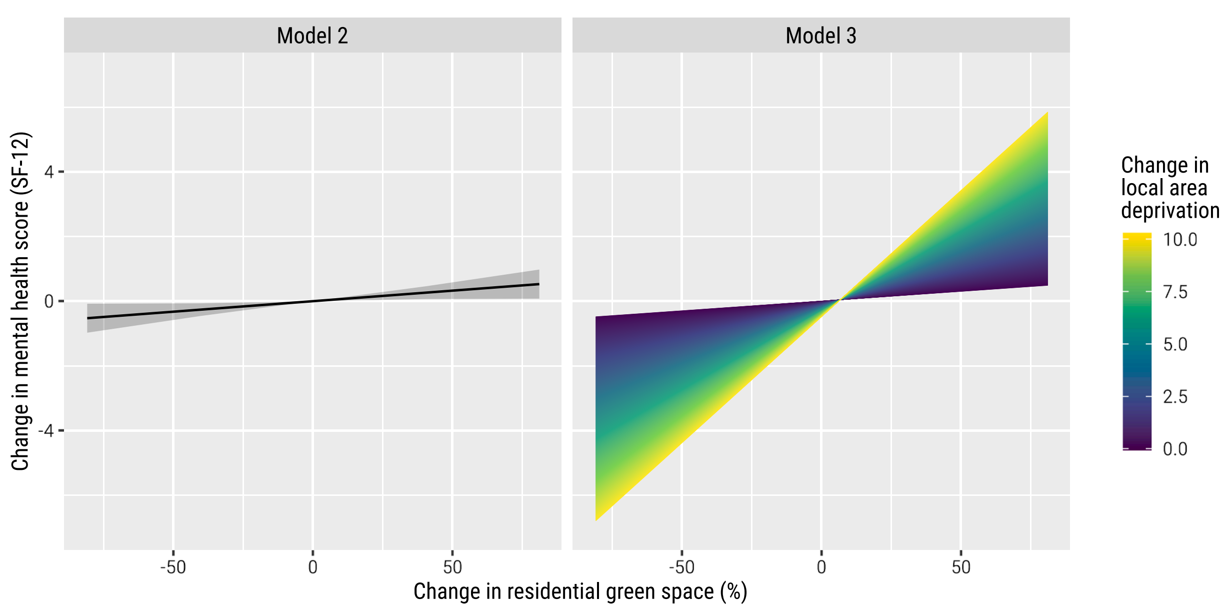

Fig. 3. Predicted associations between residential green space change and mental health score change under effect modification from a change in local area deprivation (see definitions in Methods). All values have been demeaned within persons, showing the effect of a change from the within-person means. The predicted model 3 surface is clipped to values where the slope of change in residential green space significantly differs from zero according to Johnson-Neyman intervals (see Fig. 2). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

and Fagg, 2012; Dennis et al., 2020; Dennis and James, 2017; Mytton et al., 2012; White et al., 2019). We did not differentiate between different types of green space, for example, arable land and forests, or use other green space exposure indicators such as neighbourhood greenness. It may be that certain green space types have a different association with health or are modified differently by local area deprivation.

We used a combination of 20 m x 20 m land cover maps to assess green space exposure for one time point, the UKCEH-LCM 2017 and the Copernicus TCD map (European Environment Agency, 2018; Morton et al., 2020). This allowed us to quantify exposure to smaller green space patches, which can be important residential green space exposures (e.g., street trees). However, only having a land cover map covering one time-point (as opposed to many of different time points) was a limitation as it makes the assumption that a local area's green space did not change over time. This may introduce misclassifications of residential green space, for example, if there was dynamic land cover change throughout the 9 Understanding Society waves. However, change in green space cover of GB cities (where most people live) is relatively stable, with a median change of 5 % between 2000 and 2015 (Richards and Belcher, 2020). We also assume that deprivation did not change during our study period. Although, area-level deprivation has been shown to be stable over time (Norman, 2010) this might not be the case for each LSOA due to local development. This might have introduced misclassification. Lastly, as we did not have the residential address of respondents, we needed to identify exposure from their LSOA PWC.

