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Population-level linkages between urban greenspace and health inequality: The case for using multiple indicators of neighbourhood greenspace

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ABSTRACT

Exposure to greenspace in urban environments is associated with a range of improved health and well-being outcomes. There is a need to understand which aspects of greenspace influence which components of health. We investigate the relationship of indicators of greenspace quantity (total and specific types of greenspace), accessibility and quality with poor general health, depression, and severe mental illness, in the city of Sheffield, UK. We find complex relationships with multiple greenspace indicators that are different for each health measure, highlighting a need for future studies to include multiple, nuanced indicators of neighbourhood greenspace in order to produce results that can inform planning and policy guidance.

1. Introduction

The biophilia hypothesis proposes that humans have an evolved affiliation with living systems, and will subconsciously seek out connections with nature (Beery et al., 2015). However, urbanisation has reduced the amount of time spent in contact with nature and changed the character of that contact (Beery et al., 2015; Nieuwenhuijsen et al., 2017). It is argued that limited access to natural ecosystems has led to disruption of the connection between humans and their local environment, such that few people have a detailed understanding of nature experienced in daily life, with negative consequences for human well-being (Beery et al., 2015; Capaldi et al., 2015).

The greenspace that remains in urban environments is valued highly: nearby urban parks, forests, fields and street trees can all increase house prices or rental values (Czembrowski and Kronenberg, 2016; Donovan and Butry, 2010; Panduro et al., 2018; Votsis and Green, 2017). Moreover, there is widely accepted evidence for an association between exposure to urban greenspace and better health and well-being (Sugiyama et al., 2018; World Health Organization, 2016), with the potential for greenspace to reduce health inequalities associated with socioeconomic deprivation (Maas et al., 2009; Mitchell and Popham, 2008).

There are at least three pathways by which improvements to health and well-being may occur (Markevych et al., 2017). First, mitigation of harm results from the lower levels of air and noise pollution generally encountered within urban greenspaces, along with localised reduction of heat island effects (Markevych et al., 2017; World Health Organization, 2016). These benefits arise because greenspaces are typically not sites of emission of major pollutants (rather than due to effective filtration of pollutants from other sources); by providing an acoustic and visual barrier from sources of noise; and by provision of shade and local cooling via evapotranspiration, respectively (Markevych et al., 2017; World Health Organization, 2016).

Second, natural environments are conducive to the restoration of depleted capacities (Markevych et al., 2017; Staats et al., 2003). Restoration may occur through reduction of stress and increases in positive emotions (Ulrich et al., 1991), and through facilitation of recovery from attentional fatigue (Staats et al., 2003). It is also hypothesised that, because strong connections with nature have historically improved survival, humans have a psychological reward response to behaviours that improve such connections (Beery et al., 2015; Capaldi et al., 2015). Evidence for this pathway is provided by experimental studies in which people are exposed to simulations of greenspace in a controlled environment through the use of photographs, video or virtual reality. Responses are measured psychologically by self-report or physiologically by use of electroencephalography (EEG), blood pressure or similar (Crossan and Salmoni, 2019; Grassini et al., 2019; Jiang et al., 2019; Markevych et al., 2017; Van den Berg et al., 2003; Yu et al., 2018). These controlled experimental studies are valuable in providing evidence for the causal mechanisms of health benefits.

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Third, greenspace exposure can contribute to building new capacities: greenspaces can encourage physical activity, which provides a range of physical and psychological health benefits; and also provide an environment in which social contact can take place, especially in areas where other opportunities for these activities are lacking (Lee et al., 2015; Markevych et al., 2017; World Health Organization, 2016). However, despite the theoretical appeal of this pathway, results of empirical studies are inconsistent, and to date it is not clear whether either physical activity or social cohesion mediate relationships between greenspace and health (Markevych et al., 2017).

These pathways complement each other to produce varied effects on health and well-being, with evidence for positive outcomes including increased physical activity; reduced rates of mental health disorders, cardiovascular disease and overweight/obesity; increased birth weight; better general health; and lower all-cause mortality rates (James et al., 2015; Lee and Maheswaran, 2011). However, many studies of these associations are limited by confounding or bias (Lee and Maheswaran, 2011), and while it is apparent that not all greenspace is equal in terms of health benefits (Brindley et al., 2019; Mears et al., 2019a; Wheeler et al., 2015), the pathways by which greenspace exposure affects health and well-being are not yet well-understood (Markevych et al., 2017). There is therefore a need to better understand the causal pathways through which various aspects of health and well-being are promoted, including the functional forms of these relationships, and who might benefit in which contexts (Lee et al., 2015; Markevych et al., 2017).

At its most basic, greenspace exposure is often measured as the total amount of greenspace in an area, usually from remotely sensed data. This may be in the form of vegetation indices, such as Normalised Difference Vegetation Index, which are calculated from light reflected from the Earth's surface, and indicate the presence of photosynthetically active plants (James et al., 2015; Markevych et al., 2017). Typically, the average of the index in defined areas around homes is used as the overall greenness indicator (Dadvand et al., 2012; Markevych et al., 2014). Other studies derive total greenspace measures from land cover/land use datasets such as Ordnance Survey (OS) MasterMap or Land Cover Map in the UK, and CORINE or the European Urban Atlas in Europe (James et al., 2015; Markevych et al., 2017). These usually contain details about the type of vegetation (e.g. broadleaved vs. coniferous trees) or its context (e.g. parks vs. roadside vegetation), and from these classifications areas containing the types of land cover/use deemed relevant can be summed (Mears et al., 2019a; Mitchell and Popham, 2008; Wheeler et al., 2015; Wüstemann et al., 2017). These measures of total green have been associated with positive health outcomes including all-cause and circulatory disease-related mortality in England (Mitchell and Popham, 2008), morbidity and self-reported general health in the Netherlands (Maas et al., 2009, 2006), and birth weight and head circumference in Spain and Germany (Dadvand et al., 2012; Markevych et al., 2014).

However, such simplistic measures fail to capture the nuanced attributes of greenspace that determine their capacity to improve health (Bedimo-Rung et al., 2005; Brindley et al., 2019; Ekkel and de Vries, 2017; Lee et al., 2015; van Dillen et al., 2012). In the UK, for example, greater cover of census areas by broadleaf woodland, arable and horticulture, improved grassland and coastal land covers is associated with better self-reported general health, while there is no relationship with other types of greenspace (Wheeler et al., 2015). Within urban greenspaces, it is important that a feeling of naturalness is able to predominate in some areas, in order to facilitate nature connections (Natural England, 2010). It is also important that greenspaces are accessible, including to individuals unable or unwilling to travel far from home due to physical or social barriers, e.g. children and elderly persons (Natural England, 2010; Ward Thompson et al., 2013). Finally, the quality of greenspaces in terms of facilities and maintenance is often found to be at least as important as quantity (Brindley et al., 2019; Sugiyama et al., 2018; van Dillen et al., 2012). Installation of new facilities, such as play equipment, or improvements to aesthetics or maintenance in existing sites can lead to increases in visitation and physical activity levels, thereby increasing the potential for benefits to health and well-being (Veitch et al., 2018; Ward Thompson et al., 2013).

