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Mears, M. orcid.org/0000-0002-9947-0349, Brindley, P. orcid.org/0000-0001-9989-9789, Jorgensen, A. orcid.org/0000-0001-5614-567X et al. (2 more authors) (2019) Greenspace spatial characteristics and human health in an urban environment : an epidemiological study using landscape metrics in Sheffield, UK. Ecological Indicators, 106. 105464. ISSN 1470-160X

https://doi.org/10.1016/j.ecolind.2019.105464

Ecological Indicators 106 (2019) 105464

Contents lists available at ScienceDirect

Ecological Indicators

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

Original Articles

Greenspace spatial characteristics and human health in an urban environment: An epidemiological study using landscape metrics in Sheffield, UK

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ARTICLE INFO

Keywords:
Landscape metrics
Health
Greenspace
Epidemiology
Urbanisation
Sheffield, UK

ABSTRACT

Cross-sectional research linking exposure to greenspace with human health rarely describes greenspace characteristics in detail, but a few studies do find that some types of greenspace have greater health benefits than others. We review literature linking landscape metrics to multiple mechanisms by which greenspace exposure is posited to benefit health. Using metrics identified in this process to describe the composition and configuration of urban greenspace, we conduct a small-area epidemiological analysis of self-reported general health for the city of Sheffield, UK. A relatively high proportion of water cover and a high diversity of tree planting are associated with lower levels of poor health; while a high proportion of grass cover, which may be indicative of low quality greenspaces, is associated with higher levels. The presence of large greenspace patches that are well interspersed with the built environment is also associated with lower levels of poor health. We demonstrate a successful methodology for identifying useful landscape metrics even where effect sizes are small, and explore the challenges of translating results of landscape metric studies into policy guidance.

1. Introduction

It is now widely accepted that exposure to greenspace, including urban greenspace, has health-promoting effects for humans (World Health Organization, 2016). These benefits derive from several processes, including reducing stress and improving psychological restoration; promoting physical activity and neighbourhood social cohesion; amelioration of air and noise pollution and of the heat island effect; and modulating immune functioning (reviewed in World Health Organization, 2016). Moreover, the benefits have been shown to be strongest in more deprived groups, such that greenspace can reduce health inequalities associated with socioeconomic deprivation (Maas et al., 2009; Mitchell and Popham, 2008).

Cross-sectional research linking greenspace with physical and psychological health outcomes has often used remotely sensed data to assess greenspace exposure. Greenspace exposure is most often measured simply as total area within e.g. a census area or a buffer around postcode areas, or as distance to the nearest greenspace, without attempting to describe that greenspace (Jorgensen and Gobster, 2010; Wheeler et al., 2015). Not all greenspace is equal in its health benefits, however: studies that split greenspace into even relatively broad typologies find that some types affect health to varying degrees, but others do not. For example, Wheeler et al. (2015) found that UK census areas with a large proportion of 'broadleaf woodland', 'arable and horticulture', 'improved grassland' and 'coastal' land covers had lower rates of self-reported poor health. Other land covers ('coniferous woodland', 'semi-natural grassland', 'mountain, heath, bog', 'saltwater' and 'freshwater') had no significant effect.

One approach to describing finer details of the structure of landscapes, without resorting to resource-intensive, difficult to scale methods such as site surveys, photographs or simulations (e.g. Dramstad et al., 2006; Fuller et al., 2007; Hoyle et al., 2017; Palmer, 2004), is to calculate landscape metrics from remotely sensed data. Landscape metrics quantify spatial heterogeneity in terms of composition (i.e. what exists – quantity and diversity of patches) and configuration (spatial arrangement, e.g. patch shape and aggregation). They have been used extensively in ecological and environmental sciences to relate spatial patterns to processes such as biodiversity, water quality, and aesthetic preference (Uuemaa et al., 2013). In recent years, a number of studies have found relationships between landscape metrics

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https://doi.org/10.1016/j.ecolind.2019.105464
Received 21 June 2018; Received in revised form 11 March 2019; Accepted 4 June 2019
1470-160X/

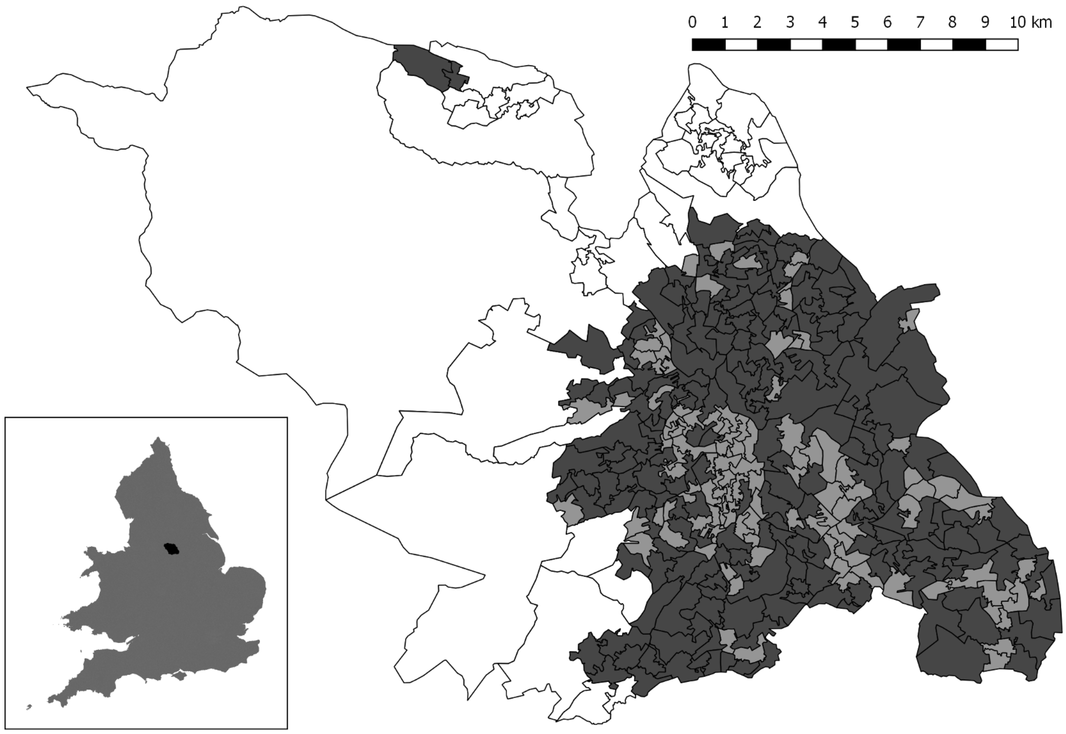

Fig. 1. Lower-layer Super Output Areas for Sheffield. White indicates LSOA excluded from analysis due to missing data. Dark grey indicates LSOA included in both main model data and sensitivity test subset; light grey indicates LSOA excluded from sensitivity test subset. Inset: location of Sheffield (black) within England and Wales.

and several of the processes from which the health benefits of greenspace are thought to derive. These processes include aesthetic preferences, which are linked to psychological restoration (Dramstad et al., 2006; Palmer, 2004; Staats et al., 2003; Van den Berg et al., 2003); neighbourhood walkability, which promotes physical activity (Hajna et al., 2014; Manaugh and Kreider, 2013); and noise and air pollution levels (Han et al., 2018; Liu and Shen, 2014; Weber et al., 2014).

These studies, however, rarely explicitly link landscape metrics to measures of human health directly. There are two notable exceptions, which have used an epidemiological approach to look at specific aspects of health. Shen and Lung (2017) used pollution and mortality data from administrative districts in Taiwan to show that landscape metrics are associated with air pollution concentrations, which in turn is related to mortality from respiratory diseases. Müller-Riemenschneider et al. (2013) investigated the relationship between metrics indicating neighbourhood walkability in buffers around addresses with cardiometabolic risk factors determined from health survey data, finding a negative relationship between walkability and prevalence of obesity and diabetes.

