Ambient greenness, access to local green spaces, and subsequent mental health: a 10-year longitudinal dynamic panel study of 2·3 million adults in Wales

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Summary

Background Living in greener areas, or close to green and blue spaces (GBS; eg, parks, lakes, or beaches), is associated with better mental health, but longitudinal evidence when GBS exposures precede outcomes is less available. We aimed to analyse the effect of living in or moving to areas with more green space or better access to GBS on subsequent adult mental health over time, while explicitly considering health inequalities.

Methods A cohort of the people in Wales, UK (≥16 years; n=2 341 591) was constructed from electronic health record data sources from Jan 1, 2008 to Oct 31, 2019, comprising 19 141 896 person-years of follow-up. Household ambient greenness (Enhanced Vegetation Index [EVI]), access to GBS (counts, distance to nearest), and common mental health disorders (CMD, based on a validated algorithm combining current diagnoses or symptoms of anxiety or depression [treated or untreated in the preceding 1-year period], or treatment of historical diagnoses from before the current cohort [up to 8 years previously, to 2000], where diagnosis preceded treatment) were record-linked. Cumulative exposure values were created for each adult, censoring for CMD, migration out of Wales, death, or end of cohort. Exposure and CMD associations were evaluated using multivariate logistic regression, stratified by area-level deprivation.

Findings After adjustment, exposure to greater ambient greenness over time (+0·1 increased EVI on a 0–1 scale) was associated with lower odds of subsequent CMD (adjusted odds ratio 0·80, 95% CI 0·80–0·81), where CMD was based on a combination of current diagnoses or symptoms (treated or untreated in the preceding 1-year period), or treatments. Ten percentile points more access to GBS was associated with lower odds of a later CMD (0·93, 0·93–0·93). Every additional 360 m to the nearest GBS was associated with higher odds of CMD (1·05, 1·04–1·05). We found that positive effects of GBS on mental health appeared to be greater in more deprived quintiles.

Interpretation Ambient exposure is associated with the greatest reduced risk of CMD, particularly for those who live in deprived communities. These findings support authorities responsible for GBS, who are attempting to engage planners and policy makers, to ensure GBS meets residents' needs.

Funding National Institute for Health and Care Research Public Health Research programme.

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Lancet Planet Health 2023; 7: e809–18

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Introduction

Poor mental health is one of the main contributors to the global disease burden, accounting for 4·9% of global disability-adjusted life-years.[1] There is growing evidence that living close to and spending time in and around green or blue spaces (GBS; eg, parks, gardens, ponds) is associated with fewer mental health problems. The proposed mechanisms underpinning this association include increased social contact, reduced cognitive impairment, reduced stress, and mental and physical health-promoting physical activity, alongside indirect mechanisms within wider ecological systems, such as improved air quality.[2,3] There is, however, limited longitudinal evidence supporting changes in GBS affecting subsequent adult mental health.[3,4]

There are inequalities in the distribution and accessibility of high-quality GBS. People in deprived areas, those from minority ethnic communities, older adults, and those with longstanding health conditions or functional limitations often have less physical access to good-quality GBS.[5] These groups also tend to use GBS less and are more likely to have negative perceptions regarding their usage and the safety of such spaces.[6] There is evidence suggesting associations between GBS exposure and reductions in health inequalities, both cross-sectional and longitudinal.[7–12] Smaller-scale longitudinal studies in the UK also suggest associations between greater GBS exposure and better mental health and wellbeing,[12] but some have been restricted to urban areas and used GBS exposures at the area level rather

Research in context

Evidence before this study

We broadly followed the search strategy of a review of green spaces by Taylor and Hochuli, searching PsycINFO (EBSCO), Scopus (Elsevier), and CINAHL (EBSCO) from Jan 1, 2009 to Aug 8, 2018, including the core collection, CABI, BioSIS Previews, and Medline, across all years. A TOPIC search for "green space" was performed, returning 133 academic publications. The search terms were (("visit*" OR "proximity" OR "distance") AND ("health*")) AND (("natur*" OR "green space*" OR "NDVI" OR "green area") AND ("income" OR "socioeconomic status" OR "ses" OR "equigenesis" OR "equigenetic")) AND ("longitudinal"). We also included blue space terms and took a pragmatic approach to reports and grey literature, searching the websites of key organisations. We excluded studies that were not relevant to the intentions of our study (for example, spaces that were artificially painted green). In addition, we reviewed the main policy literature used in Wales, including the Fields in Trust guidelines, Recreation Opportunity Spectrum, Future Landscapes, and WHO, to collate green space definitions and typologies. We excluded conference proceedings and planning policy documents.

Substantial evidence, from both cross-sectional and some longitudinal studies, indicates associations between green and blue space (GBS) exposure and mental health and wellbeing. Existing studies mostly had small cohorts, assessed change over a short duration, and did not investigate socioeconomic inequalities. Cross-sectional studies cannot determine whether GBS exposure precedes good mental health. A recent National Institute for Health Research study, led by Ward Thompson, evaluated Forestry Commission Scotland's Woods in and Around Towns programme (designed to increase access to urban woodlands) by collecting primary data at three sites. It found no benefit to community-level mental health within 6 months; however, it concluded that increasing the number of sites and the follow-up duration by using routine data (the type of data used in the present study) could capture the community mental health benefits of such low-cost nature-based interventions.

Added value of this study

Using medical records of an entire adult population, this study presents the largest, most comprehensive longitudinal evaluation of the effect of differences in exposure to GBS on mental health and wellbeing over a 10-year period. The study suggests that GBS exposure has a protective effect against common mental health disorders (CMD), particularly for adults living in deprived communities. Time-aggregated exposure data, censored at CMD recording, reduces the potential for reverse causality while maximising the spatial–temporal differences in exposure to GBS between different people at a highly granular household level.

Implications of all the available evidence

Evidence from our research highlights the likely beneficial role of adequate ambient greenness and access to GBS in reducing socioeconomic-related inequalities in mental health. Investing in improved ambient greenness and in public green spaces might bring population mental health benefits, especially for those with a history of CMD. Future research should investigate why those living in lower-income and higher-income areas are affected differently by greenness exposure and potential GBS access, and explore further potential effect modifiers of the association between GBS and mental health outcomes.

than household level.[13,14] Although studies using experimental designs have been used to investigate the effects of GBS change in the UK on mental health, the results have been inconclusive, with, for example, potential time lags in realisation of benefits highlighted.[15]

This study analysed the effect of accrued household ambient greenness and availability of GBS over time on subsequent adult mental health, explicitly considering health inequalities and disentangling the mental health benefits of GBS from living in greener areas. We did this by anonymously tracking individuals over time and allocating GBS exposures at the more granular household, rather than small-area, level. Many previous studies measured green space exposure across small areas at a single time point, assuming the amount of vegetation did not vary within these areas or change through time.[16–18] Apart from a few quasi-experimental studies in which people were allocated to social housing units with different levels of surrounding green space,[17] results of place-based interventions investigating health effects using small areas might have recorded the health outcomes of a different, healthier population rather than the effects of exposure to green space. Individuals are mobile and might change residence, particularly when a neighbourhood is gentrified; thus, the small-area population characteristics will change over a period of years. Here, we use routinely updated addresses to overcome the challenge of tracing mobility within these datasets.[19] We focus on individuals and their aggregated household exposure as it changes over time, thereby avoiding the issues of measuring outcomes of an incorrect historical population that can affect small-area studies.

