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Developing an openly accessible multi-dimensional small area index of 'Access to Healthy Assets and Hazards' for Great Britain, 2016

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ABSTRACT

Health geographers have been long concerned with understanding how the accessibility of individuals to certain environmental features may influence health and wellbeing. Such insights are increasingly being adopted by policy makers for designing healthy neighbourhoods. To support and inform decision making, there is a need for small area national level data. This paper details the creation of a suite of open access health indicators, including a novel multidimensional index summarising 14 health-related features of neighbourhoods for Great Britain. We find no association of our overall index with physical health measures, but a significant association to mental wellbeing.

1. Introduction

1.1. Accessibility and the geographical determinants of health

Geographical accessibility most commonly relates to the "distance" of an object (or individual) to a feature of interest (although see Brennan and Martin, 2012). It is one of the core underpinning concepts of health geography since it makes the spatial explicit. In the pursuit of understanding about *how* and *why* geographical determinants of health operate, it can be important to demonstrate how living close to a feature or having greater exposure to it will influence the risk of disease and ill health.

The role of access to and utilisation of health services forms one of the classical studies into the geographical determinants of health. Studies have sought to understand whether living far from a health service may discourage individuals from using them (Lovett et al., 2002; Haynes et al., 2003; Jordan et al., 2004; Macintyre et al., 2008; Jones et al., 2010). Understanding which populations have access to different types of health care has led to researchers considering whether access is equitable. Tudor Hart (1971) proposed the 'Inverse Care Law', whereby health services are hypothesised to be located in areas with less need for them, with considerable evidence to support the inequitable distribution of services (Furler et al., 2002; Shaw and Dorling, 2004; Mercer and Watt, 2007). The implications of promoting universal and equitable access to health care remains prominent among policy discussions (Ware and Mawby, 2015; NHS England, 2017).

Within the wider accessibility and health geography literature, there has also been consideration of broader geographical determinants of health beyond service provision and use. The location of different types of retail outlets has formed one area of interest across health geography, motivated by the rationale that the sources of services and goods we have access to may shape our behaviours. For example, research has demonstrated that individuals who have a greater number of fast food outlets within their vicinity can be associated with risk of obesity (Fraser and Edwards, 2010; Hobbs et al., 2018); the density of on- and off-trade alcohol-related outlets have been shown to be associated with acute and chronic alcohol-related harms (Shrek et al., 2018); and other studies have demonstrated similar associations related to tobacco outlets and risk of smoking (Shortt et al., 2016). Other work has explored how proximity to gambling outlets may affect the risk of problem gambling behaviours (which is independently associated with poorer mental wellbeing) (Pearce et al., 2008). The considerable evidence in favour of the health damaging aspects of retail outlet location has seen interest in restricting their location through planning restrictions among policy makers (Public Health England, 2017a).

It is also important to consider context as extending beyond the built environment, and there has been considerable investigation into how the natural environment may impact health. Air pollution has been extensively demonstrated to be associated with poorer respiratory health (Wheeler and Ben-Shlomo, 2005; Shah et al., 2015), and has

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been a longstanding policy issue (DEFRA, 2015; Royal College of Physicians, 2016; NICE, 2017). Conversely, accessibility to green space (i.e. natural vegetation including parks, grasslands or woodlands) has also been shown to be positively associated with physical health and mental wellbeing (Mitchell and Popham, 2008; Cherrie et al., 2018). Although these issues are not traditional components of ‘access’, we argue that the nature of their exposure has an inherently spatial extent, and as such can be conceptualised alongside access (as we introduce in Section 2.1.1).

1.2. Measuring accessibility to health-related features of environments

The importance of the role that geographical determinants play on health and wellbeing are being given greater priority by policy makers when designing intervention strategies (Public Health England, 2017b). It is therefore a policy imperative to have access to open data and tools that can be used to measure aspects of the environment, and that can help support such decision-making processes; as well as for researchers wanting to evaluate the influence of these contexts within their domain of application.