Given the potential for urban greenspace to improve population health and well-being, it is desirable that analyses are focused on producing clear implications for planning and policy (Lee et al., 2015; Moseley et al., 2013; Sugiyama et al., 2018). This requires studies using population level data at fine spatial scales (to minimise loss of information associated with aggregation; Mears and Brindley, 2019; Weigand et al., 2019) and for large geographic areas (to include a wide range of socioeconomic and environmental conditions), which also capture nuances of the types, features and locations of urban greenspaces (Bedimo-Rung et al., 2005; Brindley et al., 2019; Ekkel and de Vries, 2017). Our aim is to examine the association between health and greenspace using detailed indicators in order to produce specific recommendations for improving public health, using the city of Sheffield, UK as a case study. We acknowledge that without data on who is (and who is not) using which greenspaces, and for what purposes, producing planning and policy recommendations that ensure all sectors of society are benefitting from greenspace is not possible (James et al., 2015; Lee and Maheswaran, 2011). Nevertheless, in the absence of such data, we have designed indicators that aim to describe the greenspace environment to a greater level and variety of detail than is commonly seen in quantitative studies. We have also used several controlling variables to reduce the risk of confounding with certain demographic factors.

Specifically, our indicators as are follows. Percentage green cover is a basic, relatively large-scale indicator of green-ness, following the many studies that find broad measures of greenspace exposure to be important for health (de Bont et al., 2019; Maas et al., 2009, 2006; Markevych et al., 2014; Mitchell and Popham, 2008). We assess specific types of greenspace that are likely to be particularly important to health using average domestic garden size and local tree density (Brindley et al., 2018; Coolen and Meesters, 2012; Jones and McDermott, 2018; Molla, 2015).

We assess greenspace accessibility as the proportion of residential addresses that are within a five minute walk of any publicly accessible greenspace, and also the proportion within five minutes' walk of a greenspace meeting size and quality criteria that increase the likelihood of health benefits (Mears et al., 2019b; Natural England, 2010; Sugiyama et al., 2018; van Dillen et al., 2012). Five minutes' walk equates to around 300m; this is a distance that most people are prepared to walk to natural spaces, and is how far many parents will allow their children to travel from home unattended (Coles and Bussey, 2000; Grahn and Stigsdotter, 2003; ; Natural England, 2010; Rojas et al., 2016). It is also the distance recommended by a recent literature review (Van Den Bosch et al., 2016).

The quality of local greenspaces is also assessed using two indicators. First, a citizen science-derived measure of bird abundance is used as an integrative measure of local biodiversity: bird biodiversity is often correlated with biodiversity of other taxa, and high levels of biodiversity in urban greenspaces can be associated with greater psychological benefits (Fuller et al., 2007; Wood et al., 2018). Second, we include a survey-based assessment of the cleanliness of selected publicly accessible greenspaces; previous work has found that this aspect of quality is related to self-reported general health (Brindley et al., 2019).

Our selection of indicators was driven first by available data, then through testing of alternative ways of constructing meaningful measures of the local greenspace environment. We look for associations between the chosen indicators and three health measures captured at Lower-layer Super Output Area (LSOA) level, a small-area census geography. Self-reported general health is a subjective composite health measure that is associated primarily with objectively assessed physical, but also mental and social factors, as well as being strongly correlated with all-cause mortality (Kyffin et al., 2004; Mavaddat et al., 2011). We also look at rates of depression and severe mental illness through the use of GP patient data. The prevalence of mental health disorders is greater in cities than in rural areas (Paykel et al., 2003; Peen et al., 2010; Sundquist et al., 2004), but this may be attenuated by living close to greenspace (de Vries et al., 2003; Gong et al., 2016; Houlden et al., 2017; Verheij et al., 2008). Our study appears to be the first of its kind to use a range of different types of greenspace indicators and multiple health measures. We use a statistical approach that accounts for several confounders and minimises the risk of over-fitting, thereby increasing the robustness of results. This approach enables us to investigate which specific and detailed aspects of greenspace are related to health, and whether it is possible to generalise findings across different aspects of health.

2. Methods

2.1. Study area

Sheffield (53°23′N, 1°28′W; map shown in Supplementary Material, section S1) is an inland city with a population of 552,000 in 2011 (Office for National Statistics, 2016). The city boundaries comprise an area of 368 km^2, with the population concentrated in the eastern part of the city, and the western part primarily containing upland moorland and agricultural land. Similar to other ex-industrial northern English cities, Sheffield has a higher than average level of deprivation overall, but there is a strong west-east gradient, with the east end suffering greater income and health deprivation compared to the historically cleaner and wealthier west (Department for Communities and Local Government, 2015). This work was undertaken within the remit of the Improving Wellbeing through Urban Nature project[1], which investigated how urban greenspace benefits health with a particular focus on Sheffield. Involvement of local health professionals and Sheffield City Council facilitated acquisition of non-public datasets that made this study possible.

Sheffield contains 345 LSOAs. LSOAs contain an average population of 1600 and have been used in previous research into associations between greenspace and health (Brindley et al., 2018; Mitchell and Popham, 2008; Wheeler et al., 2015). LSOAs are a suitable scale for investigating intra-urban spatial patterns, while minimising the risk of random statistical fluctuations that would arise from units with small numbers of people.

2.2. Health data

We used three measures of LSOA population health. The first, self-reported poor general health, is taken from the 2011 census question "how is your health in general?", with the possible answers: very good; good; fair; bad; very bad. Following previous research, we summed the 'bad' and 'very bad' categories to obtain a count of individuals with poor general health per LSOA (Brindley et al., 2018; Mitchell and Popham, 2008; Wheeler et al., 2015).

The depression measure is the count of diagnoses of depression from GP registry data (to January 2017) from each LSOA. Severe mental illness is a similar measure, including diagnoses of bipolar disorder and disorders involving psychosis. These data were obtained from NHS Clinical Commissioning Group.

For each health measure we controlled for LSOA age and sex distribution by including the expected count of individuals with the health condition as an offset term (a term with an assumed coefficient of 1) in statistical modelling. This was calculated using indirect standardisation (Naing, 2000). Maps of the ratios of observed:expected counts of health measures are shown in Fig. 1.

2.3. Greenspace data

We included seven greenspace indicators, selected according to area characteristics that could reasonably be expected to be associated with health, based either on theory or previous studies. The geographic distribution of these variables in shown in the Supplementary Material, section S2.