The relationship between the composition and configuration of urban greenspace and more general measures of health does not appear to have been studied previously. There are many dozens of landscape metrics, with little consensus on which may be most useful in particular situations (Cushman et al., 2008; Uuemaa et al., 2009). In order to guide the choice of metrics used in our analysis, we therefore undertake a literature search for studies that have used landscape metrics to describe the urban environment and relate them to the processes through which health benefits are thought to derive.

The aim of this study is therefore to test the utility of landscape metrics as indicators of aspects of urban greenspace that contribute to human health benefits, where health is measured directly instead of using processes such as physical activity promotion or air pollution reduction as a proxy. Specifically, we use self-reported general health, a subjective composite measure that is associated with a range of physical, mental and social factors as well as all-cause mortality (Kyffin et al., 2004; Mavaddat et al., 2011). Our aims are:

- To review landscape metrics that have previously been found to have utility as indicators in studies linking landscape patterns (greenspace composition and configuration) to processes that drive benefits to human health from urban greenspace.
- To use these metrics to explore the relationship between landscape patterns and self-reported general health in an urban environment, using Sheffield, UK as a case study.
- To evaluate the usefulness of the landscape metric indicator approach to planning and designing cities to minimise health inequalities.

2. Methods

2.1. Literature review

The purpose of our literature review was to identify studies that have found statistically significant associations between landscape metrics and mechanisms through which benefits to human health from greenspace arise. We identified mechanisms from a World Health Organization (2016) review. Eight mechanisms were considered: aesthetic preference (related to restoration and relaxation), physical activity promotion, social value, air pollution reduction, noise pollution reduction, immune function regulation, exposure to sunlight and promotion of pro-environmental behaviour (another mechanism identified in the review, heat island mitigation, was not considered because our study area has a temperate climate and excessive heat is rarely a problem).

We used Scopus to search for papers including either “landscape metrics” or “fragstats” (a widely used landscape metric software package), plus a term relating to one of the above mechanisms, in the title, abstract or keywords. The full list of search strings is shown in Supplementary Material 1.1, along with the criteria for inclusion. In general, papers and individual metrics were rejected if they did not link neighbourhood or intra-urban landscape metrics calculated from remotely sensed data to a mechanism of benefit (or harm) to human health, or if they focused exclusively on measuring the built (rather than green) environment. The results from Scopus were supplemented using references contained within relevant studies, and by using the same keywords with Google Scholar.

A different approach was taken for a ninth mechanism, presence of biodiversity, which was identified by the World Health Organization (2016) as a co-benefit of greenspace but has been shown to be associated with psychological benefits from greenspace (Fuller et al., 2007). Beninde et al. (2015) provide a recent synthesis of factors influencing intra-urban biodiversity. We selected metrics that measure the significant factors identified in this meta-analysis.

2.2. Study area and units

The city of Sheffield, UK (53°23′N, 1°28′W; Fig. 1) is an inland city covering an area of 368 km^2, with a population in 2011 of 552,000 (Office for National Statistics, 2016). Sheffield lies over a wide altitudinal range of nearly 600 m, and includes a large expanse of moorland in the west. The eastern part of the city was a centre of industry until the mid-twentieth century. Consequently, there remains a strong west-east gradient in deprivation, with ex-industrial areas suffering income and health deprivation relative to the historically wealthier and cleaner west (Department for Communities and Local Government, 2015). Sheffield is similar to other ex-industrial northern English cities in having a higher level of socioeconomic deprivation than the national average (Department for Communities and Local Government, 2015), and approximately two thirds of households living in semi-detached or terraced housing according to the 2011 census.

This study uses Lower-layer Super Output Areas (LSOAs) as the units of analysis. LSOAs are an English census geography used for reporting small area statistics. They contain an average population of approximately 1500 and have been used in previous research into relationships between greenspace and health (Brindley et al., 2018; Mitchell and Popham, 2008; Wheeler et al., 2015). Many Office for National Statistics data are available at LSOA scale and not at the smaller Output Area scale, because the smaller headcounts involved mean fluctuations due to chance are more likely and, in some cases, identification of individuals becomes possible. Larger geographies, such as Middle-layer Super Output Areas, however, are more likely to average out genuine patterns at the intra-urban scales that we are interested in.

Sheffield contains 345 LSOAs, although due to LIDAR data availability, the more rural areas with lower population density have been excluded from analysis (n = 307 LSOAs included; Fig. 1). This study is therefore focusing on the more urbanised parts of the city, containing 89% of Sheffield's resident population (according to the 2011 Census). Excluding rural areas also has the benefit that rural greenspace (predominantly large expanses of agricultural and extensively managed natural/semi-natural land) is not conflated with urban greenspace (mostly much smaller, planned, intensively managed sites) in analysis. Two LSOAs that are discontiguous with the rest are included from the Stocksbridge suburb. These LSOAs are unremarkable other than one having a high proportion of water cover, and within sensitivity analysis (not shown here) their inclusion/exclusion made no qualitative difference to analytical results. Generalised LSOA boundaries were used (generalised to 20 m), as this reduced fragmentation of small, thin sections of LSOAs following conversion of vector polygons to a raster surface.

2.3. Data sources

2.3.1. GIS data

Landscape metrics were calculated using three GIS raster layers: land cover, land use, and a combined vegetation heights/types map. The land cover map identifies what is located on the land surface, with classes describing different types of woodland, grassland, other vegetation, and water, as well as buildings and artificial surfaces. The vegetation heights/types map combines the green land covers from the land cover map with heights derived from LIDAR satellite imagery, in order to differentiate e.g. short and tall coniferous and broadleaved trees. In contrast, the land use map describes what the land is used for, e.g. residences, commerce, agriculture, leisure and recreation. These maps were used as appropriate for each landscape metric (e.g. land use patch density with the land use map; vegetation Shannon diversity on the combined vegetation heights/types map).

The land cover and use maps were produced by Ersoy (2015), based on the National Land Use Database classification schemes and created using data sources dating between 2007 and 2012. These maps are best-efforts using data available at the time of creation; it is possible to create maps of similar resolution and typology using available national and local datasets. Briefly, maps were based primarily on Ordnance Survey (OS) MasterMap topography area polygons and attributes, with additional land cover detail provided by Land Cover Map 2007, Forestry Commission National Inventory Woodland and Trees, and OS 1:10000 scale raster; and land use detail provided by OS AddressBase Plus, Sheffield City Council Green and Open Spaces, and OS 1:10,000 scale raster.

MasterMap captures individual features that are considered important in a landscape, such that in complex urban landscapes many more small features are mapped than in rural landscapes. For example, tree rows and some individual trees are mapped in urban parks, while only larger areas of woodland are mapped in the countryside. Thus the distribution of parcel areas is heavily right-skewed, for example with broadleaf tree land cover parcels in the study area having a mean area of 7568 m^2 but a median area of 576 m^2.

Vegetation heights were calculated from the difference between 50 cm resolution LIDAR Digital Surface and Terrain Models, and categorised to represent broad vegetation types (< 0.5 m = short grass; 0.5–2 m = long grass/shrubs; 2–10 m = small trees; 10–15 m = medium trees; 15–20 m = tall trees, > 20 m = very tall trees; height categories following Grafius et al. (2017)). These were then combined with vegetation types from the land cover map to create the combined vegetation height/type map.

Details of the map typologies, and of the composition of the study area, can be found in Supplementary Material 1.2.

2.3.2. Population data

Self-reported general health was obtained from 2011 UK census data, which asked of every individual the question "how is your health in general?", with the possible answers: very good; good; fair; bad; very bad. The measure used in this study, which we term poor health, combines the 'bad' and 'very bad' categories. The measure was aggregated to LSOA scale. We used indirect standardisation (Naing, 2000) to calculate expected rates of poor health given the age and sex distribution of the LSOA population, for use as an offset term in the statistical model. This health measure has been used in previous epidemiological studies of greenspace and health (Brindley et al., 2018; Mitchell and Popham, 2008; Wheeler et al., 2015). The geographical distribution of poor health is shown in Fig. 2.