Although there are increasing quantities of data that exist and can be used to measure a variety of environmental features, there are barriers which limit their potential usage. Data may be costly, and perhaps held by commercial organisations, thus limiting access for individuals without suitable funding. Processing of contextual data will often require heavy data manipulation skills that users may not have, and can be further complicated when the data have additional geographic characteristics. Data sources may have known or unknown bias, and may not be complete at the national level. For example, they may be stored by local governments with no mechanism for sharing data between institutions to create a single collective resource. Given such constraints, it is perhaps unsurprising that in many studies that have explored the role of geographic context on health or wellbeing, these have tended to focus on relatively small regions (e.g. Lovett et al., 2002; Macintyre et al., 2008; Fraser and Edwards, 2010). Although these studies provide great insight into these localities, they may not be representative at the national level at which many policy decisions are made at. Creating open source metrics of accessibility that are nationally extensive we argue can therefore address these barriers.

One further limitation of developing univariate measures of accessibility are that they imply that different components of context are considered in isolation (Cummins et al., 2007). However, there is a lengthy history of how context within urban and social research can be more effectively represented as a complex series of different interacting influences; and that these contexts lead to particular “neighbourhood” effects that may substantially influence outcomes of measured social phenomena (Diez-Roux, 2001; Gatrell, 2005; Cummins et al., 2007; Sampson, 2012). There is therefore a need to develop multidimensional measures of the health-related features of neighbourhoods to help describe the inherent multiplicity of features.

Such composite indicators are commonly created within other policy-related fields, but perhaps most commonly in the study of deprivation which is considered as inherently complex, and comprised of multiple features of an individual's socioeconomic context (Townsend, 1987). The UK's Index of Multiple Deprivation (IMD) represents one attempt to capture these competing dimensions of deprivation and includes data on education, occupation, income, housing, health, crime and access to services (Noble et al., 2006; Smith et al., 2015). The power and relevance of the measure can be demonstrated through a plethora of studies showing its association with a multitude of health outcomes (Mitchell and Popham, 2008; Newton et al., 2015), and its wide policy appeal for identifying deprivation (Smith et al., 2015).

There are few examples that have applied such an approach to health-related features of environments, despite the pathways and resulting harms associated with the geographical determinants of health being multidimensional in nature. Richardson et al. (2010) provide an exemplar index of the physical environment that included data on air quality, climate, green space, radiation etc, and was demonstrated to be predictive of mortality rates (Pearce et al., 2010). Green et al. (2014) explored the multidimensionality of mortality rates for Great Britain finding that diseases clustered in different areas suggesting that simple measures of mortality rates fail to capture the variation in experiences across cause of death. Hobbs et al. (2018) applied a similar approach focusing on features of the obesogenic environment only, demonstrating that the interactions between the food and physical activity environments produce differing harms relating to risk of obesity.

Developing open metrics of access may benefit policy officials in two ways: (1) in being able to identify areas to intervene at, (2) help identify pathways that interventions can be designed to address. Composite measures can enable the possibility to identify *if* geography may matter leading to further investigation of *why*. They are also useful descriptive tools that, like the IMD, may help feed into the comparison and targeting of areas.

1.3. Aim

The aim of the study is to develop an open-access multi-dimensional index of the accessibility to health-related features of the environment for small areas across Great Britain (2016). We will outline the development of the index, Access to Healthy Assets and Hazards (AHAH), as well as examine what the index reveals and whether it is associated with health and wellbeing at both the area- and individual-level.

2. Methodology

2.1. Creating the index ‘Access to Healthy Assets and Hazards’ (AHAH)

2.1.1. Data and indicators

The inclusion of variables was informed based on a scoping exercise to identify environment features that had been shown to be associated to health and/or wellbeing within the literature, and with a clear direction of association. We identified nationally extensive data that could be compiled into measures related to our framework of three domains of accessibility: health services, retail outlets, and environmental quality.