Green cover is an LSOA-scale measure of percent greenspace cover. It is derived from OS MasterMap Topography Layer, which captures all physical features considered important in the landscape. Greenspace is defined broadly in this indicator, including all features representing natural land covers, including water, but excluding domestic gardens. Domestic gardens are excluded for two reasons. First, while domestic gardens can be identified from OS MasterMap, the extent to which these gardens are vegetated cannot. A recent report using automated image classification found that, on average across Great Britain, 38% of garden area is not vegetated (Bonham et al., 2019). There is evidence that, in cities, gardens have even less vegetation cover: the same study found non-vegetated cover of 46% for Cardiff and 55% for Bristol, while a site survey study of four UK cities (Leicester, Cardiff, Edinburgh and Bristol) found an average of 65% (Bonham et al., 2019; Loram et al., 2008). The second reason is that domestic gardens (if presumed to be fully vegetated) comprise a substantial proportion of the total greenspace in LSOAs (the average LSOA in Sheffield has 49% of its greenspace in domestic gardens). As previous work has highlighted the importance of gardens in particular to health (Brindley et al., 2018), we wished to keep gardens as a separate variable (see below) in order to reduce collinearity.

Tree density is a measure of local tree density around residential addresses. It is derived from Bluesky's National Tree Map, which includes trees and shrubs over 3m in height. We used GIS to create a raster of the number of trees within a 100m circular radius of each 5m cell, and extracted the value for each residential address point (from OS AddressBase Plus). We took the average across address points for each LSOA. The 5m cell size was selected as it is a similar scale to the smallest houses within the study area. A circular radius of 100m was selected as this is the scale at which humans readily grasp the scene around them (Gehl, 2010). Due to lack of certainty that this was the most appropriate basis on which to define the scale at which tree density matters, we performed sensitivity testing. Testing of shorter and greater distances (50m and 200m) indicated that these were strongly correlated with values for 100m (Pearson's $r = 0.98$ and 0.97 respectively); using 50m made no qualitative difference to the results of statistical analysis, while using 200m resulted in poorer model fit due to inability to capture variation at an adequately fine level.

Garden size is the mean domestic garden size across residential properties. Gardens were identified from OS MasterMap Topography Layer as polygons recorded as a 'multi surface'; these polygons are nearly exclusively private domestic gardens (M. Mears, personal observation). The total area of these polygons was divided by the number of residential address points within each LSOA.

We included two indicators measuring the proportion of residential addresses within each LSOA that have access to a greenspace within 300m by the road and path network to a greenspace access point (i.e. not as the crow flies, but as a pedestrian on the ground would travel; Mears et al., 2019b). Any public greenspace accessibility is the proportion of addresses within 300m of any greenspace included in Sheffield City Council's 2008 green and open space assessment (data provided by Sheffield City Council). The assessment includes publicly accessible greenspaces considered to have leisure or recreational value, including those not owned by the council. It includes sports pitches, parks and gardens, (semi-)natural greenspaces, cemeteries/churchyards, allotments and community gardens, children's play facilities, and amenity greenspaces such as central greens in residential areas (Strategic Leisure Limited, 2008).

Similarly, good public greenspace accessibility is the proportion of addresses within 300m of a greenspace of at least 2 ha in size, with a predominantly natural feeling, and with a 'good' or better overall quality rating in the 2008 assessment. These criteria were chosen as they

[1] Project website is at http://www.iwun.uk (accessed 04/12/2019).

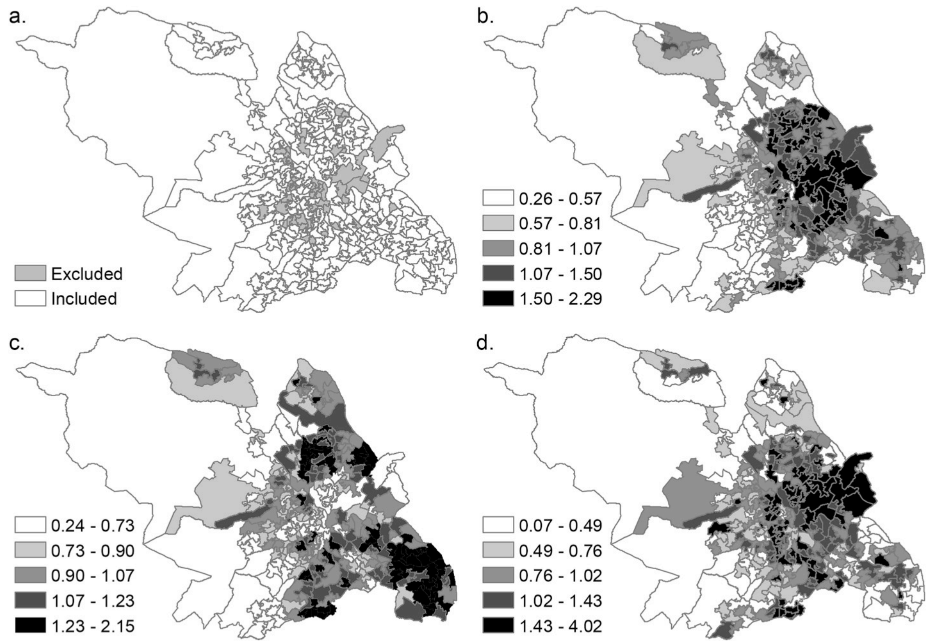

Fig. 1. (a) LSOAs excluded from analysis. Quintiles of (b) poor general health, (c) depression and (d) severe mental illness within LSOAs as ratio of observed:expected counts.

reflect factors related to the likelihood that exposure to a greenspace will provide benefits, and the extent to which they are actually used (Bedimo-Rung et al., 2005; Ekkel and de Vries, 2017; Haq, 2011; Lee et al., 2015). Full details of the accessibility measures are given in Mears et al. (2019b).

Garden biodiversity measures avian abundance in domestic gardens, using data from the Royal Society for the Protection of Birds' Big Garden Bird Watch citizen science surveys. Participants observe birds in their domestic garden over a period of one hour on a weekend morning in late January, recording for each species the maximum number of individuals observed at one time. We used data from 2011 (n = 2214 respondents) and 2013 (n = 2106) to calculate the mean number of birds (summing across all species) observed by respondents in each LSOA. We used numbers of birds instead of numbers of species due to concerns about misidentification. However, we considered misidentification within functional guilds of species less likely, so we also tested models with counts of functional guilds and Shannon diversity of functional guilds. We used functional guilds developed for overwintering birds in Scotland (French and Picozzi, 2002), as no existing classification for birds in England could be found. Functional guilds for five species observed in Sheffield but missing from this dataset were assigned using expert knowledge. However, these alternative indicators made no qualitative difference to results, so we chose to use the simplest indicator. Twenty-four LSOAs did not have at least one respondent in either year, so are missing data for this variable.