Methods

Study design and data sources

We performed a population-scale study using a new electronic cohort of people (aged ≥16 years) in Wales, UK between 2008 and 2019. The cohort was constructed using data from the Welsh Demographic Service Dataset, containing individual-level anonymised demographic characteristics of everyone registered with a National

Health Service (NHS) general practitioner (GP) in Wales. This dataset includes addresses provided by patients with from–to dates of residency in each home (updated when patients informed their GP they moved home, or changed GP), used to calculate residency dates in each home and house moves.[20] All household members aged 16 years or older were included in the cohort, with individuals nested within each household. The Welsh Demographic Service Dataset contains demographic characteristics of all people registered with an NHS GP in Wales that is free at the point of care, who provides data to the Secure Anonymised Information Linkage (SAIL) Databank unless individuals have requested to opt out (80% population coverage[21]). Thus, using these routinely collected data provides a largely inclusive population dataset most suitable to apply a health equity lens.

The cohort was linked to data from GP records (to derive the common mental health disorders [CMD] outcome), the Annual District Death Extract from the Office for National Statistics mortality register (for censoring), the Welsh Index of Multiple Deprivation (WIMD 2011 applied up to 2014 and WIMD 2014 applied from 2014), and rural–urban Office for National Statistics classifications for Lower Layer Super Output Areas.[22] These data were available in the SAIL Databank, an anonymised data safe haven.

We created one measure of household ambient greenness (within 300 m radius) and two of local GBS access (within a 1600 m footpath or road-accessible network buffer; table 1). Ambient greenness was measured, reflecting the density of vegetation using a validated measure called the Enhanced Vegetation Index (EVI), which has the advantage over normalised difference vegetation index of optimising the vegetation signal and reducing atmospheric noise. The substantial topographical variation in our study area (Wales, UK) made EVI the most appropriate measure as it is less susceptible to the effects of topographic seasonal factors. We calculated this within 300 m of each home in Wales. Based on earlier work, we hypothesised that some benefits of exposure to greenness will be gained without necessarily having to physically visit GBS (reduced noise, green views, etc). This measure captures the presence of green space (eg, parks, domestic gardens) and other green infrastructure (eg, street trees, green roofs). The ambient greenness measure was derived from satellite data (Landsat 2008–2019).[23] We selected images from springtime to minimise the number of poor-quality images due to cloud cover. Cloud-free images taken between May and July were downloaded for each year. We applied the Dark Object Subtraction 1 atmospheric correction method to each image as recommended by Young and colleagues[24] and calculated the EVI for each image using the vegetation index GRASS tool in QGIS.[25] We also created cloud masks for each image using the Cloud Masking for Landsat Products plugin.[26] We used the cloud masks to set pixels covered by cloud in the satellite imagery to NULL to prevent these values from influencing the final greenness density. A larger EVI score does not necessarily equate to more greenness by area but instead represents a larger volume (increased biomass) of green. A small forest, for example, could produce the same EVI score as a large area covered in grass.

The primary GBS access metric estimated the potential access to GBS (eg, park, woodland, lake, river) within 1600 m (approximately 1 mile) of the home. The 1600 m cutoff was informed by the Monitor of Engagement with the Natural Environment survey, which indicated that this is the distance within which a rapid decline in greenspace use is reported.[27] We created two access measures: the first counted the numbers of GBS, and the second was the distance to the nearest GBS. Both measured potential access to GBS within 1600 m of the home and were generated from a combination of the Ordnance Survey MasterMap Topography Layer (2018) to capture natural and human-made features, including the outline of homes and parks, and Ordnance Survey Greenspace dataset (2018).[28] These data were augmented with local authority technical advice notes (TAN 16), containing legally mandated data on sport, recreation, and open spaces managed by local authorities; open-source portal data (forestry or urban tree cover, publicly available at DataMapWales); and OpenStreetMap road and footpath data.[17] Although farmland constitutes large areas in rural regions, this is privately owned land. We were unable to obtain data on rights of way in rural areas and therefore excluded privately owned farmland, which might have included sections that are publicly accessible. We only included publicly accessible green spaces (and therefore excluded farmland from our GBS access measures) because our aim was to provide evidence on modifiable aspects of the built and natural environment for planning and policy guidelines.

For **DataMapWales** see http://datamap.gov.wales

EVI and our GBS access measures capture different aspects of the environment surrounding, or close to, the home (and at different proximity). EVI includes private gardens and farmland, and does not differentiate between spaces that are accessible or inaccessible. Our GBS access measures include both green and blue spaces but are restricted to those that are potentially accessible to the public, excluding farmland for example. Rural areas, therefore, might have high EVI values but low GBS accessibility, whereas coastal or seafront areas might have low EVI values (due to large areas of blue space) but high GBS accessibility.

We used a GBS typology (appendix pp 2–3) to categorise land parcels into types of GBS that people can potentially access, both visually and physically. To create realistic travel distances, rather than use radial distances, we defined access points based on feature types that were attached to the closest footpath or road network access point. We estimated the distance to all GBS access points within 1600 m of each home in Wales in 2018.

See **Online** for appendix

	Measure (source)	Description	Data type
Ambient greenness within 300 m of all homes			
Presence of green space (eg, parks, domestic gardens) and other green infrastructure (eg, street trees, green roofs) within a 300 m linear buffer of each home, without assumptions on availability for public use	Annual mean EVI within 300 m of each household (Landsat satellite imagery 2008–2019)	Measure of vegetation within 300 m of the home; measurements derived from remotely sensed satellite images	Continuous (0·1 unit increase in regression analyses)
Potential to access GBS within 1600 m of all homes			
Number of GBS that people can potentially access within a 1600 m footpath or road-accessible network buffer of each home	Count of GBS within 1600 m of each household location using a network model (various vector data)	Measure of density of potentially accessible GBS within 1600 m of the home	Continuous (0·1 unit increase in regression analyses)
Distance to nearest potentially accessible GBS within a 1600 m footpath or road-accessible network buffer of each home	Distance to nearest GBS within 1600 m of each household location using a network model (various vector data)	Distance from residential address to nearest access point for potentially accessible GBS within 1600 m of the home	Continuous (0·1 unit increase in regression analyses)

EVI=Enhanced Vegetation Index. GBS=green and blue spaces.