Data on retail outlets were acquired from the ‘Local Data Company’ (LDC) who provide a rolling and nationally extensive survey of retail outlets for Great Britain in 2016. The data are collected via a combination of administrative databases and continuous field work to validate and update outlets. They included the location of an outlet (full address) and a classification of the outlet type. Using the data, we identified all (i) fast food outlets, (ii) pubs, bars and nightclubs, (iii) off-licenses, (iv) tobacconists, (v) gambling outlets. For all postcodes in Great Britain, we calculated the road network distance (km) to the nearest of each service using the open source software ‘Routino’ (www.routino.org), which integrates with an extract of ‘OpenStreetMap’ that details the road network.

Data on the location of health services in 2016 were acquired from multiple sources. For England and Wales, the location of GP practices, hospitals with an accident and emergency (A&E) department, pharmacies and dentists were supplied by NHS Digital. The equivalent data for Scotland were acquired from the Information Services Division (ISD) in NHS Scotland. We also included data on the location of private leisure services (e.g. gym, sports hall) among these indicators. While not a traditional health service, it is a retail outlet that offers health promotion facilities. We calculated the road network distance of a postcode to the nearest of each service.

The final domain, environmental quality, included data from two sources. The location of green space was identified from ‘OpenStreetMap’ (2017). We extracted the location of all ‘accessible’ green space (i.e. that is open to the public) by utilising the following “tags”: cemetery, common, dog park, scrub, fell, forest, garden, greenfield, golf course, grass, grassland, heath, meadow, nature reserve, orchard, park, pitch, recreation ground, village green, vineyard and wood. We then defined the amount of green space within a 900 m^2 buffer of a postcode. The buffer size was based on the recommendation by the European Environment Agency as the maximum distance individuals should be located from green space (Stanners and Bourdeau, 1995).

Measures of air quality were calculated using 2016 modelled estimates extracted from data provided by DEFRA (Brookes et al., 2016), which are created as an extrapolation from a combination of 1500 monitoring sites and drawing upon the location of industry, houses and the road network. Annual estimates of a variety of pollutants are estimated at a 1×1 km^2 gridded resolution for Great Britain. We included data on Sulphur Dioxide (SO_2), Nitrogen Dioxide (NO_2) and Particulate Matter < 10 µm (PM_{10}). Other pollutants were not included due to their collinearity, and as such they added little to our measure.

For all indicators, we aggregated the data (by taking the mean value) to small geographical areas to broaden the applicability of each indicator. For public dissemination, we selected Lower Super Output Areas (LSOAs) since they are the smallest zones (mean population 1500) routinely used by policy makers, and enable the created inputs and index to be compared to a range of other indicators. LSOAs are, however, only available for England and Wales; we opted to use Data Zones (DZs) for Scotland which are equivalent zones, albeit smaller (population range 500–1000). For both geographies, we used their 2011 versions.

2.1.2. Creating AHAH

Given wide stakeholder familiarity and adoption of the IMD, we adapted this approach to create the AHAH index (Smith et al., 2015). Each indicator was standardised due to differences in their distributions and units through ranking of LSOAs from most to least ‘healthiest’ (based on hypothesised directions – see Table B1 in Appendix B). In sum, each of the indicators in the retail domain and the air quality measures were defined as health-negating, and all of the health services indicators and green space measure were health promoting. Each standardised variable was transformed using the Rankit method which approximates a standard normal distribution (Dunn-Rankin, 1983). We then combined the indicators within each domain together to create a domain score. Indicators were equally weighted within domain since there was no clear theoretical justification for specific weightings per indicator.