The final indicator, public greenspace cleanliness, is derived from Sheffield City Council's 2008 assessment of accessible green and open space provision (Strategic Leisure Limited, 2008). The assessment is based on the nationally recognised Green Flag Award, but goes into greater depth. Assessment involved site surveys to quantify aspects of the quality relevant to the type of greenspace, including: signage; provision of facilities such as bins, seats and toilets; maintenance of paths; safety; planting and plant management; and cleanliness. Of these, previous research has found cleanliness to be the only aspect of assessed quality that is related to health in Sheffield (Brindley et al., 2019 and unpublished research). The cleanliness of each greenspace was scored on a scale of 0–20 according to observations of litter, dog fouling, graffiti and chewing gum. An LSOA-scale score was derived by calculating the area-weighted mean score of greenspaces intersecting with the LSOA. Full details are given in Brindley et al. (2019). A cleanliness score could not be calculated for 32 LSOAs, due to not having any quality-assessed greenspaces within their boundaries.

2.4. Controlling variables

To minimise confounding, we included in our statistical models socioeconomic factors known to influence health that are likely to correlate with aspects of urban greenspace. Income deprivation, air pollution and smoking rates were selected as they have been used in other analyses of health and greenspace (Brindley et al., 2018, 2019; Mitchell and Popham, 2008; Richardson et al., 2010); address density was added following observations that the urban matrix was not adequately controlled for. Maps of these variables are shown in the Supplementary Material, section S2.

Socioeconomic deprivation was controlled for using the income deprivation domain of the English Indices of Deprivation (2015), which is based on the number of individuals receiving various forms of state financial support in 2012–13.

Air pollution was controlled for using the Department for Environment, Food and Rural Affairs 1 km grid model of PM_{10} annual mean concentrations for 2010, with LSOA-scale values calculated using population-weighted averages, where the population represented census headcounts at unit postcode level.

We controlled for smoking rates using the proxy of hospital admissions for lung cancer between April 1, 2002 and March 31, 2014. LSOA-level ratios of observed to expected counts were calculated, adjusted for age and sex distribution.

Finally, residential address density was controlled for using a local-scale measure (i.e. measured for each address individually then averaged across LSOAs). Address points were identified from OS AddressBase Plus. Each individual address (including flats/apartments within single buildings) is geocoded individually. We used the same method as used to calculate tree density (Section 2.3), instead counting address points. Values calculated for 50m and 200m distances were closely correlated with that for 100m (Pearson's $r \geq 0.97$ in both cases), and using these alternatives made no qualitative difference to analytical results. We also tested an LSOA-scale measure, number of address points divided by LSOA area, but this resulted in poorer model fit.

2.5. Analysis

Fifty-one LSOAs were excluded from analysis due to missing garden biodiversity or public greenspace cleanliness data. One further LSOA was dropped due to large influence (measured by Cook's distance) on results; this LSOA contains almost exclusively student residences, and has the highest address density yet lowest income deprivation. The final sample size was $n = 293$. The locations of excluded LSOAs are shown in Fig. 1a.

Following previous work (Brindley et al., 2018; Mitchell and Popham, 2008), we used negative binomial regression to test for associations between health measures and greenspace variables, controlling for confounding as described. Due to the paucity of evidence for the functional form relationships between health outcomes and aspects of greenspace in the literature (Markevych et al., 2017), we did not have *a priori* hypotheses regarding linearity vs. non-linearity of relationships. However, during data exploration we did find visual evidence for quadratic effects for at least one health outcome for all greenspace and controlling variables. In order to make models more comparable, we therefore included quadratic terms for all variables for all health outcomes. This resulted in a large number of variables, and so to reduce the risk of overfitting we used an information theoretic multi-model inference approach to model building. Following Symonds and Moussalli (2011) and Richards et al. (2011), we constructed a 'base' model including the offset term and linear terms for the controlling variables, then tested all possible combinations of predictors, plus quadratic terms for all variables (including controlling variables), observing marginality rules (i.e. quadratic term only included if linear term included). We used orthogonal transformation to minimise collinearity and variance inflation between linear and quadratic; this also minimised variation in the numerical scales of predictor variables and improved coefficient stability during averaging. We used AICc (Akaike Information Criterion corrected for small sample size) to construct a plausible set of models within 6 AICc units of the best model, excluding models that were more complex versions of a simpler model with lower AICc. This plausible set was averaged, imputing zero as the coefficient for terms not appearing in individual models (to prevent inflation of coefficients for unimportant variables appearing in few models).

As a measure of model fit, we show the range of Nagelkerke's pseudo-R^2 for models in the plausible set. (There is currently no accepted way to calculate pseudo-R^2 for averaged models.) To assess the shape of relationships between individual greenspace indicators and health outcomes, we plotted the marginal effects. In order to plot data on raw (as opposed to orthogonally transformed) scales, we used coefficients from a version of the averaged model using untransformed data. It should be noted that both averaged models use the same plausible set of models (data transformation was the only difference) and that fitted values are identical regardless of whether raw or orthogonal data are used.

Spearman's correlation coefficients and variance inflation factors (VIFs) were used to check for potential effects of multicollinearity on model results. The correlation matrix is shown in the Supplementary Material, section S3. Garden size and address density were the only variables with an absolute $rho > 0.55$, with $rho = -0.91$. When calculating VIFs on models containing linear terms only, no VIF was higher than 3.7 for any model; however, when including orthogonal polynomial terms, VIFs for garden size and address density were in the range 9.6–11.2 for the three models. This is borderline unacceptable when using the rule of thumb that VIFs should be less than 10 (O'Brien, 2007). However, we decided not to exclude either variable for several reasons. First, address density was added due to the observation that urbanicity was not being adequately controlled for in models without it. Second, in light of previous research (Brindley et al., 2018), we specifically wished to investigate the relationship between garden size and the health outcomes. Third, for poor general health and depression, when repeating the multi-model inference process while excluding one of these variables, the range of AICc values in the plausible set was >6 units higher than the range found when including both variables (although similar ranges were present for severe mental illness). Finally, simulation studies indicate that multicollinearity increases Type II, but not Type I, errors (Lavery et al., 2019). Despite this, address density is significant in all models, and garden size in two. We therefore suspect that in this case, VIFs are over-estimating the actual variance inflation due to these two variables containing non-redundant information about the health outcomes (Curto and Pinto, 2011).

All analyses were performed in R (R Core Team, 2019), using package 'MASS' (Venables and Ripley, 2002) to build negative binomial models are package 'MuMIn' (Barton, 2017) for multi-model inference. The package 'car' (Fox and Weisberg, 2019) was used to calculate VIFs.