4.2. Recommendations

Our findings support conserving and providing green space in more deprived areas to address health disparities across a deprivation gradient—a global population health issue (UN General Assembly, 2015), evident in the UK (Marmot, 2020) and also a key to the United Nations Sustainable Development Goal (SDG) 11.7 to provide "universal access to green and public spaces" (UN General Assembly, 2015). The moderate negative correlation between change in residential green space and change in local area deprivation shows that individuals moving to a more deprived area are less likely to have green space nearby. It also adds to cross-sectional evidence that green space provision is lower in more deprived areas (Ridgley et al., 2020). We recommend caution on extrapolating these results to outside of the UK, due to the impact of how green space is used across different cultures and climates.

5. Conclusion

This is one of the relatively few studies that investigate how a change in local area deprivation modifies the benefits to mental health from changing residential green space exposure, which varied due to individuals moving to a different local area. By using a fixed-effects approach, our findings add robustness to the limited cross-sectional evidence that green space is more beneficial to the mental health of those living in (or moving to) more deprived areas. We also add to the broader evidence that adding green space to socioeconomically deprived areas can reduce inequalities in health. These findings support calls from international bodies such as the World Health Organization and the United Nations SDG 11.7 to provide universal access to urban green space by 2030.

Funding statement

This work was supported by the UK Natural Environment Research Council grant number NE/S007415/1. This work was partly supported by the MRC Centre for Environment and Health, which is funded by the Medical Research Council (MR/S019669/1). Infrastructure support for the Department of Epidemiology and Biostatistics was provided by the National Institute for Health Research (NIHR) Imperial Biomedical Research Centre (BRC). DF acknowledges funding from the National Institute for Health and Care Research (NIHR) Health Protection Research Unit in Chemical and Radiation Threats and Hazards (NIHR-200922), a partnership between UK Health Security Agency (UKHSA) and Imperial College London. The views expressed are those of the author(s) and not necessarily those of the NIHR, UKHSA, MRC or the Department of Health and Social Care. The funding sources had no role in the design of this study nor its execution, analyses, interpretation of the data, or decision to submit the results.

CRediT authorship contribution statement

Richard N. Belcher: Writing – review & editing, Writing – original draft, Visualization, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Kris A. Murray:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Jonathan P. Reeves:** Writing – review & editing, Supervision, Resources, Funding acquisition, Conceptualization. **Daniela Fecht:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

Acknowledgements

We would like to thank Dr Francesca McGrath for proofreading and feedback on ideas in the manuscript, and Dr Daniel R Richards for his thoughts on the analysis.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envint.2024.109036.

References

Abadie, A., Athey, S., Imbens, G.W., Wooldridge, J., 2017. When should you adjust standard errors for clustering? National Bureau of Economic Research.

European Environment Agency, 2018. Tree Cover Density 2015 (raster 20 m), Europe, 3-yearly, Mar. 2018.

Alcock, I., White, M.P., Lovell, R., Higgins, S.L., Osborne, N.J., Husk, K., Wheeler, B.W., 2015. What accounts for 'England's green and pleasant land'? A panel data analysis of mental health and land cover types in rural England. Landsc. Urban Plan., Special Issue: Critical Approaches to Landscape Visualization 142, 38–46. https://doi.org/10.1016/j.landurbplan.2015.05.008.

Alcock, I., White, M.P., Wheeler, B.W., Fleming, L.E., Depledge, M.H., 2014. Longitudinal Effects on Mental Health of Moving to Greener and Less Green Urban Areas. Environ. Sci. Technol. 48, 1247–1255. https://doi.org/10.1021/es403688w.

Astell-Burt, T., Feng, X., Kolt, G.S., 2013. Mental health benefits of neighbourhood green space are stronger among physically active adults in middle-to-older age: evidence from 260,061 Australians. Prev. Med. 57, 601–606. https://doi.org/10.1016/j.ypmed.2013.08.017.

Bärnighausen, T., Oldenburg, C., Tugwell, P., Bommer, C., Ebert, C., Barreto, M., Djimeu, E., Haber, N., Waddington, H., Rockers, P., Sianesi, B., Bor, J., Fink, G., Valentine, J., Tanner, J., Stanley, T., Sierra, E., Tchetgen, E.T., Atun, R., Vollmer, S., 2017. Quasi-experimental study designs series—paper 7: assessing the assumptions. J. Clin. Epidemiol. 89, 53–66. https://doi.org/10.1016/j.jclinepi.2017.02.017.