2.3.3. Controlling variables

To minimise confounding with socioeconomic factors known to influence health that might reasonably correlate with aspects of urban greenspace, we included three controlling variables as covariates in the statistical model (stratification was not a suitable approach to controlling for confounding due to inclusion of multiple confounders; McNamee, 2005; Pourhoseingholi et al., 2012). To control for deprivation, we used the income deprivation domain of the English Indices of Deprivation 2015, which is calculated from the proportion of individuals in receipt of various forms of state financial support (data relating mostly to 2012–13). Air pollution was controlled for using

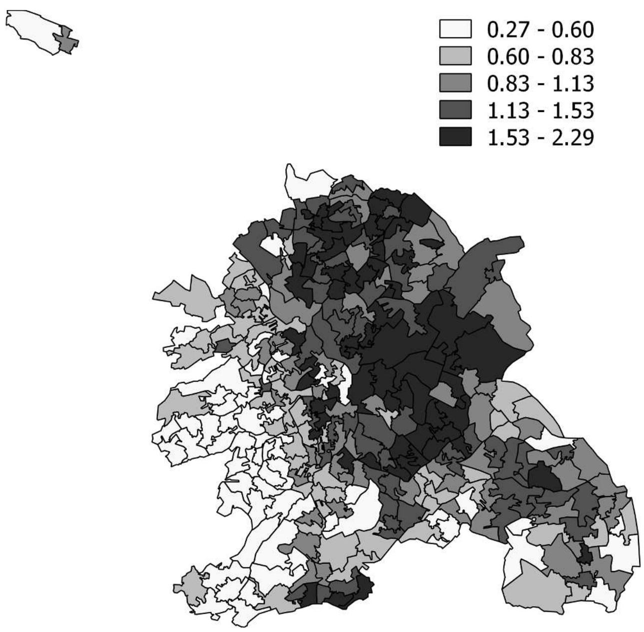

Fig. 2. Poor health (quintiles) in Sheffield Lower-layer Super Output Areas (LSOAs) as ratio of observed: expected counts, standardised for population age and sex. Only LSOAs included in statistical analysis are shown.

estimates of PM_{10} concentrations for 2010, generated from 1 km modelled data from the UK's Department for Environment, Food and Rural Affairs and assigned to LSOAs using population weighted averages, where the population represented the census headcounts at postcode unit level. Smoking rates were controlled for using lung cancer hospital admissions from 1st April 2002 to 31st March 2014 as a proxy. The ratio of observed to expected admission counts was calculated for each LSOA, with expected counts adjusted for age and sex. These three variables were selected as they are used as confounders in other analyses exploring the health effects of greenspace (Brindley et al., 2019, 2018; Mitchell and Popham, 2008; Richardson et al., 2010).

2.4. Landscape metrics

We used Fragstats v4.2.1 (McGarigal et al., 2012) to calculate the metrics identified in the literature search for each LSOA. For compatibility with Fragstats, vector input data were rasterised with a 2 m cell size, and the vegetation height raster surface was aggregated to the same size.

We aimed to match our metrics as closely as possible to those identified in the literature review in terms of the focal land cover/use types (e.g. tree land covers, recreation land uses), including land cover/use differentiation or aggregation (e.g. broadleaved and coniferous trees considered separately or as one category). Prior to metric calculation, we therefore reclassified the land cover and use maps accordingly. Studies rarely indicated whether they counted water as a green land cover; we have included it as such. Some additional modifications were made to improve relevance of metrics to the present study, e.g. conversion of area- and count-based metrics to percentage- or density-based (due to variation in the size of LSOAs), and aggregating grey land covers to keep the focus on greenspace. Details of the reclassifications and modifications can be found in Supplementary Material 1.2. All GIS manipulations were performed in ESRI ArcGIS 10.1.

2.5. Analysis

2.5.1. Statistical model

Negative binomial regression was used to test for associations between self-reported poor health counts and landscape metrics, after standardising by expected poor health counts given LSOA age and sex composition and controlling for potential confounding factors as described. Inclusion of a quadratic term for income deprivation was indicated from visual inspection and confirmed using AIC corrected for small sample size (AICc). No other polynomial and no interaction terms were included due to lack of *a priori* expectations or indication from visual inspection. We transformed some variables to reduce skew in the distribution: several landscape metrics were log-transformed and income deprivation was square root-transformed. Models were run in R v4.3.2 using package MASS v7.3 (R Core Team, 2017; Venables and Ripley, 2002).

2.5.2. Multi-model inference

Due to the large number of landscape metrics (eighteen) with no *a priori* expectations of which might impact on poor health, we used an information theoretic approach, following the methods of Symonds & Moussalli (2011). All possible subsets of landscape metrics were tested (but with the controlling variables and offset included in all models), and the AICc value calculated for each. As there were a large number of models within a few AICc units of the model with lowest AICc, we used multi-model inference and averaging to gain insight into the importance of the metrics as determinants of health, and to create the final inferential model.

A measure of the probability that each landscape metric would appear in the true best model was obtained by summing over the Akaike weights of the models in which the metric was included. This measure is often termed relative importance, but does not indicate effect size or indeed the probability of statistical effect (Galipaud et al., 2014), so is instead referred to here as probability of appearing in the best model, or appearance probability. Given the expected distributions of appearance probabilities for weakly or uncorrelated predictor variables (Galipaud et al., 2014), we consider there to be good support for variables with appearance probability $> = 0.75$ and tentative support for variables with appearance probability $> = 0.5$ and < 0.75.

A 'plausible set' of models was created by taking all models within six AICc units of the lowest AICc and removing those that were more complex versions of a simpler model with lower AICc (Richards et al., 2011). The plausible set was then model-averaged using full averaging, i.e. average of coefficients weighted by the AICc value for each model, with the coefficients for terms not appearing in a model set to zero to prevent inflation of coefficients for unimportant variables.

Multi-model inference was performed in R using package MuMIn v1.4 (Barton, 2017).

2.5.3. Imputation of missing values and sensitivity test

Amongst the selected landscape metrics were Shannon diversity index of tree, shrub and grass habitats, which were calculated from the combined vegetation heights/types map (described in Section 2.3.1). Some LSOAs did not contain any of one or more of these land covers. In these cases, a value of zero was imputed for the Shannon diversity index (a Shannon diversity of zero otherwise results from a monoculture).

As the Shannon diversity of tree habitats was found to be relatively likely to appear in the best model, in order to test the sensitivity of the analysis to this imputation we repeated the analysis using only LSOAs with each of these land covers present, i.e. those without imputed values (n = 196).

The results of the sensitivity test are shown in full in Supplementary Material 3.1. In general, the effect of using this subset of LSOAs was that AICc values were lowest for smaller models as compared to using the full dataset. This is likely due to a loss of statistical power arising from the reduction of sample size and also, in some cases, due to reduction of the numerical range of landscape metric values (variable distributions for both full data and subset are shown in Supplementary Material 2). Consequently, fewer landscape metrics appear in the plausible set, and the probability of metrics appearing in the true best model is uniformly lower. However, tree habitat Shannon diversity remained amongst the

Table 1
Studies linking landscape metrics to mechanisms through which benefits to human health may derive. For original studies, only metrics with statistically significant relationships are reported.