3. Results

Overall, the negative binomial models fit the data well. The range of Nagelkerke's pseudo-R^2 for models comprising the plausible set for poor general health is 0.89–0.90. The fit for the depression and SMI models is lower, at 0-56-0.58 and 0.52–0.53 respectively. The results of the averaged models are shown in Table 1, with plots of marginal effects for each greenspace variable shown in Fig. 2 (these should be interpreted in combination with the box and whisker plots, which show the data distribution). Results for controlling variables are shown in the Supplementary Material, section S4.1.

3.1. Poor general health

Three greenspace indicators have significant effects on poor general health. Garden size has the greatest effect size, with LSOAs with a larger average garden size having lower levels of poor general health. Any public greenspace accessibility is also significant: LSOAs that have a higher proportion of addresses within 300m of any greenspace tend to have higher rates of poor general health (the response is curvilinear, but it is in this direction in the range where the majority of data points lie). Finally, at low levels of green cover, increases in the proportion of green cover are associated with reduced levels of poor general health. This pattern reverses at high levels of green cover (although again, there are few LSOAs with very high levels of green cover; see box and whisker plot in Fig. 2a).

3.2. Depression

Garden size is again significant and has the largest effect size of the greenspace indicators, with smaller gardens associated with higher rates of depression. Any public greenspace accessibility is also significant. The marginal effects plot again shows a U-shaped relationship; however, given the numerical distribution of data points, the most likely interpretation is that increases in greenspace accessibility while it is still low in absolute terms are not related to rates of depression, while increases in accessibility at higher absolute levels are associated with increased rates of depression. Finally, greater public greenspace cleanliness is associated with lower rates of depression.

3.3. Severe mental illness

The only greenspace indicator significantly related to SMI is tree density, which shows a relationship between high rates of SMI and high tree density.

4. Discussion

4.1. Relationships between greenspace indicators and health

After de-confounding the strong associations found with controlling variables (Supplementary Material, section S4.2), we found significant

Table 1
Averaged negative binomial regression models for rates of poor general health, depression and severe mental illness in Sheffield LSOAs. Empty lines indicate that the variable did not appear in the plausible set (quadratic terms that did not appear in any plausible set are not shown). Significant terms are shown in bold (linear terms with corresponding significant quadratic terms are also shown in bold, regardless of p-value, as the variable is considered significant overall).

	Poor general health				Depression				Severe mental illness			
	Estimate	SE adj.	z value	p	Estimate	SE adj.	z value	p	Estimate	SE adj.	z value	p
(Intercept)	**−0.082**	**0.009**	**9.174**	**<0.001**	0.002	0.012	0.196	0.844	**−0.115**	**0.026**	**4.473**	**<0.001**
Income deprivation	**6.268**	**0.220**	**28.501**	**<0.001**	**1.036**	**0.298**	**3.476**	**0.001**	**6.433**	**0.581**	**11.070**	**<0.001**
Income deprivation ^2	**−1.505**	**0.163**	**9.257**	**<0.001**	**−0.884**	**0.224**	**3.939**	**<0.001**	**−1.895**	**0.460**	**4.116**	**<0.001**
Smoking	0.233	0.174	1.341	0.180	0.253	0.235	1.075	0.282	−0.163	0.484	0.336	0.737
Air pollution	0.292	0.204	1.431	0.152	**−0.873**	**0.285**	**3.068**	**0.002**	−0.067	0.538	0.124	0.901
Air pollution ^2					**−1.085**	**0.243**	**4.467**	**<0.001**				
Address density	**−0.646**	**0.376**	**1.721**	**0.085**	**−1.441**	**0.341**	**4.223**	**<0.001**	**2.922**	**0.704**	**4.152**	**<0.001**
Address density ^2	**1.181**	**0.230**	**5.133**	**<0.001**								
Green cover	**−0.258**	**0.188**	**1.372**	**0.170**								
Green cover ^2	**0.454**	**0.222**	**2.044**	**0.041**								
Tree density	−0.422	0.233	1.811	0.070	−0.400	0.332	1.205	0.228	**2.590**	**0.544**	**4.757**	**<0.001**
Tree density ^2	−0.230	0.205	1.120	0.263								
Garden size	**−1.938**	**0.454**	**4.272**	**<0.001**	**−1.805**	**0.424**	**4.262**	**<0.001**	−0.831	0.966	0.860	0.390
Any public greenspace accessibility	**0.553**	**0.197**	**2.811**	**0.005**	**0.973**	**0.261**	**3.732**	**<0.001**				
Any public greenspace accessibility ^2	0.184	0.192	0.957	0.338	0.407	0.280	1.452	0.147				
Good public greenspace accessibility	−0.121	0.177	0.686	0.493								
Garden biodiversity	0.273	0.188	1.454	0.146								
Public greenspace cleanliness					**−0.683**	**0.295**	**2.317**	**0.020**				

associations with greenspace indicators for all three health measures, albeit a different selection of indicators in each case. Our indicator of greenspace quantity, green cover, was important for general health only. The relationship indicates an association between increasing green cover and reduced poor general health across LSOAs with less than about 50% green cover, which saturates at the high end of the inter-quartile range. The curve reverses at very high levels of green cover, but further investigation (results not shown) suggests this is driven by a few data points where green cover is approaching 100%. An association between more green cover and lower incidence of poor general health has been observed previously (Maas et al., 2006; Mitchell and Popham, 2008), but the saturating response has not. Our result suggests that once a critical level of greenspace is reached – according to our results, around 50% – adding more does not further benefit health in an urban environment. This indicator is measured at LSOA scale, such that all addresses in an LSOA receive the same value regardless of local conditions. In inner-city LSOAs, which tend to be small, this may be not an issue. However, in larger suburban LSOAs, greenspace may be in areas rarely visited by most residents.

Significant relationships are most common for the indicators of specific types of greenspace. Larger garden size is associated with lower rates of poor general health and depression. This matches the finding of a national study (Brindley et al., 2018), indicating that private as well as public greenspace has a positive effect on health. Private gardens have different functions and meanings from public greenspaces (Coolen and Meesters, 2012), so it is not surprising that additional health benefits accrue from access to a garden (de Vries et al., 2003).

Higher tree density appears to be associated with higher rates of severe mental illness. We have not been able to find an epidemiological explanation for this counterintuitive result, especially considering that there is only 11% overlap between the quintiles of highest tree density and highest severe mental illness ratio, and zero overlap between the lowest quintiles. There is no relationship between rates of severe mental illness and number of people living in medical/care establishments within LSOAs (results not shown). The result may be as a result of selective migration, although while we have no way to investigate this using an ecological approach, we consider it unlikely given that sufferers of severe mental illness are more likely to locate to more deprived areas (Tunstall et al., 2015), whereas higher income deprivation is associated with lower tree densities in our data ($rho = -0.37$). It may also be a result of the comparatively low prevalence of several mental illness (mean of 14 cases per LSOA, compared to 100 for poor health and 220 for depression), meaning counts are more likely to be subject to random fluctuations. This is likely to be one reason for the limited success in detecting significant effects in the severe mental illness model more generally; another is that severe mental illness may have a larger genetic and smaller environmental component than e.g. depression (Sariaslan et al., 2015).