Bauer, D.J., Curran, P.J., 2005. Probing Interactions in Fixed and Multilevel Regression: Inferential and Graphical Techniques. Multivar. Behav. Res. 40, 373–400. https://doi.org/10.1207/s15327906mbr4003_5.

Belcher, R.N., Suen, E., Menz, S., Schroepfer, T., 2019. Shared landscapes increase condominium unit selling price in a high-density city. Landsc. Urban Plan. 192, 103644. https://doi.org/10.1016/j.landurbplan.2019.103644.

Bellis, M.A., Hughes, K., Anderson, Z., Tocque, K., Hughes, S., 2008. Contribution of violence to health inequalities in England: demographics and trends in emergency hospital admissions for assault. J. Epidemiol. Community Health 62, 1064–1071. https://doi.org/10.1136/jech.2007.071589.

Bu, F., Mak, H.W., Steptoe, A., Wheeler, B.W., Fancourt, D., 2022. Urban greenspace and anxiety symptoms during the COVID-19 pandemic: A 20-month follow up of 19,848 participants in England. Health Place 77, 102897. https://doi.org/10.1016/j.healthplace.2022.102897.

Carstairs, V., Morris, R., 1990. Deprivation and health in Scotland. Health Bull. (edinb.) 48, 162–175.

Cheung, K.-S., Wong, D., 2022. Measuring the Stress of Moving Homes: Evidence from the New Zealand Integrated Data Infrastructure. Urban Sci. 6, 75. https://doi.org/10.3390/urbansci6040075.

Cleary, A., Roiko, A., Burton, N.W., Fielding, K.S., Murray, Z., Turrell, G., 2019. Changes in perceptions of urban green space are related to changes in psychological well-being: Cross-sectional and longitudinal study of mid-aged urban residents. Health Place 59, 102201. https://doi.org/10.1016/j.healthplace.2019.102201.

Collins, P.Y., Patel, V., Joestl, S.S., March, D., Insel, T.R., Daar, A.S., Bordin, I.A., Costello, E.J., Durkin, M., Fairburn, C., Glass, R.I., Hall, W., Huang, Y., Hyman, S.E., Jamison, K., Kaaya, S., Kapur, S., Kleinman, A., Ogunniyi, A., Otero-Ojeda, A., Poo, M.-M., Ravindranath, V., Sahakian, B.J., Saxena, S., Singer, P.A., Stein, D.J., Anderson, W., Dhansay, M.A., Ewart, W., Phillips, A., Shurin, S., Walport, M., 2011. Grand challenges in global mental health. Nature 475, 27–30. https://doi.org/10.1038/475027a.

Dowle, M., Srinivasan, A., Gorecki, J., Chirico, M., Stetsenko, P., Short, T., Lianoglou, S., Antonyan, E., Bonsch, M., Parsonage, H., Ritchie, S., Ren, K., Tan, X., Saporta, R., Seiskari, O., Dong, X., Lang, M., Iwasaki, W., Wenchel, S., Broman, K., Schmidt, T., Arenburg, D., Smith, E., Cocquemas, F., Gomez, M., Chataignon, P., Groves, D., Possenriede, D., Parages, F., Toth, D., Yaramaz-David, M., Perumal, A., Sams, J., Morgan, M., Quinn, M., @javrucebo, @marc-outins, Storey, R., Saraswat, M., Jacob, M., Schubmehl, M., Vaughan, D., 2019. data.table: Extension of "data.frame.".

Cummins, S., Fagg, J., 2012. Does greener mean thinner? Associations between neighbourhood greenspace and weight status among adults in England. Int. J. Obes. 36, 1108–1113. https://doi.org/10.1038/ijo.2011.195.

Dennis, M., Cook, P.A., James, P., Wheater, C.P., Lindley, S.J., 2020. Relationships between health outcomes in older populations and urban green infrastructure size, quality and proximity. BMC Public Health 20, 626. https://doi.org/10.1186/s12889-020-08762-x.