Table 1: **Summary of green and blue space exposure metrics**

We included all GBS that met any included categorical type (appendix pp 2–3), regardless of size, because our outcomes were not dependent on the use of a space, eg, for physical activity, but could include micro-parks where people go to relax, or other types of space (eg, verges) that contribute to local residential greenness. A single park could comprise several hundred small green or blue shapes. Within a single park there might be a botanic garden, a children's play area, and a boating lake, each comprising several shapes. Additionally, grass verges and other 'green infrastructure' components were included; thus, there might be 200 GBS counts equating to a small park, and several other spaces within 1600 m of home. By counting each small shape, we obtained a near-continuous measure of GBS for each resident in Wales (mean 6·1, SD 4·5). The metric was scaled to a 0–1 range, with normalised GBS access values ranging from 0 to 0·55. A 0·1-unit increase equated to 236 additional GBS.

Environmental data were linked to individuals in the cohort using a residential version of the split file linkage process.[20,29,30] Data for each GBS metric (table 1) were aggregated into normalised single values for ambient greenness or potential to access GBS for each individual based on their home location(s). Although our focus for access was on the number of GBS within 1600 m of the home, we also explored the distance to the nearest GBS in sensitivity analyses. The period of aggregation used all quarters, up to and including that before a CMD was recorded, the individual died, moved out of Wales, or the cohort ended in 2019.

We identified people with a CMD (anxiety or depression) by applying a validated algorithm of read codes recorded in the GP dataset. The algorithm (appendix pp 4–6) was based on a combination of current diagnoses or symptoms (treated or untreated in the preceding 1-year period), or current treatment of historical diagnoses from before the current cohort began, looking back up to 8 years (to 2000). A CMD treatment was defined as at least one prescription for an antidepressant, anxiolytic, or hypnotic in the 1-year current period. The algorithm required a diagnosis or symptom of a CMD prior to counting treatments, to account for multiple prescribing purposes of some treatments. Although we could count non-drug treatments, because these data were not available in the GP data, the algorithm will have extracted some people with a CMD diagnosis or symptoms who will have been prescribed alternative non-medication treatments. Hereafter, we refer to this as our CMD outcome.

Covariates included a binary measure of sex as recorded in each individual's electronic health record from the Welsh Demographic Service Dataset (hereafter referred to as male [reference] or female), age group (categorised as 16–21 [reference], 22–30, 31–40, 41–50, 51–60, 61–70, 71–80, and 80 years or older), area-level socioeconomic deprivation (quintiles of the full WIMD score, with least deprived as the reference), home moves (yes, one, more than one), birth(s) in household (yes, no), death(s) in household (yes, no), and urban or rural category (village, hamlet, and isolated dwellings; town and fringe; or urban conurbation >10 000 population), defined using Office for National Statistics settlement type categories.[22] The full WIMD score was used in analyses, as this is the Welsh Government's official measure of relative deprivation for small areas in Wales. It identifies areas with the highest concentrations of several different types of deprivation. WIMD is calculated for all small areas (Lower Layer Super Output Areas) in Wales. Following the 2011 Census, 1909 Lower Layer Super Output Areas were defined in Wales with an average population of 1600 people. The methodology used within WIMD 2014 is the same as used for WIMD 2011.[31] For each individual, covariates were derived from data in the same time interval as the environmental measures. This included all quarters up to and including that before a CMD was recorded, or the individual moved out of Wales, or the cohort end in 2019. Data on sex were extracted from NHS electronic health records and so are likely to reflect participants' sex assigned at birth. A new NHS number would be generated as part of gender reassignment, but sensitive code policies mean those data are not available in the SAIL Databank and these people would appear lost to follow-up.

We structured the data to ensure environmental exposures preceded CMD outcomes by only using exposure data prior to the first recorded CMD. This allowed us to test the question: does household ambient greenness and availability of GBS affect subsequent adult mental health, explicitly considering health inequalities and disentangling the mental health benefits of GBS from living in greener areas? Thus, differences between individuals in accrued household ambient greenness and availability of GBS are the focus. As such, we have a hybrid of cross-sectional and longitudinal studies in our framework.

Procedures

Health and ambient greenness (EVI) data were available from Jan 1, 2008 to Oct 31, 2019. The cohort included everyone aged 16 years or more and registered with a GP providing patient records to the SAIL Databank during the same period. People entered the dynamic cohort each quarter as they either reached 16 years of age or moved to Wales. We excluded from the study sample those not registered with an appropriate GP, those without a Welsh residential address between January, 2008 and October, 2019, those without their sex or week of birth recorded, or those with a CMD recorded in the first cohort quarter.[32]

Statistical analysis

The cohort contained 2 341 591 adults and 19 141 896 person-years of follow-up data. We used multivariate logistic regression to assess associations between normalised time-aggregated ambient greenness (average EVI within a 300 m buffer from home), and access measures (total number of GBS, or distance to nearest GBS, within 1600 m of the home), with having a subsequent CMD. We stratified by deprivation and historical CMD diagnosis (pre-cohort entry) to assess effect modification. We normalised EVI and GBS access to between 0 and 1. Regression results are presented for increments of 0·1 units. In our regression analyses, we adjusted for rurality when investigating associations between ambient greenness and CMD. We did not adjust for rurality when investigating associations between GBS access and CMD because the spaces that characterise rural areas, such as farmland, which is not accessible to the public, were excluded from the overall GBS measure. Predicted probabilities were calculated from the adjusted regression models to illustrate how the probability of CMD varied with differences in GBS exposure or access, keeping all other variables constant.

Additional sensitivity analyses examined associations between additional normalised time-aggregated access measures (distance to nearest GBS and average distance to GBS, both within 1600 m of the home) and the likelihood of having a subsequent CMD. We also examined associations for a subgroup with a historical CMD diagnosis.

Role of the funding source

The funder of the study had no role in study design, data collection, data analysis, data interpretation, or writing of the report, or the decision to submit for publication.