Reference and summary	Land use/cover typology	Scale	Response variable	Predictor variable (direction of effect)
Aesthetic value				
Dramstad et al. (2006): Study of aesthetic preference of students and local residents for Norwegian agricultural landscapes.	> 100 categories; common categories are cereal fields, meadows, build-up land, deciduous woodland, coniferous woodland. Unclear if only land cover or mixed cover/use.	Viewshed	Aesthetic preference elicited from photographs of agricultural landscapes; locals and students	Number of patches (+) Land type richness (+) Total open land area, locals only (+) Length of edge, locals only (+) Percent open land, students only (−) Shannon diversity index of land types, students only (+) Heterogeneity index of land types, students only (+)
Palmer (2004): Study of change in scenic preferences of residents due to temporal change in land cover/use in Dennis, Massachusetts.	Mixed land cover/use: 24 categories (six green LC, three blue LC, five recreation LU, ten grey LC).	Viewshed	Scenic value elicited from photographs of scenes in and around a town	% landscape under agriculture and open land (+) % landscape under wetland and open water (+) % landscape under recreation land uses, one time period only (+) Edge density of land covers/uses (+)
Franco et al. (2003): Study of the impacts of agroforesty around Venice, Italy on landscape preferences of local students, farmers and residents.	Unclear	Viewshed	Perceived scenic beauty in agroforestry landscape photographs	Proportion of viewshed containing agroforestry land cover (+) Shannon diversity index of landscape patches (+)
Nassauer (1995): Discussion paper about relationship between culture and landscape ecology, including preferences	n/a	n/a	Universal landscape preferences (converted to landscape metrics)	Landscape includes canopy trees (+) Landscape includes water features (+) Landscape allows open views (+)
Physical activity				
Su et al. (2013): Study of factors affecting whether children in the Los Angeles metropolitan area walk to school.	Land use: residential; agriculture and open; government and institutional; commercial and industrial; transportation and communication.	500 m buffer around homes and schools	Likelihood of children walking to school	% landscape under agriculture and open land uses around homes (+) Contagion index (measure of dispersion and interspersion) around homes (+) Area-weighted mean contiguity index (measure of patch shape) around homes (−)
Kim et al. (2016): Study of relationship between health-related quality of life (correlated with BMI (-), physical activity time (+) and time watching TV (-)) of Hispanic children in Houston and the quality of the natural environment around their homes.	Tree/forest land cover only.	400 m and 800 m buffer around homes	Paediatric health-related quality of life	Number of patches of tree/forest land covers (+) Mean Euclidean nearest neighbour distance (measure of patch isolation) of tree/forest land covers (+) % landscape under tree/forest cover, 1/2 mile buffer only (+)
Lee & Moudon (2004): Review of studies of characteristics of the environment that promote walking and cycling.	n/a	n/a	Promotion of walking and cycling (characteristics converted to landscape metrics)	Availability of recreation destinations (+) Mix of recreation destinations (+)
Manaugh & Kreider (2013): Study testing a metric combining land use mixture measured as proportional abundance of land uses with land use interspersion, using data from three Canadian cities.	Land use: residential; commercial, institutional, governmental, resource & industrial; park, recreational & water	Census tracts	Percent of people who using walking or cycling as their primary mode of transport	Entropy i.e. Shannon evenness index (+) Interaction between complementary land uses i.e. edge density (+)
Müller-Riemenschneider et al. (2013): Study of association between neighbourhood walkability and cardiometabolic risk factors, using health surveillance data from the Perth metropolitan area.	Unclear	800 m and 1600 m buffer around homes	Obesity and diabetes prevalence in adults	Combined walkability index including Shannon evenness index (other index components focus on built environment); only for certain sex, disease and buffer distance combinations (−)
Air pollution				

(*continued on next page*)

Table 1 (*continued*)

Reference and summary	Land use/cover typology	Scale	Response variable	Predictor variable (direction of effect)
Wu et al. (2015): Study of the relationship between $PM_{2.5}$ pollution and landscape metrics in Beijing, China.	Land cover: built; vegetation; water; bare land; crop.	Various buffers (100 m-5 km) around monitoring stations	$PM_{2.5}$ concentrations, recorded over one year and individual seasons within year	% landscape under vegetation at 5000 m buffer, except autumn (−) Contagion index (measure of dispersion and interspersion) at 3000 m buffer, annual and summer only (+) Shannon evenness index at 3000 m buffer, annual and summer only (−) Edge density of vegetation at 5000 m buffer, except winter (−)
Shen & Lung (2017): Study of effects of greenspace on respiratory mortality, mediated by air pollution and temperature, using data from Taipei Metropolitan Area, Taiwan.	Aggregated 'green' only	Administrative districts (4–321 km^2)	Mortality from pneumonia and chronic lower respiratory diseases due to air pollutants (CO, NO_x, $PM_{2.5\text{-}10}$, SO_2, O_3)	Largest patch index (measure of dominance) of greenspace patches (−) Patch density of greenspace patches (+)
Noise pollution				
Han et al. (2018): Study relating noise levels in Shenzhen, China to landscape metrics.	Land cover: buildings; roads; vegetation	440 m × 440 m cell around monitoring stations	Environmental noise (EN) and traffic noise (TN), recorded over one month	% landscape under vegetation (−) Mean patch area of vegetation (−) and of landscape (TN +, EN −) Splitting index (measure of subdivision) of vegetation (EN only +) and of landscape (TN only −) Largest patch index (measure of dominance) of vegetation and landscape, EN only (−) Landscape division index (measure of subdivision) of vegetation and landscape, EN only (+) Mean shape index (measure of patch shape complexity) of landscape, EN only (−) Landscape shape index (measure of patch shape complexity and patch disaggregation) of vegetation and landscape, TN only (+)
Sakieh et al. (2017): Study of relationship between landscape metrics and noise levels in Karaj City, Iran.	Aggregated 'green' only	300 m, 600 m, 1 km buffers around monitoring stations	All-source noise between 4 and 8 pm (peak traffic period), recorded over one month	Area (-) and % landscape under green (−) Number of patches (+) and patch density (−) Largest patch index (measure of dominance) (-) Mean patch area (−) Mean shape index (measure of patch shape complexity) (−) Patch cohesion index (measure of interspersion) (−) Aggregation index (measure of dispersion) (−) Splitting index (measure of subdivision) (+) Interspersion and juxtaposition index (−) Clumpiness index (measure of dispersion) (−) Mean contiguity index (measure of spatial connectedness) (−)
Biodiversity				

(*continued on next page*)

Table 1 (*continued*)

Reference and summary	Land use/cover typology	Scale	Response variable	Predictor variable (direction of effect)
Beninde et al. (2015): Meta-analysis of factors affecting intra-urban variation in biodiversity.	Habitat vs. non-habitat; herbs, shrubs and trees within habitat.	n/a	Species richness	Herb cover (+) Shrub cover (+) Tree cover (+) Water cover (+) Habitat richness (+) Habitat patch area (+) Corridor (+) Vegetation structure (+) Herb structure (+) Shrub structure (+) Tree structure (+)
			Species richness and diversity	Green area % (+)

metrics most likely to appear in the best model, and had a similar coefficient in both averaged models. The grass and shrub Shannon diversity metrics also had a low appearance probability in both the full dataset and subset. We therefore do not consider imputation to have biased these metrics.

3. Results

3.1. Literature review

The literature search identified eleven original studies that found significant relationships between landscape metrics and aesthetic values (Dramstad et al., 2006; Franco et al., 2003; Palmer, 2004), physical activity (Kim et al., 2016; Manaugh and Kreider, 2013; Müller-Riemenschneider et al., 2013; Su et al., 2013), air pollution (Shen and Lung, 2017; Wu et al., 2015) and noise pollution (Han et al., 2018; Sakieh et al., 2017). No studies were found that looked at social values, immune functioning, exposure to sunlight or promotion of pro-environmental behaviour. Two review papers of aesthetic preferences (Nassauer, 1995) and physical activity levels (Lee and Moudon, 2004), and a meta-analysis of urban biodiversity (Beninde et al., 2015), were also identified. A total of 63 metrics were identified from these papers, although some are duplicates both within and between mechanisms. The studies and metrics are summarised in Table 1.