Dennis, M., James, P., 2017. Evaluating the relative influence on population health of domestic gardens and green space along a rural-urban gradient. Landsc. Urban Plan. 157, 343–351. https://doi.org/10.1016/j.landurbplan.2016.08.009.

Dibben, C., 2016. The Routledge Handbook of Census Resources, Methods and Applications.

Feng, Z., Boyle, P., 2014. Do long journeys to work have adverse effects on mental health? Environ. Behav. 46, 609–625. https://doi.org/10.1177/0013916512472053.

Fox, J., Weisberg, S., 2019. An R Companion to Applied Regression, 3rd ed. Sage, Thousand Oaks CA.

Flouri, E., Papachristou, E., Midouhas, E., 2018. The role of neighbourhood greenspace in children's spatial working memory. Br. J. Psychol. 359–373. https://doi.org/10.1111/bjep.12243. @10.1111/(ISSN)2044-8295.EFPAEuropeanSemesterofPsychologyVI.

Fox, J., Weisberg, S., 2018. Visualizing Fit and Lack of Fit in Complex Regression Models with Predictor Effect Plots and Partial Residuals. J. Stat. Softw. 87, 1–27. https://doi.org/10.18637/jss.v087.i09.

Fuller, R.A., Gaston, K.J., 2009. The scaling of green space coverage in European cities. Biol. Lett. 5, 352–355. https://doi.org/10.1098/rsbl.2009.0010.

Giesselmann, M., Schmidt-Catran, A.W., 2020. Interactions in Fixed Effects Regression Models. Sociol. Methods Res. 0049124120914934. https://doi.org/10.1177/0049124120914934.

Government Office for Science, 2021. Trend Deck 2021: Urbanisation. https://www.gov.uk/government/publications/trend-deck-2021-urbanisation/trend-deck-2021-urbanisation (accessed 7.16.24).

Gubbels, J.S., Kremers, S.P.J., Droomers, M., Hoefnagels, C., Stronks, K., Hosman, C., de Vries, S., 2016. The impact of greenery on physical activity and mental health of adolescent and adult residents of deprived neighborhoods: A longitudinal study. Health Place 40, 153–160. https://doi.org/10.1016/j.healthplace.2016.06.002.

Gunasekara, F.I., Richardson, K., Carter, K., Blakely, T., 2014. Fixed effects analysis of repeated measures data. Int. J. Epidemiol. 43, 264–269. https://doi.org/10.1093/ije/dyt221.

Hijmans, R.J., Etten, J. van, Sumner, M., Cheng, J., Bevan, A., Bivand, R., Busetto, L., Canty, M., Forrest, D., Ghosh, A., Golicher, D., Gray, J., Greenberg, J.A., Hiemstra, P., Geosciences, I. for M.A., Karney, C., Mattiuzzi, M., Mosher, S., Nowosad, J., Pebesma, E., Lamigueiro, O.P., Racine, E.B., Rowlingson, B., Shortridge, A., Venables, B., Wueest, R., 2019. raster: Geographic Data Analysis and Modeling.

Houlden, V., Weich, S., de Albuquerque, J.P., Jarvis, S., Rees, K., 2018. The relationship between greenspace and the mental wellbeing of adults: A systematic review. PLOS ONE 13, e0203000.

Howard, F., N., B.G., Jo, B.S., Bobby, C., H., K.J.P., Lawler Joshua J., Levin Phillip S., Tandon Pooja S., Varanasi Usha, Wolf Kathleen L., Wood Spencer A., 2017. Nature Contact and Human Health: A Research Agenda. Environ. Health Perspect. 125, 075001. Doi: 10.1289/EHP1663.

Hunter, R.F., Christian, H., Veitch, J., Astell-Burt, T., Hipp, J.A., Schipperijn, J., 2015. The impact of interventions to promote physical activity in urban green space: A systematic review and recommendations for future research. Soc. Sci. Med. 124, 246–256. https://doi.org/10.1016/j.socscimed.2014.11.051.

Institute for Social and Economic Research, 2021. Understanding Society: Waves 1-11, 2009-2020 and Harmonised BHPS: Waves 1-18, 1991-2009, User Guide, 30 October 2021.