	Adults		Common mental health disorder*		Ambient greenness		Potential to access GBS: number of GBS	
	n	%	n	%	Mean	SD	Mean	SD
Total	2 341 591	100%	513 239	21·9%	0·29	0·09	441·58	340·72
Age group, years								
16–21	363 314	15·5%	70 282	19·3%	0·30	0·10	491·82	392·31
22–30	385 643	16·5%	102 992	26·7%	0·26	0·09	523·48	408·53
31–40	327 874	14·0%	87 550	26·7%	0·27	0·09	453·19	332·24
41–50	338 303	14·4%	88 904	26·3%	0·29	0·09	412·64	298·63
51–60	302 774	12·9%	67 545	22·3%	0·30	0·09	401·53	296·20
61–70	284 096	12·1%	47 105	16·6%	0·30	0·09	382·49	285·34
71–80	201 279	8·6%	30 401	15·1%	0·30	0·09	395·23	290·27
>80	138 308	5·9%	18 460	13·3%	0·28	0·09	401·08	301·52
Sex								
Male	1 193 240	51·0%	205 546	17·2%	0·29	0·09	440·58	337·83
Female	1 148 351	49·0%	307 693	26·8%	0·29	0·09	442·62	343·69
Birth in household								
No	2 076 801	88·7%	460 262	22·2%	..	..	..	..
Yes	264 790	11·3%	52 977	20·0%	..	..	..	..
Death in household								
No	2 151 488	91·9%	489 243	22·7%	..	..	..	..
Yes	190 103	8·1%	23 996	12·6%	..	..	..	..
WIMD quintile								
1—most deprived	473 404	20·2%	131 843	27·8%	0·25	0·08	495·13	253·75
2	462 492	19·8%	110 898	24·0%	0·27	0·08	443·93	291·10
3	480 278	20·5%	98 673	20·5%	0·30	0·10	413·21	347·62
4	445 002	19·0%	83 768	18·8%	0·31	0·11	405·72	401·33
5—least deprived	480 415	20·5%	88 057	18·3%	0·29	0·08	448·14	382·03
Moved home								
Did not move	1 439 204	61·5%	343 734	23·9%	0·29	0·10	446·32	334·40
Moved once	520 509	22·2%	99 694	19·2%	0·29	0·10	432·63	360·11
Moved more than once	381 878	16·3%	69 811	18·3%	0·28	0·09	435·91	335·67
Rurality								
Urban	1 611 516	68·8%	365 931	22·7%	0·25	0·07	554·64	346·99
Rural	354 961	15·2%	62 285	17·5%	0·41	0·09	162·60	115·21
Town and fringe	375 114	16·0%	85 023	22·7%	0·31	0·07	219·84	130·79

Ambient greenness is the annual mean EVI within 300 m of each household location. Number of GBS is the count of GBS within 1600 m of each household location using a network model. For those who moved home during the study period, these measures are averages including exposures at each location. EVI=Enhanced Vegetation Index. GBS=green and blue spaces. WIMD=Welsh Index of Multiple Deprivation. *Common mental health disorder in the National Health Service general practitioner record, updated quarterly during follow-up—see Methods section for details. Births/deaths in households were those occurring during follow-up.

Table 2: **Characteristics of cohort members including GBS exposure**

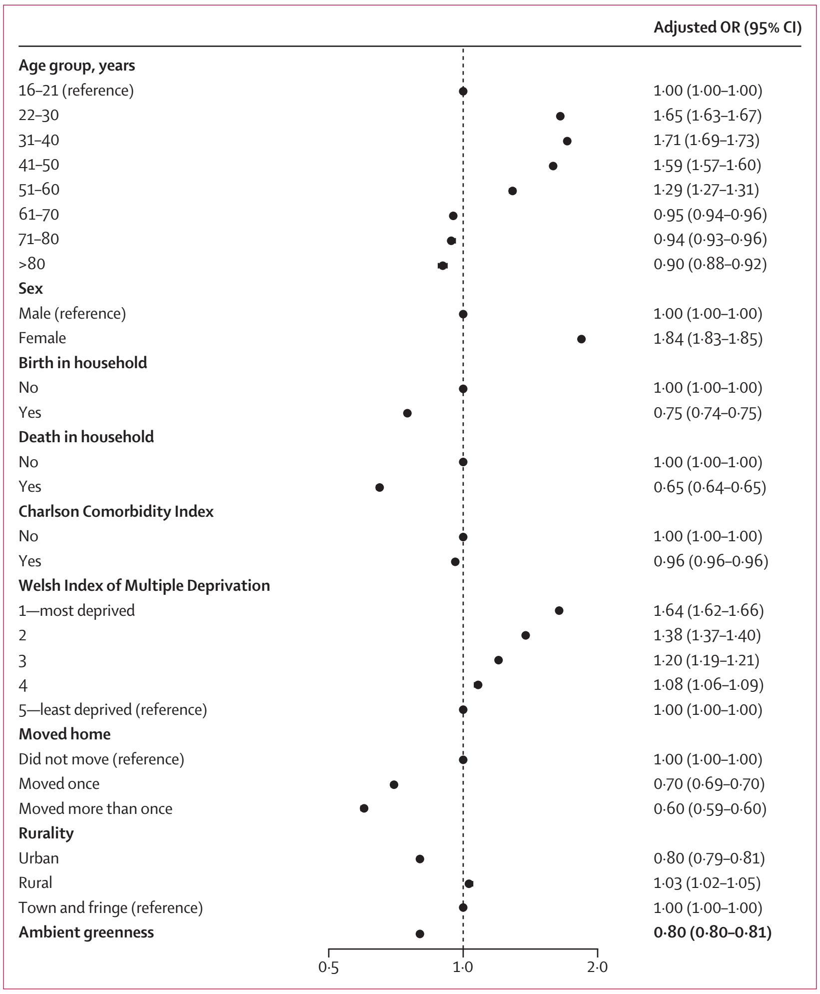

Figure 1: **Factors associated with risk of CMD, including mean ambient greenness**
CMD=common mental health disorders. OR=odds ratio. Association with CMD is after adjustment for other variables listed. The results in each category of each factor show the adjusted OR of CMD compared to the reference category of that factor.

Results

Within the cohort, 1 193 240 (51·0%) adults were men and 1 148 351 (49·0%) were women. 513 239 (21·9%) had a CMD at least once during their time in the cohort (table 2). A higher proportion of women than men had a CMD (307 693 [26·8%] women *vs* 205 546 [17·2%] men; table 2), and younger people (aged 22–50 years) were more likely to have sought care for a CMD than those in older age groups (102 992 [26·7%] of those aged 22–30, 87 550 [26·7%] of those aged 31–40, and 88 904 [26·3%] of those aged 41–50, *vs* 47 105 [16·6%] for those aged 61–70 years; table 2). Ambient greenness within 300 m of a home in Wales between 2008 and 2019 was in the range 0·10–0·62 (non-normalised mean EVI values).

After adjustment for age, sex, area-level deprivation, individual mobility, births and deaths in the household, and comorbidities, a 0·1-unit greater EVI, representing ambient greenness around the home, was associated with lower odds of having a CMD (adjusted odds ratio [OR] 0·80, 95% CI 0·80–0·81; figure 1). There were even lower odds of CMD among adults with a historical CMD diagnosis (recorded up to 8 years before 2008; adjusted OR 0·68, 0·68–0·68) than among those without (0·84, 0·84–0·85; table 3). Potential access to GBS followed a similar pattern to ambient greenness, although the magnitude of the effect was smaller; a 0·1-unit greater number of GBS of any size within 1600 m of the home (equivalent to 236 more GBS) was associated with lower odds of CMD (0·93, 0·93–0·93; figure 2). Unlike for EVI, a 0·1-unit greater number of GBS was only associated with lower odds of a CMD among those without a historical CMD (0·91, 0·91–0·92; table 3). For those with a historical CMD, there was no association between GBS access and likelihood of subsequent CMD (1·00, 0·99–1·00; table 3).