There was considerable diversity in the typologies of the maps that the landscape metrics were calculated on. Some calculated metrics on a two-class scheme of green versus built land covers (Shen and Lung, 2017; Sakieh et al., 2017), while others differentiated up to 100 land covers (e.g. Dramstad et al., 2006; Palmer, 2004). Some included built land covers in calculations of e.g. diversity (Han et al., 2018; Palmer, 2004; Wu et al., 2015), while others treated these as background (Kim et al., 2016; Shen and Lung, 2017; Sakieh et al., 2017). There was often conflation between land cover and land use (e.g. Manaugh and Kreider, 2013; Palmer, 2004), although on balance land cover seemed to be more central. The exception to this was studies of physical activity levels, where land use was the focus.

The studies analysed a diverse range of response variables, and there was little consistency in metric choice between studies. There was also variation in the scales at which landscape metrics and response variables were measured. For aesthetic preference studies, the viewshed was the unit of analysis (Dramstad et al., 2006; Franco et al., 2003; Palmer, 2004). For physical activity studies, buffers of between 400 m and 1600 m around homes were commonly used, in efforts to capture the distance most people are prepared to walk (Kim et al., 2016; Müller-Riemenschneider et al., 2013; Su et al., 2013). The studies of noise pollution and one of air pollution used buffers centred around monitoring stations, at scales relevant to noise attenuation (300–1000 m) and air pollutant dispersion (100–5000 m) respectively (Han et al., 2018; Sakieh et al., 2017; Wu et al., 2015). One study of physical activity and one of air pollution analysed administrative geographies (Manaugh and Kreider, 2013; Shen and Lung, 2017).

Most of the metrics identified from the review of intra-urban biodiversity related to habitat structural heterogeneity (Beninde et al., 2015). This is posited to be the mechanism by which humans perceive biodiversity (Fuller et al., 2007).

It was not computationally feasible to include all the identified metrics in our statistical analysis; in addition, many metrics were theoretically similar (e.g. different diversity indices calculated on the same data) or were empirically highly correlated. We therefore selected fifteen metrics to carry forward for statistical analysis by theoretical and empirical comparison, with the aim of minimising redundancy. We also calculated an additional three metrics to relate air pollution removal to tree land covers where original studies had used a single aggregated 'green' category, as trees are known to be especially valuable for air pollution removal in the study area (Mears, 2010). The selected metrics are described in Table 2. Full details of their calculation and behaviour

Table 2
Details of landscape metrics included in statistical analysis. *indicates the metric did not appear in the plausible set of models. **indicates that graphical examples of metric sensitivity are given in Supplementary Material 1.3.

	Landscape metric	Typology	Description
1–4	Percentage of landscape under each of: Water, Trees*, Grass, Shrubs	Land covers (individual)	Gives a picture of the composition of the greenspace.
5	Green land cover Shannon diversity index	Green land covers (individual)	A measure of land cover diversity. Increases with more land cover types and more even land cover distributions.**
6	Land cover contagion index	Green land cover (individual) and grey land covers (aggregated)	A measure of patch 'clumpiness' (the probability that two random adjacent cells belong to classes i and j, summed over all i and j). Increases with more land covers, fewer individual patches, increasing dominance of individual patches, lower patch shape complexity, and lower dispersion and interspersion (intermixing) of land covers.**
7	Greenspace patch density	Green land covers (aggregated)	A simple measure of greenspace subdivision i.e. degree of fragmentation – the number of greenspace patches, standardised to landscape area; although individual patches may be small.
8	Greenspace splitting index	Green land covers (aggregated)	A measure of subdivision derived from landscape coherence, or the probability that two animals placed at random in an area will be on the same patch. Increases with more individual patches, more even land cover distribution, and increasing subdivision of land covers.**
9	Greenspace mean contiguity index	Green land covers (aggregated)	A measure of patch spatial connectedness and shape based on the average degree of contiguity of pixels in a raster map. Increases with patch area and more strongly with lower shape complexity (i.e. increasing contiguity).**
10	Greenspace mean shape index	Green land covers (aggregated)	A measure of patch shape complexity. Increases with greater diversion of patch shape from the simplest square.**
11	Green/grey mean shape index*	Green land covers (aggregated) and grey land covers (aggregated)	As per metric 10.
12	Green/grey landscape shape index	Green land covers (aggregated) and grey land covers (aggregated)	A measure of dispersion of land covers. Measures shape complexity as per metric 10, adjusted for the size of the landscape.**
13	Tree land cover patch density	Tree land covers (aggregated)	As per metric 7. Interpreted as area-standardised number of patches of trees.
14	Recreation-relevant land use patch density	Recreation-relevant land uses (individual)	As per metric 7. Interpreted as area-standardised number of destinations for recreation.
15	Recreation-relevant land use mean Euclidean nearest neighbour distance	Recreation-relevant land uses (aggregated)	The average-straight line distance between destinations for recreation. Is a measure of isolation.**
16–18	Shannon diversity index of combined land cover/vegetation height categories for: Grass, Shrubs*, Trees (3 metrics)	Land covers + vegetation heights (individual) for categories of vegetation	As per metric 5. Interpreted as habitat diversity.

are shown in Supplementary Material 1.3, including graphical examples. Supplementary Material 2 shows the geographical and numerical distribution of the metrics, as well as their relationships to the response and controlling variables and each other.

3.2. Multi-model inference

Multi-model analysis yielded a large number of models with low Akaike weights (Akaike weight for best model = 0.001). The plausible set included 70 models (plausible sets shown in Supplementary Material 3.2). The final, averaged model explains a high proportion of variation in poor health (Pearson's r of observed poor health versus fitted values = 0.949).

Fig. 3 shows the probability of landscape metrics appearing in the best model, and Table 3 shows model coefficients for the plausible set averaged model. Two metrics have a high probability of appearing in the best model (> =0.75). The greenspace splitting index (Fig. 4a, appearance probability = 0.99), which is also a significant term in the averaged model, shows an association between subdivision of greenspace within an LSOA and higher levels of poor health. Less water cover is also associated with increased poor health (Fig. 4b, appearance probability = 0.79).

Five further metrics have a moderate probability of appearing in the best model (> =0.5 and < 0.75). Lower tree habitat Shannon diversity, greater grass cover, greater recreation land use patch density, greater greenspace mean contiguity index (i.e. larger patches with less complex shape), and lower green/grey landscape shape index (i.e. less complex patch shape) are all associated with higher levels of poor health (Fig. 4c–g). The remaining metrics have low probability of appearing in the best model (< 0.5), and three do not appear at all in the plausible set: tree cover, shrub habitat Shannon diversity index, and green/grey mean shape index.

4. Discussion

4.1. Selecting useful and parsimonious landscape metrics

Landscape metrics have been widely used in studies of ecosystem services, which benefit humans directly or indirectly (Uuemaa et al., 2013). This study, which appears to be the first to link landscape metrics to a measure of small-area population general health, adds to the evidence (Müller-Riemenschneider et al., 2013; Shen and Lung, 2017) indicating that they also have utility in linking landscape patterns directly to measures of human health.

The process of selecting a suitable and adequate suite of metrics to describe landscapes for a particular purpose is challenging, due to issues of redundancy, scale dependence, and interpretation (Cushman et al., 2008; Lustig et al., 2015; Uuemaa et al., 2009). Moreover, attempts to identify a parsimonious suite of metrics do not produce consistent results (Cushman et al., 2008; Lustig et al., 2015). Some of the studies identified in our literature search reported using "common" metrics (Dramstad et al., 2006; Han et al., 2018; Palmer, 2004), yet did not always use the same ones, while others did not report any rationale; there was also little consistency in their chosen metrics, scales of analysis, or greenspace typologies. Given the large number of metrics that exist, in combination with the range of possible typologies and resolutions at which landscapes can be mapped, it can be difficult to deduce from theory which metrics will describe the landscape for the subject under study most effectively. However, there were a few cases in which choices seem to have been driven by theoretical expectations.