Institute for Social and Economic Research, 2018. British Household Panel Survey: Waves 1-18 [data collection]. https://doi.org/10.5255/UKDA-SN-5151-2.

Kaplan, S., Berman, M.G., 2010. Directed Attention as a Common Resource for Executive Functioning and Self-Regulation. Perspect. Psychol. Sci. 5, 43–57. https://doi.org/10.1177/1745691609356784.

Kondo, M.C., Fluehr, J.M., McKeon, T., Branas, C.C., 2018. Urban Green Space and Its Impact on Human Health. Int. J. Environ. Res. Public. Health 15. https://doi.org/10.3390/ijerph15030445.

Krekel, C., Kolbe, J., Wüstemann, H., 2016. The greener, the happier? The effect of urban land use on residential well-being. Ecol. Econ. 121, 117–127. https://doi.org/10.1016/j.ecolecon.2015.11.005.

Lloyd, C.T., Sorichetta, A., Tatem, A.J., 2017. High resolution global gridded data for use in population studies. Sci. Data 4, 170001. https://doi.org/10.1038/sdata.2017.1.

Long, J.A., 2019. interactions: Comprehensive, User-Friendly Toolkit for Probing Interactions.

Long, J.A., 2021. panelr: Regression Models and Utilities for Repeated Measures and Panel Data.

Lynn, P., 2009. Sample design for understanding society. Underst Soc Work Pap Ser 2009.

Lynn, P., Cabrera-Álvarez, P., Clarke, P., 2023. Sample composition and representativeness on Understanding Society. Fisc. Stud. 44, 341–359. https://doi.org/10.1111/1475-5890.12357.

Markevych, I., Thiering, E., Fuertes, E., Sugiri, D., Berdel, D., Koletzko, S., von Berg, A., Bauer, C.-P., Heinrich, J., 2014. A cross-sectional analysis of the effects of residential greenness on blood pressure in 10-year old children: results from the GINIplus and LISAplus studies. BMC Public Health 14, 477. https://doi.org/10.1186/1471-2458-14-477.

Marmot, M., 2020. Health equity in England: the Marmot review 10 years on. BMJ 368, m693. https://doi.org/10.1136/bmj.m693.

Marselle, M.R., Hartig, T., Cox, D.T.C., de Bell, S., Knapp, S., Lindley, S., Triguero-Mas, M., Böhning-Gaese, K., Braubach, M., Cook, P.A., de Vries, S., Heintz-Buschart, A., Hofmann, M., Irvine, K.N., Kabisch, N., Kolek, F., Kraemer, R., Markevych, I., Martens, D., Müller, R., Nieuwenhuijsen, M., Potts, J.M., Stadler, J., Walton, S., Warber, S.L., Bonn, A., 2021. Pathways linking biodiversity to human health: A conceptual framework. Environ. Int. 150, 106420. https://doi.org/10.1016/j.envint.2021.106420.

McEachan, R.R.C., Prady, S.L., Smith, G., Fairley, L., Cabieses, B., Gidlow, C., Wright, J., Dadvand, P., van Gent, D., Nieuwenhuijsen, M.J., 2016. The association between green space and depressive symptoms in pregnant women: moderating roles of socioeconomic status and physical activity. J. Epidemiol. Community Health 70, 253–259. https://doi.org/10.1136/jech-2015-205954.

Mitchell, R.J., Richardson, E.A., Shortt, N.K., Pearce, J.R., 2015. Neighborhood environments and socioeconomic inequalities in mental well-being. Am. J. Prev. Med. 49, 80–84. https://doi.org/10.1016/j.amepre.2015.01.017.

Morton, C.S., R. D;Marston, C.G. ;O'Neil, A. W;Rowland, 2020. Land Cover Map 2017 (20m classified pixels, GB). NERC Environmental Information Data Centre. Doi: 10.5285/f6f86b1a-af6d-4ed8-85af-21ee97ec5333.

Morris, T., Manley, D., Sabel, C.E., 2018. Residential mobility. Prog. Hum. Geogr. 42, 112–133. https://doi.org/10.1177/0309132516649454.