We stratified by deprivation, finding that ambient greenness and access to GBS were both associated with CMD across all area-level deprivation quintiles (table 3). We did not find a modifying effect of deprivation for increasing ambient greenness; there was no clear trend in the magnitude of association between ambient greenness and CMD with increasing deprivation categories (table 3). However, the association between access to GBS and CMD was modified by increasing deprivation. The magnitude of association between a 0·1 unit increase in GBS (equivalent to 236 more GBS) and CMD was greater in the most deprived areas (0·90, 0·90–0·91) than in the least deprived areas (0·94, 0·94–0·95; table 3).

We also stratified by moving home, finding that ambient greenness was associated with lower odds of a CMD in all moving home groups but that the effect was strongest for those who did not move (0·77, 0·77–0·78) compared with those who moved (moved once: 0·86, 0·86–0·87; moved more than once: 0·92, 0·91–0·93; table 3).

In sensitivity analyses, further distance from home to GBS, representing reduced potential access, was associated with greater odds of a CMD. Each additional 360 m (0·1 units) to the nearest GBS was associated with higher odds of having a CMD (1·05, 1·04–1·05; appendix pp 7–8). For the average distance to a GBS, each additional 625 m (0·1 units) was also associated with higher odds of a CMD (1·02, 1·01–1·03; appendix pp 7–8).

In our study, ambient greenness was calculated from normalised EVI exposure values and ranged from 0·25 to 0·80. We used predicted probabilities to illustrate that there was approximately 30% lower probability of a CMD at the bottom of this range compared with the top. Once normalised, GBS access values ranged from 0 to 0·55. There was a prediction of approximately 10% lower CMD probability at the bottom of this range compared with the top (appendix pp 9–10).

Discussion

Based on an analysis of comprehensive data from all adults registered with a GP in the SAIL Databank, more ambient greenness around the home and greater potential access to GBS were both separately associated with a reduced likelihood of subsequently having a CMD. Stratification by deprivation showed that the association of CMD odds with potential GBS access for adults living in the most deprived areas (10% reduction per 0·1-unit increase) was stronger than for those living in the least deprived areas (6% reduction), indicating the greatest benefits to mental health for people living in deprived areas with more GBS (adjusted OR for most deprived areas 0·90, 95% CI 0·90–0·91; for least deprived areas 0·94, 0·94–0·95). Our findings advance previous research, by showing that deprivation modifies the relationship between GBS and mental health, with the potential to reduce health inequalities.[9] Mechanisms for greater mental health benefits of GBS among those living in more deprived areas might vary and be multiple. Mechanisms could include deprivation contributing to stress and mental health, and allowing a greater potential benefit of GBS for those living in more deprived areas. Local neighbourhood conditions might be more important for those in more deprived circumstances, who have fewer financial resources available to enable them to travel to spend recreational time outside their local environment than people in less deprived circumstances.

This study has several strengths. The cohort is subject to minimal attrition due to the inclusion of all adults registered with a GP service that is free at the point of use (unless they have opted out from having their data used for research purposes). By using routine data, we reduced selection, participation, and recall bias, resulting in more than 19 million person-years of follow-up. By ensuring that exposures preceded outcomes, we reduced the potential for reverse causality, which has only previously been possible in a small number of GBS mental health studies.[33]

Household-level metrics of ambient greenness exposure and potential access to GBS were derived and linked at a granular spatial resolution, thereby reducing spatial smoothing and ecological fallacy. These occur when data are aggregated over larger statistical areas and can introduce biases to the extent that the direction of associations are reversed. We used data linkage to nest people in their homes and to capture their immediate environment centred on their home. Our privacy-protecting data linkage mechanisms made it possible to link health and environment data at the same spatial and temporal scales, enabling a more robust exploration of the longitudinal effect of changing environments on health.[20,29,30] Over a long duration, place-based improvements might displace the original population. The results of place-based intervention studies investigating area-level health effects might have recorded health outcomes of a different, healthier population. Organisations holding health outcome data should make available anonymised individual-level and household-level data to enable researchers to consider the effects of gentrification. Gentrification might increase health inequities by displacing less affluent residents, or through changing social environments that lead to an area becoming accessible only for people from more privileged social backgrounds.[34] Here, we took an important step to disentangle the mental health benefits of GBS while taking into account individual mobility by anonymously tracking individual residential exposure over time, instead of measuring green space exposure across small areas at a single time point.[7] This reduces the potential for exposure misclassification and subsequent bias that might occur in various other study types, including prospective cohort studies.[35] Using time-varying exposures rather than consistently allocated intervention and control groups makes translating our results into policy more challenging, but also more reflective of the lived realities policies seek to influence.

	Proportion of cohort	Ambient greenness	Potential to access GBS: number of GBS
WIMD			
1—most deprived	20·2%	0·86 (0·85–0·87)	0·90 (0·90–0·91)
2	19·8%	0·78 (0·78–0·79)	0·92 (0·92–0·93)
3	20·5%	0·77 (0·77–0·78)	0·94 (0·94–0·95)
4	19·0%	0·83 (0·82–0·83)	0·93 (0·92–0·93)
5—least deprived	20·5%	0·77 (0·77–0·78)	0·94 (0·94–0·95)
CMD			
Validated prediction of historical CMD	10·1%	0·68 (0·68–0·68)	1·00 (0·99–1·00)
No record of validated prediction of historical CMD	89·9%	0·84 (0·84–0·85)	0·91 (0·91–0·92)
Moved home			
Did not move	61·5%	0·77 (0·77–0·78)	0·94 (0·93–0·94)
Moved once	16·3%	0·86 (0·86–0·87)	0·91 (0·91–0·92)
Moved more than once	22·2%	0·92 (0·91–0·93)	0·89 (0·89–0·90)

Data are % or adjusted OR (95% CI). Models were adjusted for age, sex, birth or death in household during follow-up, Charlson Comorbidity Index, and moving home. Adjusted OR is for a 0·1-unit increase in ambient greenness or number of GBS. Ambient greenness is the annual mean EVI within 300 m of each household location. Number of GBS is the count of GBS within 1600 m of each household location using a network model. CMD=common mental health disorder. EVI=Enhanced Vegetation Index. GBS=green and blue spaces. OR=odds ratio. WIMD=Welsh Index of Multiple Deprivation.