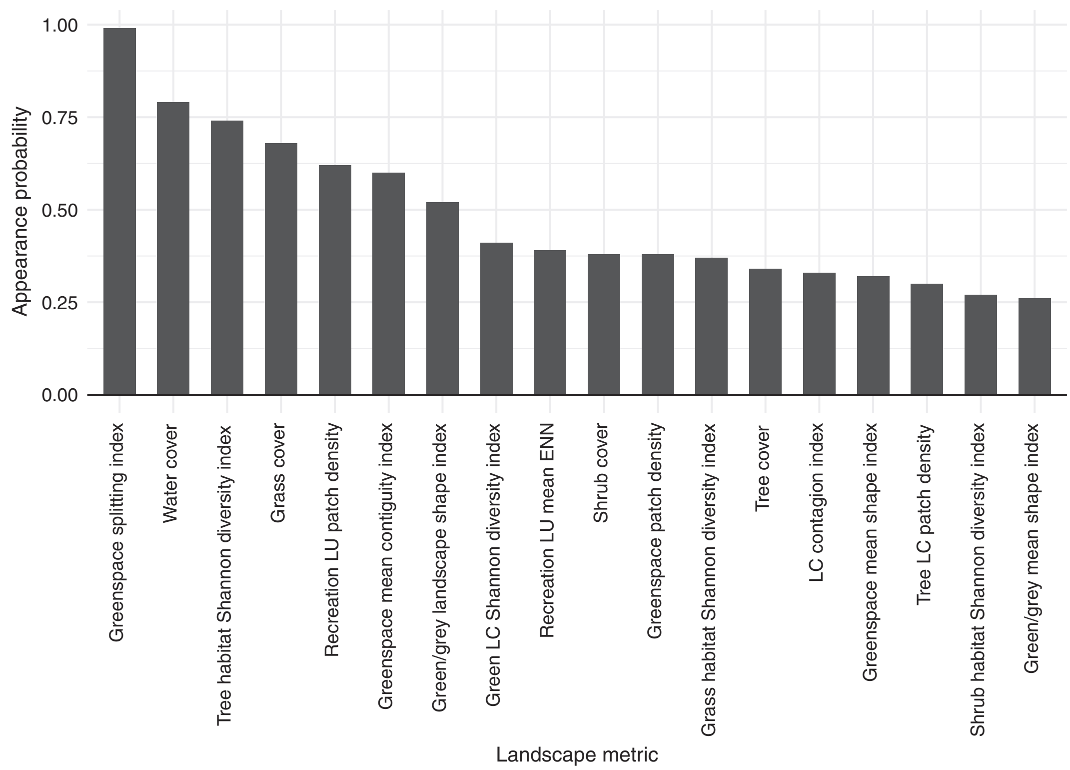

Fig. 3. Probability of landscape metrics appearing in the true best regression model, calculated as sum of Akaike weights of models in which the metric appears.

Table 3
Results of plausible set averaged negative binomial regression models. Terms significant at $p < 0.05$ are shown in bold. NB tree cover, green/grey mean shape index and shrub habitat Shannon diversity index were not included in the plausible set.

	Estimate	SE (adj.)	p
Grass cover (ln)	0.0069	0.0063	0.276
Shrub cover (ln)	−0.0004	0.0016	0.809
Water cover (ln)	−0.0062	0.0039	0.111
Green LC Shannon diversity index	0.0175	0.0375	0.640
LC contagion index	0.0005	0.0016	0.767
Greenspace patch density (ln)	−0.0120	0.0227	0.599
Greenspace splitting index (ln)	**0.0480**	**0.0139**	**0.001**
Greenspace mean contiguity index	0.1110	0.1449	0.444
Greenspace mean shape index	0.0073	0.0202	0.718
Green/grey landscape shape index	−0.0029	0.0037	0.438
Tree LC patch density (ln)	−0.0002	0.0021	0.915
Recreation LU patch density (ln)	0.0242	0.0290	0.404
Recreation LU mean ENN distance (ln)	0.0063	0.0189	0.737
Grass habitat Shannon div. index	0.0036	0.0150	0.812
Tree habitat Shannon div. index	−0.0365	0.0289	0.206
Income deprivation (sqrt)	**4.5160**	**0.3970**	**< 0.001**
Income deprivation (sqrt)^2	**−2.3216**	**0.4607**	**< 0.001**
Lung cancer admissions	0.0155	0.0111	0.163
Mean PM10	**0.0378**	**0.0104**	**< 0.001**
(Intercept)	**−2.3213**	**0.2685**	**< 0.001**

Studies of aesthetic preferences, for example, used metrics corresponding to the universal preference for savannah-type landscapes (Nassauer, 1995). Metrics indicating land use mixture were important to physical activity levels, consistent with the ‘walkability’ concept (Manaugh and Kreider, 2013). Overall, however, the small number of studies limits the extent to which patterns in the usage and analytical relevance of metrics can be observed.

In this study, although we used a literature search to select metrics previously found to have statistically significant relationships with processes that drive benefits to human health from greenspace, the majority of included metrics did not show strong associations with our measure of health. This may result from the fact that most previous studies did not look at health directly, but rather at mechanisms from which health benefits may result, so their response variables were a level of abstraction away from ours. Interestingly, one of the two previous epidemiological studies found that greenspace patch density was significantly positively related to mortality from respiratory disease, while the proportion of area occupied by the single largest greenspace patch showed a significant negative relationship (Shen and Lung, 2017). These measures are similar respectively to the recreation land use patch density and greenspace splitting index metrics found to be important in our study (the splitting index is affected by patch size distribution and patch number; we did not include largest patch index in our statistical analysis due to its high correlation with the splitting index). These similarities may hint at the generalisable importance of these aspects of greenspace patterns.

Alternative approaches to selecting metrics are to use ordination or clustering techniques (e.g. principle components analysis (PCA), self-organising maps) to define dimensions to the data (Cushman et al., 2008; Lustig et al., 2015); and machine learning techniques such as random forests, which produce a simple measure of variable importance (Marston et al., 2014). Our approach using theoretical similarities and pairwise correlations seems to have produced broadly similar results to Cushman et al. (2008), who used PCA to find a parsimonious suite of metrics, with our selected metrics representing many of the groupings identified in that study; although our approach to reduction would have been challenging had a much larger number of metrics been considered. However, the results of any approach to selecting a subset of metrics will depend on the composition of the suite initially tested. Furthermore, the interpretation of output from clustering and machine learning techniques is not always obvious (Cushman et al., 2008; Cutler et al., 2007; Lustig et al., 2015). This limits their usefulness for producing planning and policy guidance.