Mummolo, J., Peterson, E., 2018. Improving the Interpretation of Fixed Effects Regression Results. Polit. Sci. Res. Methods 6, 829–835. https://doi.org/10.1017/psrm.2017.44.

Mytton, O.T., Townsend, N., Rutter, H., Foster, C., 2012. Green space and physical activity: An observational study using Health Survey for England data. Health Place 18, 1034–1041. https://doi.org/10.1016/j.healthplace.2012.06.003.

Nagasu, M., Yamamoto, I., 2020. Impact of socioeconomic- and lifestyle-related risk factors on poor mental health conditions: A nationwide longitudinal 5-wave panel study in Japan. PLoS ONE 15, e0240240.

Nguyen, P.-Y., Astell-Burt, T., Rahimi-Ardabili, H., Feng, X., 2021. Green space quality and health: a systematic review. Int. J. Environ. Res. Public. Health 18, 11028. https://doi.org/10.3390/ijerph182111028.

Nichani, V., Dirks, K., Burns, B., Bird, A., Grant, C., 2017. Green Space and Depression during Pregnancy: Results from the Growing Up in New Zealand Study. Int. J. Environ. Res. Public. Health 14, 1083. https://doi.org/10.3390/ijerph14091083.

Noordzij, J.M., Beenackers, M.A., Groeniger, J.O., Lenthe, F.J.V., 2020. Effect of changes in green spaces on mental health in older adults: a fixed effects analysis. J. Epidemiol. Community Health 74, 48–56. https://doi.org/10.1136/jech-2019-212704.

Norman, P., 2010. Identifying Change Over Time in Small Area Socio-Economic Deprivation. Appl. Spat. Anal. Policy 3, 107–138. https://doi.org/10.1007/s12061-009-9036-6.

OECD, 2024. Income inequality. https://www.oecd.org/en/data/indicators/income-inequality.html (accessed 7.16.24).

Pathirana, T.I., Jackson, C.A., 2018. Socioeconomic status and multimorbidity: a systematic review and meta-analysis. Aust. N. Z. J. Public Health 42, 186–194. https://doi.org/10.1111/1753-6405.12762.