Table 3: **Associations of mean ambient greenness and number of GBS with CMD, stratified by area-level deprivation and historical CMD**

For more on **SAIL data** use see https://saildatabank.com/faq

We used a validated algorithm with high specificity and positive predictive value for detecting CMD (anxiety and depression) from GP data, and including historical diagnoses with current treatment and symptoms increased the measure's sensitivity. Nevertheless, we might still be missing about a third of true cases of CMD.[36] We were limited by the insufficient detail captured on CMD case severity, and we were unable to stratify between anxiety and depression. It is plausible that CMD symptom severity might differ between those who seek help in general practice and those who do not; the CMD algorithm might be insufficiently sensitive to capture less severe symptoms. It is also plausible that less severe symptoms might be more amenable to treatment or prevention from exposure to ambient

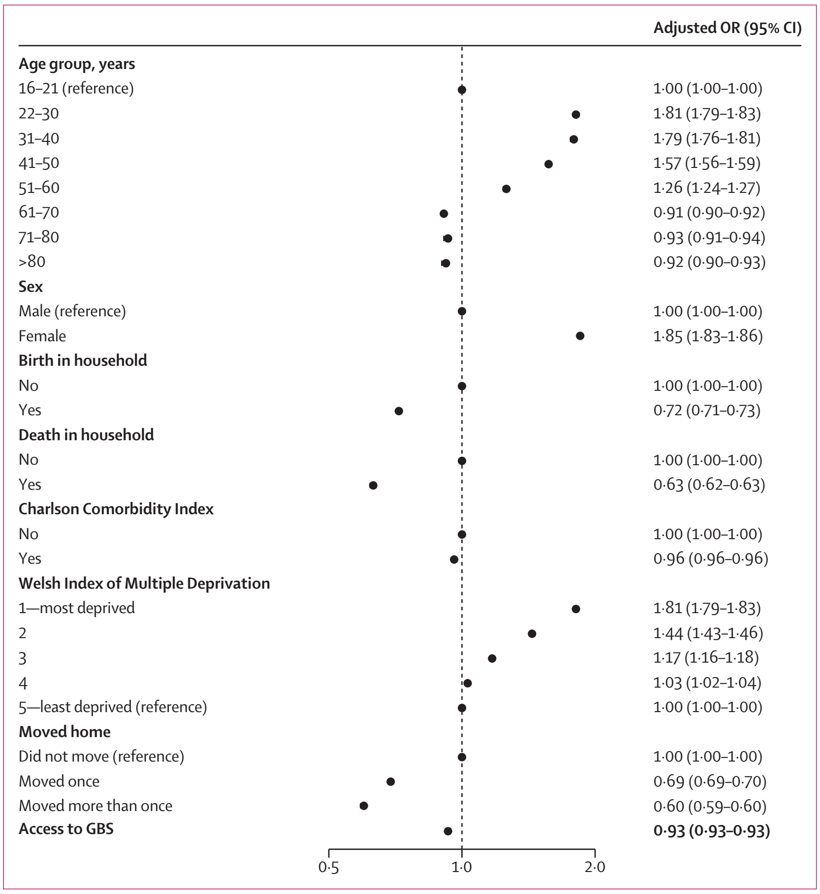

Figure 2: **Factors associated with risk of CMD, including access to GBS**
We did not adjust for rurality for GBS access because the spaces characterising rural areas, such as farmland, were not included in the access measures. Each 0·1-unit increase in GBS was an additional 236 spaces. CMD=common mental health disorders. GBS=green and blue spaces. OR=odds ratio. Association with CMD is after adjustment for all other variables listed.

greenness or access to GBS around the home than the CMD that were captured by the algorithm. If milder CMD symptoms are more likely to respond positively to GBS, but those with these milder symptoms are less likely to seek care in general practice, this could have diluted associations between change in GBS and milder CMD in our study. Cognitive behavioural therapies and other non-medication treatments were not included in our CMD case definition as this information is not available in the Welsh Longitudinal General Practice dataset. Low sensitivity and insufficient data on non-drug treatments might have reduced the number of cases of CMD we were able to identify, with associated reductions in the precision of estimates. This might also affect the ability of electronic health record algorithms to capture changes in numbers of those seeking help for CMD over time, because referrals to talking therapies are increasing.[37]

We uncovered temporal limitations in the high-quality spatial data. We set out to generate quarterly exposures of ambient greenness and annual GBS access but were only able to derive annual EVI due to cloud cover, and a single measure of GBS access for 2018, due to inconsistent temporal updates and changes to land use classification in the map data. However, we did capture temporal variations in GBS access for people who moved home. We believe the specificity of capturing changes in greenspace through moving home contributed to finding that cohort members had 20% lower odds of CMD for greater exposure to ambient greenness and 7% lower odds for an increase in GBS access, despite having only annual exposure updates for the rest of the population. There are numerous ways in which ambient greenness can be measured; although the options for a temporally consistent exposure metric for this study were constrained, the choice of measure might have had an influence on the observed relationship. Finally, we adjusted associations for the Welsh Index of Multiple Deprivation, a measure of deprivation assessed in small geographical areas, and for moving (a proxy for stability) and the association between GBS and CMD outcome remained. While residual confounding might have remained, we did not have access (through routinely collected data) to more detailed measures of individual-level or household-level stability or economic resources.

Our results indicate that the relationships between ambient greenness or access to GBS and CMD likelihood are modified by an individual's CMD history, although in opposite directions for the two types of GBS metric. For those with historical CMD before entering the cohort (defined as historical diagnoses in the GP dataset in the 8 years before the current cohort began), exposure to greater ambient greenness was associated with lower risk of a future CMD than for those without a history of previous CMD. This suggests that exposure to ambient greenness might be important for CMD prevention in addition to providing restorative benefits and is a potentially important point for reducing mental health inequality. In contrast, greater potential access to GBS was associated with mental health improvements for those without a history of CMD. This might reflect the different mechanisms through which ambient greenness, or access to GBS, are hypothesised to affect mental health.[38,39] It would be useful to understand how people who have current CMD symptoms might use these spaces for recovery rather than for prevention.[40]

Ambient greenness and GBS exposures are important, and the relationships are complex and potentially differ depending on multiple factors, including the population group (eg, elderly, marginalised, physically frail) and life circumstances (eg, retired). We adjusted our analyses for age group, but there is likely to be residual confounding that might not neatly correspond to age group. Evidence suggests that ambient greenness and access to GBS are not the only elements of GBS that affect health; qualities of GBS, such as benches, lighting, or perceived safety, can affect GBS use and thus health outcomes that require activity in a space.[41,42] Authorities responsible for designing and maintaining GBS have an opportunity to engage with seldom heard groups to ensure GBS are not only distributed equitably but also meet the satisfaction and needs of residents.

Although the study period for this research preceded the COVID-19 pandemic, the need for GBS to access or view was brought to the fore during the early stages of the pandemic, particularly for those living in urban areas with poor or no access to private or communal garden spaces. Our results suggest that investing in improved ambient greenness, as well as making public GBS accessible, might lead to future mental health benefits for adults with and without a history of CMD. There might also be additional co-benefits: job or food creation, biodiversity promotion, and flood prevention or carbon sequestration. Realising these requires a shift in the balance of decision making to place weight on protecting, enhancing, and providing more appropriate GBS designed for local communities. Urban GBS can therefore be thought of as a public health and social investment, providing a chance to rebalance our relationship with nature, to help address our climate change challenges, and to protect against the mental health challenges of future pandemics.[43]

We have generated environmental health equity evidence that is important for policy and practice in the long-term prevention of common mental health disorders. This evidence would have otherwise been intractable to generate without using routinely collected environmental and health data and systems to dynamically link individuals into households and so to their changing environmental exposures.[44] It is challenging to convince governments to invest in preventative strategies that take decades to come to fruition. Here we provide evidence of the need for facilities to improve the health and wellbeing of all adults, especially those living in the most deprived areas. The burden of health care for this portion of our population, and on health-care systems to provide preventative treatments, could be reduced through the enhancement of our built environments by including appropriate GBS. Linking data on individuals and households across different organisations is essential as part of a population health management strategy to understand how we might alter the wider determinants of health to most effectively spend across local government and health care to promote public mental health.