It is interesting that tree density is not significantly related to either poor general health or depression. Although the indicator used achieved a better model fit than an alternative tested measure (LSOA-scale tree cover) and two other buffer distances, trees directly around the home may not be a useful indicator of tree exposure as it relates to these health measures.

With regards to indicators of accessibility, high accessibility to any public greenspace is associated with higher rates of poor health and depression. This seemingly counterintuitive finding can be explained by the history of public parks in many English industrial cities, where parks were established as a public health measure to improve the health of the working class living with high levels of air pollution in high density, unsanitary housing conditions (Crompton, 2013; Mears et al., 2019b). In Sheffield, deprivation remains highest in the same areas of the city, especially in the east end (Abercrombie, 1924). Thus, greenspace accessibility remains good in the most income- and health-deprived parts of the city. The curvilinear relationship suggests that at low levels of accessibility (less than around a third of households having access), poor health and depression may also decrease, but the most likely explanation for this is that LSOAs with low accessibility include the most rural areas, where there is much greenspace that is not captured in the council's assessment exercise.

When only greenspaces that are large, natural-feeling and assessed as being good quality are considered, the pattern of better accessibility in more deprived areas is no longer apparent (Mears et al., 2019b). There is also no relationship between this indicator and any health measure. This may be because our method of assessing which greenspaces are 'good' does not capture the aspects of greenspace that most affect health (Brindley et al., 2019; Lee et al., 2015).

The only significant relationship for a greenspace quality indicator is that higher public greenspace cleanliness is associated with lower rates of depression. Cleanliness may therefore be more important than greenspace size, overall quality and whether or not it is natural-feeling (the criteria used in the 'good' greenspace accessibility indicator). The second quality indicator, garden biodiversity, is not significant in any model. This is unexpected, given that biodiversity can influence psychological affect and health (Fuller et al., 2007; Lovell et al., 2014; Wood et al., 2018). However, as our biodiversity measure is based on a citizen

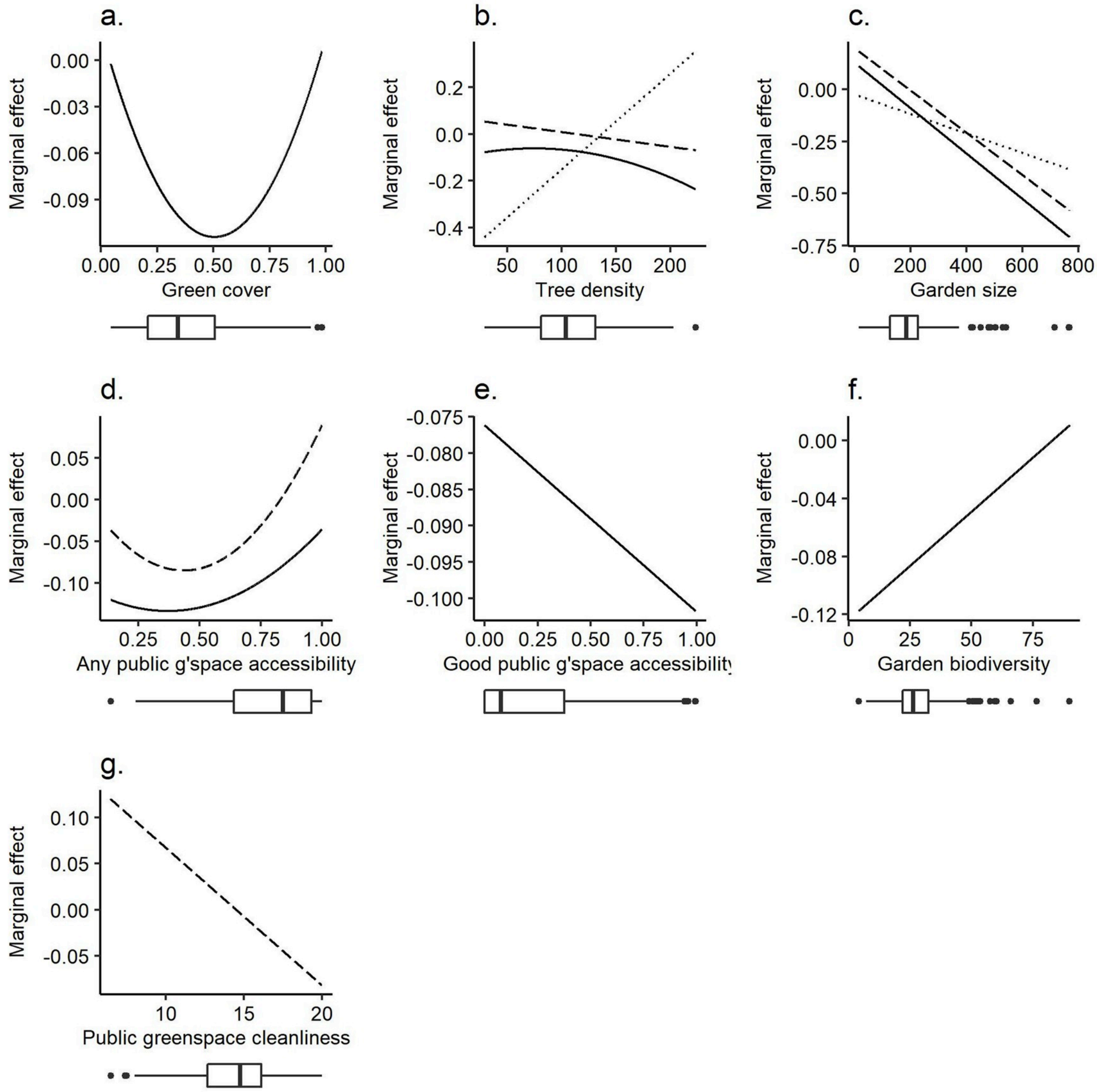

Fig. 2. Marginal effects of greenspace and controlling variables on poor general health (solid lines), depression (dashed lines) and severe mental illness (dotted lines) in Sheffield LSOAs. Marginal effects are shown on log scale (as per negative binomial GML link function). Missing lines indicate the variable did not appear in the plausible set for the health measure. Box and whisker plots indicate variable distribution, with the box encompassing the interquartile range and whiskers indicating a further 1.5x the interquartile range. Units: (a) proportion cover, (b) count of trees within 100m of addresses, (c) m^2, (d, e) proportion of addresses with access, (f) count of birds, (g) score out of 20.

science garden bird survey there may be a number of issues with the data, including spatially highly variable sample sizes. We used counts of birds, rather than species diversity, in order to avoid issues with possible mis-identification of birds; although mis-counting is a possibility. It is somewhat surprising that the quality indicators are not more prominent in our results, as previous work suggests that greenspace quality is important for population health (Sugiyama et al., 2018; van Dillen et al., 2012). This highlights a need to identify which aspects of greenspace quality are important for health.