4.2. Evaluation of multi-model inference approach

This appears to be the first landscape metric study that has used a

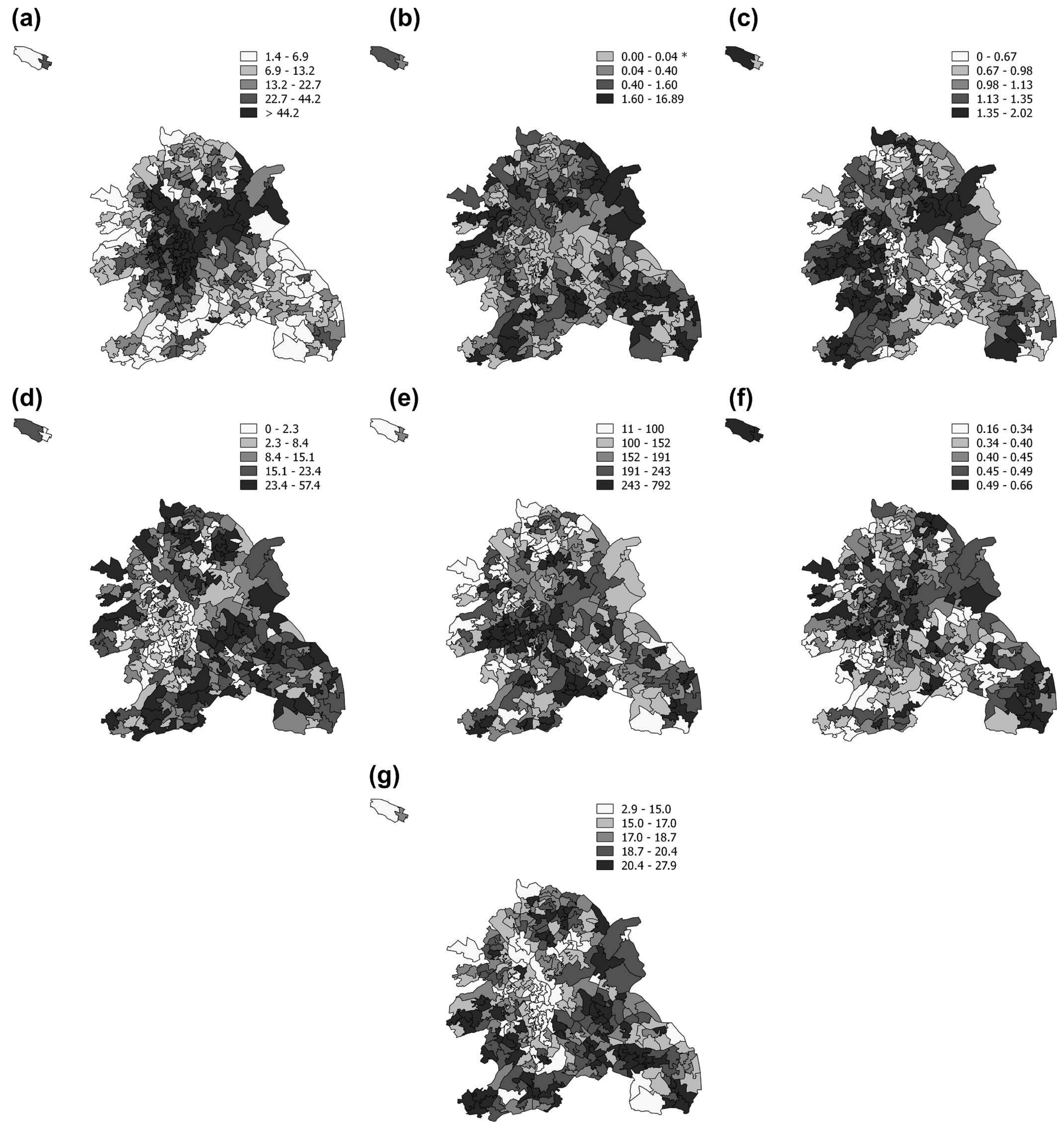

Fig. 4. Geographic distribution of landscape metrics found to be likely to be important to self-reported poor health at Lower-layer Super Output Area scale. Quintiles, except in b where two lowest quintiles aggregated due to frequency of zeroes (indicated by *). Only LSOAs included in statistical analysis are shown. (a) Greenspace splitting index (no units, positively associated with poor health); (b) water cover (%, negative association); (c) tree habitat Shannon diversity index (no units, negative association, zero imputed where data not available); (d) grass cover (%, positive association); (e) recreation land use patch density (patches per ha, positive association); (f) greenspace mean contiguity index (no units, positively associated); (g) green/grey landscape shape index (no units, negatively associated).

multi-model inference approach with a plausible set constructed using both ΔAICc and nested models. We found the approach to be useful in identifying important metrics, while reducing the likelihood of overfitting compared with a non-averaged model with all variables included. The plausible set has increased inferential power over the all-combinations averaged model due to slightly reduced variance for terms with a relatively large effect size (compare Table 3 with Supplementary Material 3.2.2). This is consistent with Richards et al.'s (2011) suggestion that this approach to building a plausible set of models for averaging can improve the accuracy of effect size estimation.

In general, the probabilities of landscape metrics appearing in the best model correspond well to the results of the plausible set averaged model, with strong correlation between metric z-values and appearance probability (Spearman's *rho* = 0.92). This correlation yields some support to the notion that metrics with a high or moderate appearance probability, but which are not statistically significant, also have some predictive value. However, results from simulation studies find that predictors that are correlated with a response variable only weakly or not at all can still have a high appearance probability (Galipaud et al., 2014). It is therefore not possible to draw firm conclusions from the appearance probability alone.

An additional benefit of using an inferential modelling approach is that the averaged model can function as a composite indicator, by combining metric values to predict the prevalence of poor health. One notable drawback of the multi-model inference approach in general is that computational requirements increase exponentially with the number of predictor variables. While it is a more robust approach to variable selection than stepwise model building (Hegyi and Garamszegi, 2011), given the vast number of landscape metrics that exist it would not be feasible to test all of them in the framework used here. It is therefore essential that a considered approach to metric selection or reduction is used (Section 4.1).

4.3. Landscape metrics as indicators of general health

We found that landscape metrics contribute to inferential models of small-area population general health, even when confounding variables with effect sizes orders of magnitude larger are included, and were able to identify particular metrics of importance (Table 3, Fig. 3). This is despite a small sample size with relatively high intra-area variation driven by demographic factors that are difficult to capture in cross-sectional data.

Of the landscape metrics included in this study, our results indicate strongest support for the importance of the greenspace splitting index and the proportion of water cover. A large greenspace splitting index, which results from green land covers being split into many patches with an even size distribution, is associated with higher levels of poor health. The splitting index is high along the river corridors to the north-west and north-east of the city centre, where greenspace was largely replaced by heavy industry in the past. It is also high in the city centre and areas to its immediate west, where population densities are highest, leaving little residual greenspace between residential developments. A large splitting index has previously been reported to be related to higher levels of urban noise (Han et al., 2018; Sakieh et al., 2017), but has not been tested in relation to any other mechanisms of benefit to human health. Fig. 4a shows the distribution of this metric across the study area. A low proportion of water cover (Fig. 4b) is associated with greater levels of self-reported bad health in an LSOA. The spatial distribution of this metric is partially dependent on topography, with natural rivers and ponds/lakes contributing, but it is notably lower on average in the city centre, where culverting, covering and filling of water bodies to make space for development is more common. Previous research has found positive relationships between water in landscapes and emotional, restoration and recreational benefits, and the presence of water plays a significant role in landscape preferences (Völker and Kistemann, 2011). Water cover was also positively associated with aesthetic preferences and biodiversity in previous landscape metric studies (Beninde et al., 2015; Franco et al., 2003; Palmer, 2004).

There is moderate support for an additional five landscape metrics. A lower Shannon diversity index of tree habitats (Fig. 4c), and a greater proportion of grass cover (Fig. 4d), are associated with higher levels of poor health. These metrics show broadly opposite spatial distributions, with high tree diversity and low grass cover in the more affluent west and along the ex-industrial river corridors. These metrics were included due to their positive influence on biodiversity (Beninde et al., 2015). Grass cover was also strongly correlated with several metrics that were identified in the literature search but not included in statistical analysis: notably the percentage cover of vegetation types permitting open views, which is usually positively associated with aesthetic preferences (Dramstad et al., 2006; Palmer, 2004); and total green cover, which in previous studies has shown a negative relationship with air and noise pollution (Han et al., 2018; Sakieh et al., 2017; Wu et al., 2015). The present result of more grass cover being associated with worse health, which is contrary to these previous studies, may arise from grassed greenspaces in the study area often being relatively low quality amenity greenspaces of utilitarian design, compared to those with more shrub, tree or water cover. This is supported by the opposite spatial distributions of these two metrics, since higher tree diversity is more likely in areas with greater overall tree cover. In particular, a diversity of tree planting might indicate that a greenspace has been designed for aesthetic impact; and is likely also to correlate with greater biodiversity in other taxa (Beninde et al., 2015). These aspects of planting design may therefore impact on health via the psychological benefits of aesthetic and biodiversity values. The particularly high tree diversity along the north-east river corridor may be explained by the presence of green corridors running along the river banks, and by small areas of decorative planting outside of the large commercial properties now in this area.