Contributors

All authors made substantial contributions to the conception or design of the work; the acquisition, analysis, or interpretation of data; and drafting the manuscript or revising it critically for important intellectual content. All authors provided final approval for publication. RSG contributed to the interpretation of data analyses, and the writing and preparation of the manuscript. DTh led the cohort preparation, data linkage for environmental and health data, and final execution of the cohort for this study; implemented the design, descriptive, and exploratory data analyses; prepared all the tables; and contributed to the writing of the final manuscript. AM led the design, data acquisition, data preparation, and execution of the GBS metrics for the study; led the development of the typology of GBS; and contributed to the interpretation of data analyses and the final manuscript. AA contributed to the design of data workflows and the final manuscript. JKG, GS, SCP, and DTs contributed to the interpretation of data analyses and to the final manuscript. FMR contributed to interpretation of data analyses, the literature review, and the final manuscript. AW oversaw the statistical analyses and contributed to the design and interpretation of data analyses and the final manuscript. RAL contributed to the design of the study and use of the record-linked data sets used in the project and the final manuscript. RL led on public and policy engagement and contributed to the interpretation of data analyses and policy impact and the final manuscript. MN, JW, and MPW contributed to the design and interpretation of data analyses and the final manuscript. JS led the initial data preparation and contributed to the final manuscript. SW contributed to the interpretation of data analyses and policy impact and the final manuscript. BWW contributed to the design of the study and interpretation of data analyses, and the final manuscript. RF oversaw the preparation of the GBS exposure metrics and contributed to the design of the study and interpretation of data analyses, and to the final manuscript. SER led the design and execution of the study, and oversaw study analyses and the preparation of the final manuscript. DTh, JKG, FMR, and AW had access to the raw health data; AM and RF had access to the raw geospatial data; and all other authors had access to the summary data. The senior statistician (AW) had full access to all the data and the corresponding author (SER) had final responsibility for the decision to submit for publication.

Data sharing

The data for this cohort are stored and maintained in the SAIL Databank at Swansea University. This is a controlled access cohort; all proposals to use SAIL data are subject to review by an independent information governance review panel. Where access is granted, it is gained through a privacy-protecting safe haven and remote access system (SAIL Gateway). The cohort data will be available for collaborative research projects after 2023. For further details about accessing the cohort, contact saildatabank.com or Sarah E Rodgers (arcnwc@liverpool.ac.uk) to discuss working with the original cohort developers.

Declaration of interests

RSG reports a grant from the UK Prevention Research Partnership (MR/V049704/1). JKG reports grants from EU Horizon 2020 (666773, 821016, 776866). MPW reports royalties from Greenkeeper. RL reports grants from the UK Department for Environment, Food & Rural Affairs (BE0155), the South West Partnership for Environmental and Economic Prosperity (subproject of NE/P011217/1), EU Horizon 2020 (821016), the Wellcome Trust, the Economic and Social Research Council, the UK Department of Health and Social Care, the UK Ministry of Housing, Communities & Local Government (BE0191), and the Medical Research Council (MR/V049704/1); participation as an advisory board member on non-NIHR-funded studies; and royalties from Greenkeeper. AW reports membership of the Health and Social Care Delivery Research Funding Committee 2018–2021 and the Health and Social Care Delivery Research Funding Committee (Bevan) 2020. AA reports grants from Health Data Research UK (HDR-9006) and the Economic and Social Research Council (ES/S007393/1). BWW reports grants from Innovate UK (TS/R013136/1), EU Horizon 2020, the South West Partnership for Environmental and Economic Prosperity, the Wellcome Trust (216035/Z/19/Z), and the UK Prevention Research Partnership (MR/V049704/1); and royalties from Greenkeeper. RAL reports grants from Health Data Research UK (HDR-9006). SER reports grants from the UK Prevention Research Partnership (MR/V049704/1); and membership of the Public Health Research Funding Board 2019–2023. All other authors declare no competing interests.

Acknowledgments

This project was funded by the NIHR Public Health Research programme (project number 16/07/07). Time for SER to contribute to this project was funded by the NIHR Applied Research Collaboration North West Coast. We thank Roberto Villegas-Diaz for drawing the forest plots.

References

1 Vigo D, Jones L, Atun R, Thornicroft G. The true global disease burden of mental illness: still elusive. *Lancet Psychiatry* 2022; **9:** 98–100.

2 Wheeler BW, Lovell R, Higgins SL, *et al*. Beyond greenspace: an ecological study of population general health and indicators of natural environment type and quality. *Int J Health Geogr* 2015; **14:** 1–17.

3 Houlden V, Weich S, de Albuquerque JP, Jarvis S, Rees K. The relationship between greenspace and the mental wellbeing of adults: a systematic review. *PLoS One* 2018; published online Sept 12. https://doi.org/10.1371/journal.pone.0203000.

4 Kivimäki M, Batty GD, Pentti J, et al. Modifications to residential neighbourhood characteristics and risk of 79 common health conditions: a prospective cohort study. *Lancet Public Health* 2021; **6:** e396–407.

5 van den Berg M, Wendel-Vos W, van Poppel M, Kemper H, van Mechelen W, Maas J. Health benefits of green spaces in the living environment: a systematic review of epidemiological studies. *Urban For Urban Green* 2015; **14:** 806–16.

6 Boyd F, White MP, Bell SL, Burt J. Who doesn't visit natural environments for recreation and why: a population representative analysis of spatial, individual and temporal factors among adults in England. *Landsc Urban Plan* 2018; **175:** 102–13.

7 Gibbons J, Barton M, Brault E. Evaluating gentrification's relation to neighborhood and city health. *PLoS One* 2018; **13:** e0207432.

8 Garrett JK, Clitherow TJ, White MP, Wheeler BW, Fleming LE. Coastal proximity and mental health among urban adults in England: the moderating effect of household income. *Health Place* 2019; **59:** 102200.

9 Mitchell RJ, Richardson EA, Shortt NK, Pearce JR. Neighborhood environments and socioeconomic inequalities in mental well-being. *Am J Prev Med* 2015; **49:** 80–84.

10 Fuertes E, Markevych I, Thomas R, et al. Residential greenspace and lung function up to 24 years of age: the ALSPAC birth cohort. *Environ Int* 2020; **140:** 105749.