A final notable result is that several variables show curvilinear responses (Fig. 2) that indicate either a minimum level of exposure before an impact on health is observed, or a saturating response in which further environmental improvements have no impact. This suggests that there may be critical levels at which greenspace improvement (or degradation) becomes important; and that if changes are made outside of this range, no changes to health will be observed. Overall, our use of a variety of greenspace and health measures has enabled us to reveal part of the complex nature of the relationship between neighbourhood greenspace and population health.

4.2. Limitations

A key limitation of this and similar studies (e.g. Brindley et al., 2018; Mitchell and Popham, 2008; Wheeler et al., 2015) is that we were not able to obtain data on usage of greenspaces. Therefore we have only captured what greenspace exists, rather than its use, which likely provides the majority of greenspace-related health benefits (Lee et al., 2015). Data on use in the quantities required for population-level studies are not readily available or easy to collect. Use is influenced by a variety of socioeconomic and cultural factors (Bedimo-Rung et al., 2005; Seaman et al., 2010; Zanon et al., 2013), meaning the relationship between greenspace availability and use is not simple. For example, people living in deprived areas may have negative perceptions of local greenspace and avoid using them (but see Hoffimann et al., 2017; Jones et al., 2009). Women in particular are affected by perceived safety issues (Scott and Munson, 1994; Zanon et al., 2013). Ethnicity and cultural heritage also play a role in park use, as well as preferences (Payne et al., 2002; Zanon et al., 2013). People with poor health are less likely to use greenspace (Scott and Munson, 1994; Zanon et al., 2013). This is despite the ability of greenspace to mitigate health inequalities associated with deprivation (Maas et al., 2009; Mitchell and Popham, 2008), suggesting that investment in facilities to aid visitation by those with poor health would bring even greater health benefits. Older people are also less likely to use parks (Mowen et al., 2005; Payne et al., 2002; Zanon et al., 2013), although this may be confounded with health (Zanon et al., 2013). Constraints such as family responsibilities or lack of company can also limit greenspace use, and these are more likely to affect women (Mowen et al., 2005; Zanon et al., 2013). A lack of social inclusion more generally can also cause people to choose not to visit local greenspaces (Seaman et al., 2010). Overcoming such constraints would require more profound societal changes than simply changing greenspace. While data on greenspace use is costly to collect, it is central to producing planning and policy recommendations that ensure socially just distribution of health benefits from greenspace.

Another major limitation of this study is that it uses a single case city. While Sheffield is typical of ex-industrial northern English cities in terms of having a relatively high level of socioeconomic deprivation (Department for Communities and Local Government, 2015), it is also unusual in having a large area of moorland and agricultural land within the district boundary. Although 96.5% of the district's households are in areas classed as urban in the 2011 Rural-Urban Classification, the presence of rural areas within the data may influence results (although the statistical leverage of these areas was small). Ideally, we would test the generalisability of our results by performing similar analyses for other areas, but due to the lack of wider availability of some variables (public greenspace cleanliness and comprehensive access points for mapping greenspace accessibility) and the computational intensity of others (those requiring GIS network analysis), analysis of other areas was not possible within the scope of this study.

As a cross-sectional study, causation cannot be implied from our analysis. Establishing causation is an on-going challenge in studies of links between greenspace and health, as associations are complex (Lee and Maheswaran, 2011), and statistically significant relationships may also indicate reverse causation or residual confounding. Another issue is related to sample size: the effects of greenspace on health may be substantially weaker than those of socioeconomic circumstances, so the absence of significant relationships may simply arise from a lack of statistical power.

A lack of significant relationships may also occur if greenspace indicators do not accurately capture aspects of the greenspace environment that affect health. We have endeavoured to design indicators that capture the environment as experienced by residents, rather than adhering to LSOA boundaries for all indicators. However, it is difficult to precisely capture the environment that is experienced on a day-to-day basis due to variation in individuals' behaviour, for example on commutes or through travel to local parks (Kwan, 2012).

Another issue in spatial analyses is that both scale and the basis of aggregation can heavily influence results (Marceau, 1999; Weigand et al., 2019). Although LSOA boundaries are drawn to capture socioeconomic homogeneity (Department for Communities and Local Government, 2015), it remains possible that alternative areas would yield different results. Similarly, data bound to aggregated units such as LSOAs may be subject to the ecological fallacy, whereby patterns observed at population-level do not hold for individuals (Lee et al., 2015; Weigand et al., 2019).

Individual indicators also have specific limitations not already mentioned. Green cover, any public greenspace accessibility and public greenspace cleanliness treat greenspace as a single class rather than looking at individual types. It is probable that some types of greenspace have a greater effect on health than others (Wheeler et al., 2015), but not all types are found in all LSOAs, so splitting out individual types would result in a loss of statistical power. The cleanliness and accessibility indicators include only greenspaces identified in Sheffield's green and open spaces assessment (Strategic Leisure Limited, 2008), which does not include rural greenspaces (although the majority of the urban population do not live close to these) or incidental greenspace such as street trees and verges.

The accessibility measures are also limited to a maximum 300m distance between houses and greenspaces, as recommended by UK guidelines and a recent literature review (Natural England, 2010; Van Den Bosch et al., 2016). Although greenspace use falls rapidly with distance from home (Schipperijn et al., 2010), and nearby greenspaces are especially important for groups such as women with young families and elderly people who may be limited to using areas close to home (Grahn and Stigsdotter, 2003; Nielsen and Hansen, 2007; Rojas et al., 2016), studies of recreational urban walks find an average distance greater than 300m (Kang et al., 2017; Millward et al., 2013), and more distant greenspaces can have a positive effect on health (Browning and Lee, 2017; Coldwell and Evans, 2018). Council surveys of park use from Sheffield and Leeds indicate a range of reasons why people may prefer to visit more distance parks, including a lack of facilities, poor maintenance and safety issues (Barker et al., 2018; unpublished results). The nationwide Monitor of Engagement with the Natural Environment survey[2] also shows that people will travel further to visit countryside than urban greenspace, and on average those who have travelled further stay for longer and may participate in different activities to those staying close to home (unpublished results). For urban residents, regularly visiting either urban greenspace or the countryside is associated with lower anxiety levels, but the relationship with urban greenspace is stronger; conversely, higher life satisfaction is more strongly associated with regular visits to countryside than urban greenspace (Coldwell and Evans, 2018). This suggests that different benefits accrue from visiting greenspaces that are further away from centres of urbanisation. However, exploring such relationships requires individual-level data and as such was not possible within the scope of this study.