The only land *use* metric that is supported is recreation land use patch density (Fig. 4e), which is positively associated with poor health, although the value of this metric is high in some of the more affluent areas of the city, such as in the west. This is again contrary to a previous study in which patch density is positively associated with physical activity (Kim et al., 2016). Our result may suggest that it is better to have fewer, but larger patches, rather than a high density of small patches. This idea is supported by the greenspace splitting index metric, which indicates an association between the presence of at least some large patches and less poor health.

The final two metrics supported by the analysis are greenspace mean contiguity index (Fig. 4f) and green/grey landscape shape index (Fig. 4g), both of which describe aspects of patch shape. The contiguity index is affected by patch size (with larger patches having higher values), but is more strongly influenced by patch shape complexity: patches with a more complex shape have lower contiguity. Shape index assesses shape complexity by focusing on the length of edge between different classes (in this case, green versus grey land covers), with more complex shapes having higher values. In both cases, compact, square-like shapes have least complexity, while complexly shaped patches that are interspersed amongst other land covers have high complexity. Poor health is associated with higher greenspace mean contiguity index and lower landscape shape index, i.e. simple patch shape with low interspersion. As would be expected, these two metrics also show broadly opposite spatial distributions. The city centre has greenspace with a simple shape, likely due to most of the greenspace in this area comprising parks, whereas other areas have more incidental greenspace e.g. small amenity areas and street greenery. In other areas, the spatial patterning of these metrics is complex and not easily explained in terms of density, deprivation or local history. Previous studies of noise pollution have found associations in the same directions for these metrics (Han et al., 2018; Sakieh et al., 2017).

It is interesting to note that both composition metrics and configuration metrics have been highlighted as important. Both cover and diversity aspects of landscape composition are represented. Patch density and splitting index are a simple and more sophisticated metric of the aggregation aspect of configuration, while the landscape shape index and contiguity index describe the shape. This confirms the importance of selecting metrics that indicate a diversity of aspects of landscape pattern (Cushman et al., 2008).

Taken in combination, the configurational metrics indicate that having greenspace well interspersed with grey land covers, and large patches of greenspace, is associated with reduced rates of poor health at the LSOA scale. A high level of interspersion means that more people are likely to have easy access to a greenspace. This is important as greenspace use falls drastically with distance to greenspace, and physical use of greenspaces (as opposed to passively experiencing nearby greenspaces) is likely to provide the majority of health benefits (Lee et al., 2015; Schipperijn et al., 2010). Large greenspaces also tend to be associated with greater benefits, possibly again mediated by how they are used (Lee et al., 2015). The compositional metrics additionally indicate that the land covers within greenspaces are also important, with the presence of water, a diversity of tree planting, and a smaller area of grass cover being associated with less poor health. As discussed above, exposure to "bluespace" is known to have health benefits via opportunities for recreation and psychological restoration, and is also aesthetically valuable in a range of contexts (Franco et al., 2003; Palmer, 2004; Völker and Kistemann, 2011). Urban trees are also widely accepted to be important to aesthetics and biodiversity, and to contribute to air and (perceived and actual) noise pollution mitigation (Beninde et al., 2015; Forestry Commission England, 2010; World Health Organization, 2016). The finding that more grass cover is associated with more poor health may simply reflect poor quality of greenspaces in these areas: greenspace quality, which includes quality of planting design and vegetation management, is at least as important as greenspace quantity with regards to the likelihood of its use (Lee et al., 2015).

4.4. Future directions

The results of this study highlight that there is value in using landscape metrics in studies of benefits to human health from urban greenspace. There are several lines of research that would strengthen the utility of this approach. First, although LSOAs enable analysis of health geographies at a relatively fine scale, and are drawn to capture homogenous areas (Department for Communities and Local Government, 2015), associations identified at population level may not hold at the individual level. The effects of greenspace exposure further from home (e.g. at work, or while commuting) and cumulative exposure from previous homes or temporal changes to local land cover/use cannot be captured. There may also be residual confounding that we have not captured in our controlling variables. Using larger or smaller census geographies may find different results; our decision to use LSOAs reflects a balance between averaging out statistical fluctuations at smaller scales, and avoiding averaging out genuine patterns at larger scales.

Moreover, it is also not possible to infer causation from cross-sectional studies; indeed, establishing causal links between greenspace and health is an on-going challenge, as the associations are complex (Lee and Maheswaran, 2011). This is important in light of the results that suggest that the presence of water, diverse tree planting, and large greenspace patches are associated with low levels of poor health. Previous studies of different areas have found that nearby water landscape features, trees, parks and other greenspaces are associated with more expensive housing (Conway et al., 2010; Escobedo et al., 2015; GLA Economics, 2003; Luttik, 2000), and income is strongly associated with health (Mitchell and Popham, 2008). Moreover, attempts to reduce socioeconomic health inequalities by improving greenspace infrastructure may prove counter-productive if housing becomes unaffordable (Anguelovski et al., 2018).

If causation could be established, one might synthesise compositional and configurational recommendations from these results as follows. In terms of landscape composition, reduced poor health might be achieved through increasing water cover, increasing the diversity of tree planting, and reducing grass cover. While this is a simple planning recommendation in the sense that it is easily interpretable, it is not necessarily straightforward to create water features in a landscape where none exist. Nevertheless, our finding supports the well-known value of water and trees in urban landscapes (Forestry Commission England, 2010; Völker and Kistemann, 2011). Further, this combination of recommendations might enable reduction of poor health without an overall increase in the amount of greenspace.

Recommendations for the configurational aspect of greenspace centre around the greenspace splitting index, recreation land use patch density, greenspace contiguity index and green/grey landscape shape index. These metrics are more difficult to translate into clear guidance, as there are multiple ways of achieving the same metric value (e.g. splitting index can be reduced by having fewer patches or greater patch dominance), not all of which are consistent with the general findings that more greenspace is better (Maas et al., 2009; Mitchell and Popham, 2008). Further exploration would be required to establish threshold values that may contribute to health, and whether particular subtypes of land cover are especially important. Nevertheless, the literal recommendation from our analysis would be that having fewer, larger patches (of greenspace generally, and of recreation land uses) instead of many small ones, and designing a high level of interspersion of green and grey land covers would promote reduction of poor health.

5. Conclusions

Landscape metrics have potential for describing and analysing the aspects of urban greenspace that have benefits to human health. One of the key challenges in landscape metric studies is the selection of a parsimonious suite of metrics. We had success in identifying a set through a literature review followed by removal of theoretically or empirically redundant metrics, yielding similar results to more sophisticated approaches used in other studies, such as ordination or clustering.

Despite the small effect sizes of landscape metrics compared to other demographic and environmental variables, we were able to use multimodel inference to identify which of our selected suite of metrics were associated with self-reported general health at the LSOA scale. Although the nature of our method does not allow demonstration of causation, our results support the well-established findings that water cover and trees (specifically diversity of trees) are important for the well-being of urban residents, and also indicate that large patches of greenspace that are interspersed with the surrounding matrix of built infrastructure are associated with lower levels of poor health. Nevertheless, while landscape metrics are a simple method for capturing details of landscape composition and configuration, care must be taken in interpretation and explanation.

Acknowledgements

This work was completed as part of the Valuing Nature Programme, a five year £6.5 M research programme which aims to improve understanding of the value of nature both in economic and non-economic terms, and improve the use of these valuations in decision making. It funds interdisciplinary research and builds links between researchers and people who make decisions that affect nature in business, policymaking and in practice. See www.valuing-nature.net.

Funding

This work was supported by the Natural Environment Research Council, ESRC, BBSRC, AHRC & Defra [NE/N013565/1].

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2019.105464.

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