11 Pearce J, Cherrie M, Shortt N, Deary I, Ward Thompson C. Life course of place: a longitudinal study of mental health and place. *Trans Inst Br Geogr* 2018; **43:** 555–72.

12 Garrett JK, Rowney FM, White MP, et al. Visiting nature is associated with lower socioeconomic inequalities in well-being in Wales. *Sci Rep* 2023; **13:** 9684.

13 Alcock I, White MP, Wheeler BW, Fleming LE, Depledge MH. Longitudinal effects on mental health of moving to greener and less green urban areas. *Environ Sci Technol* 2014; **48:** 1247–55.

14 White MP, Alcock I, Wheeler BW, Depledge MH. Would you be happier living in a greener urban area? A fixed-effects analysis of panel data. *Psychol Sci* 2013; **24:** 920–28.

15 Ward Thompson C, Silveirinha de Oliveira E, Tilley S, et al. Health impacts of environmental and social interventions designed to increase deprived communities' access to urban woodlands: a mixed-methods study. 2019. https://www.ncbi.nlm.nih.gov/books/NBK535742/ (accessed June 6, 2022).

16 Collins RM, Spake R, Brown KA, Ogutu BO, Smith D, Eigenbrod F. A systematic map of research exploring the effect of greenspace on mental health. *Landsc Urban Plan* 2020; **201:** 103823.

17 Kuo FE, Sullivan WC. Environment and crime in the inner city: does vegetation reduce crime? *Environ Behav* 2001; **33:** 343–67.

18 Geneshka M, Coventry P, Cruz J, Gilbody S. Relationship between green and blue spaces with mental and physical health: a systematic review of longitudinal observational studies. *Int J Environ Res Public Health* 2021; **18:** 9010.

19 Fecht D, Garwood K, Butters O, et al. Automation of cleaning and reconstructing residential address histories to assign environmental exposures in longitudinal studies. *Int J Epidemiol* 2020; **49:** i49–56.

20 Rodgers SE, Demmler JC, Dsilva R, Lyons RA. Protecting health data privacy while using residence-based environment and demographic data. *Health Place* 2012; **18:** 209–17.

21 Lyons RA, Jones KH, John G, et al. The SAIL databank: linking multiple health and social care datasets. *BMC Med Inform Decis Mak* 2009; **9:** 3.

22 Office for National Statistics. 2011 rural/urban classification. 2011. https://www.ons.gov.uk/methodology/geography/geographicalproducts/ruralurbanclassifications/2011ruralurbanclassification (accessed Nov 1, 2021).

23 Rokni K, Musa TA. Normalized difference vegetation change index: a technique for detecting vegetation changes using Landsat imagery. *CATENA* 2019; **178:** 59–63.

24 Young NE, Anderson RS, Chignell SM, Vorster AG, Lawrence R, Evangelista PH. A survival guide to Landsat preprocessing. *Ecology* 2017; **98:** 920–32.

25 i.vi GRASS GIS manual. https://grass.osgeo.org/grass78/manuals/i.vi.html (accessed April 2, 2020).

26 Cloud Masking—Qgis plugin. https://smbyc.bitbucket.io/qgisplugins/cloudmasking/ (accessed April 2, 2020).

27 UK Government. Monitor of Engagement with the Natural Environment (MENE). 2014. https://www.gov.uk/government/collections/monitor-of-engagement-with-the-natural-environment-survey-purpose-and-results (accessed July 2, 2021).

28 Mizen A, Song J, Fry R, et al. Longitudinal access and exposure to green-blue spaces and individual-level mental health and well-being: protocol for a longitudinal, population-wide record-linked natural experiment. *BMJ Open* 2019; **9:** 1–10.

29 Rodgers SE, Lyons RA, Dsilva R, et al. Residential Anonymous Linking Fields (RALFs): a novel information infrastructure to study the interaction between the environment and individuals' health. *J Public Health* 2009; **31:** 582–88.

30 Johnson RD, Griffiths LJ, Hollinghurst JP, et al. Deriving household composition using population-scale electronic health record data—a reproducible methodology. *PLoS One* 2021; **16:** e0248195.

31 Welsh Government. Welsh Index of Multiple Deprivation. 2014. https://gov.wales/welsh-index-multiple-deprivation (accessed Nov 8, 2021).

32 Thompson DA, Geary RS, Rowney FM, et al. Cohort profile: the Green and Blue Spaces (GBS) and mental health in Wales e-cohort. *Int J Epidemiol* 2022; **51:** e285–94.

33 Houlden V, Weich S, de Albuquerque JP, Jarvis S, Rees K. The relationship between greenspace and the mental wellbeing of adults: a systematic review. *PLoS One* 2018; published online Sept 12. https://doi.org/10.1371/journal.pone.0203000.

34 Cole HVS, Lamarca MG, Connolly JJT, Anguelovski I. Are green cities healthy and equitable? Unpacking the relationship between health, green space and gentrification. *J Epidemiol Community Health* 2017; **71:** 1118–21.

35 Medgyesi DN, Fisher JA, Cervi MM, et al. Impact of residential mobility on estimated environmental exposures in a prospective cohort of older women. *Environ Epidemiol* 2020; **4:** e110.

36 John A, McGregor J, Fone D, et al. Case-finding for common mental disorders of anxiety and depression in primary care: an external validation of routinely collected data. *BMC Med Inform Decis Mak* 2016; **16:** 35.

37 Nuffield Trust. Improving Access to Psychological Therapies (IAPT) programme. 2018. https://www.nuffieldtrust.org.uk/resource/improving-access-to-psychological-therapies-iapt-programme (accessed Oct 19, 2021).

38 Markevych I, Schoierer J, Hartig T, et al. Exploring pathways linking greenspace to health: theoretical and methodological guidance. *Environ Res* 2017; **158:** 301–17.

39 Holland I, DeVille NV, Browning MHEM, et al. Measuring nature contact: a narrative review. *Int J Environ Res Public Health* 2021; **18:** 4092.

40 Tester-Jones M, White MP, Elliott LR, et al. Results from an 18 country cross-sectional study examining experiences of nature for people with common mental health disorders. *Sci Rep* 2020; **10:** 19408.

41 Cohen DA, Han B, Isacoff J, et al. Impact of park renovations on park use and park-based physical activity. *J Phys Act Health* 2015; **12:** 289–95.

42 Weimann H, Rylander L, van den Bosch MA, et al. Perception of safety is a prerequisite for the association between neighbourhood green qualities and physical activity: results from a cross-sectional study in Sweden. *Health Place* 2017; **45:** 124–30.

43 Geary RS, Wheeler B, Lovell R, Jepson R, Hunter R, Rodgers S. A call to action: improving urban green spaces to reduce health inequalities exacerbated by COVID-19. *Prev Med* 2021; **145:** 106425.

44 Lyons RA, Ford DV, Moore L, Rodgers SE. Use of data linkage to measure the population health effect of non-health-care interventions. *Lancet* 2014; **383:** 1517–19.