Pebesma, E., 2018. Simple Features for R: Standardized Support for Spatial Vector Data. R J. 10, 439–446.
Pedersen, T.L., 2020. patchwork: The Composer of Plots.
Pierse, N., Carter, K., Bierre, S., Law, D., Howden-Chapman, P., 2016. Examining the role of tenure, household crowding and housing affordability on psychological distress, using longitudinal data. J. Epidemiol. Community Health 70, 961–966. https://doi.org/10.1136/jech-2015-206716.
Prince, M., Patel, V., Saxena, S., Maj, M., Maselko, J., Phillips, M.R., Rahman, A., 2007. No health without mental health. The Lancet 370, 859–877. https://doi.org/10.1016/S0140-6736(07)61238-0.
Quintana, R., 2021. Thinking within-persons: Using unit fixed-effects models to describe causal mechanisms. Methods Psychol. 5, 100076. https://doi.org/10.1016/j.metip.2021.100076.
R Core Team, 2019. R: A Language and Environment for Statistical Computing.
Rees-Punia, E., Hathaway, E.D., Gay, J.L., 2018. Crime, perceived safety, and physical activity: A meta-analysis. Prev. Med. 111, 307–313. https://doi.org/10.1016/j.ypmed.2017.11.017.
Richards, D.R., Belcher, R.N., 2020. Global changes in urban vegetation cover. Remote Sens. 12, 23. https://doi.org/10.3390/rs12010023.
Ridgley, H., Hands, A., Lovell, R., Petrokofsky, C., Stimpson, A., Feeley, A., Bedford, A., Fenech, B., Leeman, D., Skykes, E., 2020. Improving access to greenspace A new review for 2020. Public Health Engl.
Rigolon, A., Browning, M.H.E.M., McAnirlin, O., Yoon, H. (Violet), 2021. Green Space and Health Equity: A Systematic Review on the Potential of Green Space to Reduce Health Disparities. Int. J. Environ. Res. Public. Health 18, 2563. Doi: 10.3390/ijerph18052563.
Richards, D.R., Belcher, R.N., Carrasco, L.R., Edwards, P.J., Fatichi, S., Hamel, P., Masoudi, M., McDonnell, M.J., Peleg, N., Stanley, M.C., 2022. Global variation in contributions to human well-being from urban vegetation ecosystem services. One Earth 5, 522–533. https://doi.org/10.1016/j.oneear.2022.04.006.
Salmond, J.A., Tadaki, M., Vardoulakis, S., Arbuthnott, K., Coutts, A., Demuzere, M., Dirks, K.N., Heaviside, C., Lim, S., Macintyre, H., McInnes, R.N., Wheeler, B.W., 2016. Health and climate related ecosystem services provided by street trees in the urban environment. Environ. Health 15, S36. https://doi.org/10.1186/s12940-016-0103-6.
Schindler, M., Le Texier, M., Caruso, G., 2022. How far do people travel to use urban green space? A comparison of three European cities. Appl. Geogr. 141, 102673.
Soga, M., Gaston, K.J., 2016. Extinction of experience: the loss of human–nature interactions. Front. Ecol. Environ. 14, 94–101. https://doi.org/10.1002/fee.1225.
Stevenson, M., Thompson, J., de Sá, T.H., Ewing, R., Mohan, D., McClure, R., Roberts, I., Tiwari, G., Giles-Corti, B., Sun, X., Wallace, M., Woodcock, J., 2016. Land use, transport, and population health: estimating the health benefits of compact cities. The Lancet 388, 2925–2935. https://doi.org/10.1016/S0140-6736(16)30067-8.
Stringhini, S., Sabia, S., Shipley, M., Brunner, E., Nabi, H., Kivimaki, M., Singh-Manoux, A., 2010. Association of Socioeconomic Position With Health Behaviors and Mortality. JAMA 303, 1159–1166. https://doi.org/10.1001/jama.2010.297.
Sugiyama, T., Villanueva, K., Knuiman, M., Francis, J., Foster, S., Wood, L., Giles-Corti, B., 2016. Can neighborhood green space mitigate health inequalities? A study of socio-economic status and mental health. Health Place 38, 16–21. https://doi.org/10.1016/j.healthplace.2016.01.002.
Svendsen, M.T., Bak, C.K., Sørensen, K., Pelikan, J., Riddersholm, S.J., Skals, R.K., Mortensen, R.N., Maindal, H.T., Bøggild, H., Nielsen, G., Torp-Pedersen, C., 2020. Associations of health literacy with socioeconomic position, health risk behavior, and health status: a large national population-based survey among Danish adults. BMC Public Health 20, 565. https://doi.org/10.1186/s12889-020-08498-8.
Tan, J.K.N., Belcher, R.N., Tan, H.T.W., Menz, S., Schroepfer, T., 2021. The urban heat island mitigation potential of vegetation depends on local surface type and shade. Urban For. Urban Green. 62, 127128. https://doi.org/10.1016/j.ufug.2021.127128.