An additional limitation associated with the quality measures, garden biodiversity and public greenspace cleanliness, is that neither was assessed fully objectively and systematically. Good public greenspace accessibility also suffers from this issue due to its dependence on quality assessments. This limits the generalisability of the models as there may be bias. Further, surveys of both biodiversity and site quality depend on local data availability, whereas our other indicators are calculated from datasets for which analogues would be available in most locations.

We were not able in this study to investigate possible interactions between indicators. This is a limitation related to our sample size ($n = 293$), which limits the number of independent variables that can be included, and our decision to prioritise inclusion of quadratic terms to investigate non-linear responses. It is likely that some interactions are present. For example, 'nature' may potentially have a different meaning in rural compared to highly urbanised areas, which could mean that green cover and/or address density may interact with the other greenspace variables. Similarly, greenspace has the potential to mitigate health inequalities associated with deprivation (Maas et al., 2009; Mitchell and Popham, 2008), meaning that income deprivation may also interact with greenspace variables.

Finally, there is a possibility of bias in the LSOAs that were excluded from analysis due to missing data. LSOAs missing public greenspace cleanliness data do not have any such greenspaces within their boundaries, and those lacking garden biodiversity data are more common in the deprived parts of Sheffield. We guarded against the possibility of bias by repeating the analysis excluding these two variables and including all LSOAs and found broadly similar results (not shown); although this does not entirely exclude the possibility of bias.

4.3. Future directions and policy implications

A clear message from our analysis is that to be able to guide policy

[2] Data available from http://publications.naturalengland.org.uk/publication/2248731?category=47018 (accessed 04/12/2019).

recommendations, studies of the effects of greenspace on health need to include multiple measures of greenspace and its specific characteristics. However, the development of detailed indicators is limited by the availability of suitable data (Lee et al., 2015; Lee and Maheswaran, 2011), and most of the data that is available is at population level, which does not capture the needs or behaviour patterns of individuals. The presence of statistically significant non-linear responses to greenspace conditions also highlights a need to investigate the functional form of relationships. This has been acknowledged by Markevych et al. (2017), and such investigations are not common at present (but see Brindley et al., 2018, 2019; Mitchell and Popham, 2008).

One approach to collecting individual-level data for indicator development is GPS tracking using smartphones (Kwan, 2012). For example, the Shmapped smartphone app was a well-being intervention tool that encouraged people in Sheffield to notice and reflect on nature, and also used GPS tracking to collect data on actual greenspace use (McEwan et al., 2019). This kind of data facilitates a more nuanced exploration of the aspects of greenspace use that influence individual-level health.

Some experimentation is required in order to find the most appropriate indicators, both in terms of capturing the appropriate geographic context and of scale/aggregation. In particular, better measures of quality are needed. In general, indicators that are objective, systematic, and calculated from widely available data are strongly preferred in order to produce generalisable models. However, in this study we were unable to develop quality indicators meeting these criteria, resulting in significant limitations. This is perhaps reflected in the fact that, contrary to expectations, our quality indicators are not prominent in the results (Brindley et al., 2019; Lee et al., 2015; Sugiyama et al., 2018; van Dillen et al., 2012). Quality standards are important in order to be able to audit and manage greenspaces effectively. Moreover, improving the quality of greenspaces may in many situations be easier than creating new greenspaces. The UK's Planning and Policy Guidance 17 (PPG17: Planning for open space, sport and recreation), which required local authorities to undertake assessments of provision and quality of greenspace, was helpful in this respect as it introduced standards and established responsibility for carrying out audits.

PPG17 was replaced in 2012 by the National Planning Policy Framework. Data and responsibility for greenspaces currently lie across organisations and departments, presenting a challenge to acquiring the types of data needed to inform specific policy and planning recommendations. A recent government report on the relationship between health and greenspace committed to setting up a cross-departmental group (Parks Action Group), which may be able to provide such a function (Department for Communities and Local Government, 2017).

A second message from our analysis is that health outcomes need to be investigated separately, as they may be influenced by different aspects of the greenspace environment. The differences between our health outcomes demonstrate that there is unlikely to be a single greenspace 'solution': it is not possible to generalise when discussing geographies of ill health, and context-specific decisions about greenspace are required. Garden size, for example, is significantly associated with both poor general health and depression, and this aligns with the body of knowledge highlighting the importance of gardens for health (Brindley et al., 2018; Coolen and Meesters, 2012; Cox et al., 2019; de Vries et al., 2003). It is not, however, clear which aspects of gardens are important for either health outcome. Poor general health is more directly related to physical health than depression, so it may be that factors of gardens influencing physical activity are more important for poor general health (e.g. total size, grassed areas, play facilities), while others (e.g. aesthetic beauty, biodiversity, serenity) may have a greater influence on depression. Other attributes of gardens that we have not measured should be explored in future studies – for example, orientation, views and topography. Similarly, green cover is only associated with poor general health, and public greenspace cleanliness only with depression, presumably because of the way these aspects of greenspace influence these different components of health (Lee et al., 2015).

Despite this, there are greenspace measures that are associated wtih more than one health outcome and therefore might deliver multiple benefits to provide maximum impact. For example, larger average garden sizes and greater public greenspace accessibility were found to be associated with lower rates of poor general health and depression. Whilst changing the fabric of developed areas would be problematic, it would be feasible to introduce guidance and best practice for new developments to ensure minimum garden provision and standards of publicly accessible greenspace. This would require collaborative action between planners, developers and health service professionals.

The relationship between health and greenspace cleanliness found in this study demonstrates that those organisations that bear the cost associated with one particular greenspace measure may not be the same organisations that benefit from the resulting health gains. It is therefore desirable to devise funding models that recognise these complexities through cross-governmental cooperation.

5. Conclusions

We have found several indicators of neighbourhood greenspace that show significant relationships with one or more measures of population health, including green cover, garden size, public greenspace accessibility and public greenspace cleanliness. This indicates a need to include multiple measures of the greenspace environment in studies of the relationships between urban greenspace and health. At present, development of indicators is hampered by a paucity of data at suitable scales and with adequate detail. Development of indicators of greenspace quality that are systematic and objectively assessed is especially difficult. Our analysis has also highlighted that different health conditions are affected by different aspects of greenspace, and that there may be critical levels of greenspace at which improvements or degradation have a strong effect on health.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.healthplace.2020.102284.

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