Tan, P.Y., Zhang, J., Masoudi, M., Alemu, J.B., Edwards, P.J., Grêt-Regamey, A., Richards, D.R., Saunders, J., Song, X.P., Wong, L.W., 2020. A conceptual framework to untangle the concept of urban ecosystem services. Landsc. Urban Plan. 200, 103837. https://doi.org/10.1016/j.landurbplan.2020.103837.
Triguero-Mas, M., Dadvand, P., Cirach, M., Martínez, D., Medina, A., Mompart, A., Basagaña, X., Gražulevičienė, R., Nieuwenhuijsen, M.J., 2015. Natural outdoor environments and mental and physical health: Relationships and mechanisms. Environ. Int. 77, 35–41. https://doi.org/10.1016/j.envint.2015.01.012.
Turek, K., Kalmijn, M., Leopold, T., 2021. The Comparative Panel File: Harmonized Household Panel Surveys from Seven Countries. Eur. Sociol. Rev. 37, 505–523. https://doi.org/10.1093/esr/jcab006.
Twohig-Bennett, C., Jones, A., 2018. The health benefits of the great outdoors: A systematic review and meta-analysis of greenspace exposure and health outcomes. Environ. Res. 166, 628–637. https://doi.org/10.1016/j.envres.2018.06.030.
Ulrich, R.S., 1983. Aesthetic and Affective Response to Natural Environment, in: Altman, I., Wohlwill, J.F. (Eds.), Behavior and the Natural Environment, Human Behavior and Environment. Springer US, Boston, MA, pp. 85–125. Doi: 10.1007/978-1-4613-3539-9_4.
UN General Assembly, 2015. Transforming our world: the 2030 Agenda for Sustainable Development. U. N. N. Y. NY USA.
van den Berg, M., Wendel-Vos, W., van Poppel, M., Kemper, H., van Mechelen, W., Maas, J., 2015. Health benefits of green spaces in the living environment: A systematic review of epidemiological studies. Urban for. Urban Green. 14, 806–816. https://doi.org/10.1016/j.ufug.2015.07.008.
Vigo, D., Thornicroft, G., Atun, R., 2016. Estimating the true global burden of mental illness. Lancet Psychiatry 3, 171–178. https://doi.org/10.1016/S2215-0366(15)00505-2.
Vilagut, G., Forero, C.G., Pinto-Meza, A., Haro, J.M., de Graaf, R., Bruffaerts, R., Kovess, V., de Girolamo, G., Matschinger, H., Ferrer, M., Alonso, J., 2013. The mental component of the short-form 12 health survey (SF-12) as a measure of depressive disorders in the general population: results with three alternative scoring methods. Value Health 16, 564–573. https://doi.org/10.1016/j.jval.2013.01.006.
Ware, J.E., Kosinski Jr, M., Turner-Bowker, D.M., Gandek, B., 2002. How to score version 2 of the SF-12 Health Survey (with a supplement documenting version 1). Lincoln, RI: QualityMetric. Inc Google Sch.
Ware, J., Kosinski, M., Keller, S.D., 1996. A 12-Item Short-Form Health Survey: construction of scales and preliminary tests of reliability and validity. Med. Care 34, 220–233. https://doi.org/10.1097/00005650-199603000-00003.
Wells, N.M., 2021. The Natural Environment as a Resilience Factor: Nature's Role as a Buffer of the Effects of Risk and Adversity. In: Schutte, A.R., Torquati, J.C., Stevens, J.R. (Eds.), Nature and Psychology: Biological, Cognitive, Developmental, and Social Pathways to Well-Being. Springer International Publishing, Cham, pp. 195–233. https://doi.org/10.1007/978-3-030-69020-5_7.
White, M.P., Alcock, I., Grellier, J., Wheeler, B.W., Hartig, T., Warber, S.L., Bone, A., Depledge, M.H., Fleming, L.E., 2019. Spending at least 120 minutes a week in nature is associated with good health and wellbeing. Sci. Rep. 9, 1–11. https://doi.org/10.1038/s41598-019-44097-3.
White, M.P., Alcock, I., Wheeler, B.W., Depledge, M.H., 2013. Would you be happier living in a greener urban area? a fixed-effects analysis of panel data. Psychol. Sci. 24, 920–928.
WHO, 2017. Urban Green Space Interventions and Health: A Review of Impacts and Effectiveness.
White, M.P., Hartig, T., Martin, L., Pahl, S., van den Berg, A.E., Wells, N.M., Costongs, C., Dzhambov, Angel.M., Elliott, L.R., Godfrey, A., Hartl, A., Konijnendijk, C., Litt, J.S., Lovell, R., Lymeus, F., O'Driscoll, C., Pichler, C., Pouso, S., Razani, N., Secco, L., Steininger, M.O., Stigsdotter, U.K., Uyarra, M., van den Bosch, M., 2023. Nature-based biopsychosocial resilience: An integrative theoretical framework for research on nature and health. Environ. Int. 181, 108234. https://doi.org/10.1016/j.envint.2023.108234.
Wickham, H., 2016. ggplot2: Elegant Graphics for Data Analysis. Springer-Verlag, New York.
Wickham, H., François, R., Henry, L., Müller, K., 2022. dplyr: A Grammar of Data Manipulation.
Wooldridge, J.M., 2010. Econometric analysis of cross section and panel data. MIT press.