The domain scores were then standardised to give them a similar distribution through ranking them from most to least ‘healthiest’ (based on hypothesised directions). We then applied an exponential transformation of the ranked domain scores. This was deemed necessary to minimise ‘cancellation effects’, so that a high value on one domain was not cancelled out by low values on another, and follows similar procedures to those implemented within the IMD (Smith et al., 2015). The exponential transformation places greater emphasis on high values representing negative environments (i.e. health damaging), which we deemed as helpful for stakeholder applications, since they will more often focus on the identification of “unhealthy” areas. The transformed score *'X'* is calculated using:

$$X = -23\ \ln\left(1 - R\left(1 - exp^{-100/23}\right)\right)$$

‘ln’ is the natural logarithm; *‘exp’* is the exponential transformation; 'R' is the rank value; '23' the scaling constant to minimise cancellation effects (the value produces 10% cancellation so that an area that was ranked as the most ‘unhealthiest’ area on one domain, but the least on another domain, would appear within the top 10% unhealthiest areas overall).

For interpretation of the AHAH index, larger scores represent areas that have poorer health-related environments through the combination of our domain scores (and vice versa). Similar interpretations can be observed for each of our domain scores. For the retail environment, larger values represent areas closer on average to the suite of services we measure (i.e. poorer health-related environments). The same is true for the health services domain, however in this instance larger values represent areas further away on average from services (i.e. we hypothesis living further away is bad for health). Finally, larger scores in the physical environment domain represent areas with poorer air quality or lack of access of green space on average.

A sensitivity analysis of the overall index is included in Appendix C.

2.2. Exploring AHAH

We present an investigation of the AHAH index to contextualise what the index is measuring. We utilise a multi-scale analysis to examine two aspects: (1) We first use ecological data to explore how the social, health and demographic characteristics of areas is associated to AHAH. This is important to understand what ‘high’ or ‘low’ values of AHAH correspond to beyond the input measures. (2) We test whether AHAH has any utility for predicting individual-level health and wellbeing. The analysis will examine whether AHAH is useful for understanding differences in health and wellbeing throughout our population, beyond simple describing area-level patterns. It also helps to minimise issues of ecological fallacy from the ecological analyses.

2.2.1. Ecological analyses

Four measures (stratified by constituent country of Great Britain) were used:

1. *Population density (2011 Census)*. The measure will examine if our indicators are associated with urban or rural areas (i.e. urban areas have higher population density). The measure is the number of individuals per hectare.
2. *The percentage of individuals with a Limiting Long-Term Illness (2011 Census)*. The measure will assess if the indicators are associated with health patterns. Limiting long-Term Illness is a commonly used measure of chronic health (Manor et al., 2001). We combined data on individuals reporting that their health limited their daily activities a lot and those where it only limited a little.
3. *The percentage of individuals reporting that their health is poor (2011 Census)*. A second health-related variable was selected since it is also a commonly used measure of health status. Individuals are asked to rate their own health using a likert scale, and we combined data on individuals who rated their health as fair, bad or very bad together. The variable is commonly used throughout the literature as a measure of physical health status and is associated with actual health status (Manor et al., 2001; Jylha, 2009).
4. *The Index of Multiple Deprivation (IMD)*. Neighbourhood deprivation has been previously demonstrated to be associated to health outcomes and health-related features (Mitchell and Popham, 2008; Newton et al., 2015). We used IMD since it offers a multidimensional measure of deprivation, which incorporates data on a wide range of factors associated with deprivation that other indicators fail to account for (Noble et al., 2006). We examine the association to the rank of areas by IMD (a rank of 1 represents the most deprived area). One of the IMD domains is ‘accessibility to services’ and while the overlap with our measure is minimal, we also include an additional comparison to the income domain to exclude any co-association that may influence the results. We used the most recent version of the index for each country: England - 2015, Scotland - 2016, and Wales - 2014.

While these measures are temporally dislocated from AHAH, they are the most recent ecological data available for each. We used Pearson's Correlation to examine the association of each of these measures to our overall index, and each domain score.

2.2.2. Individual-level analyses

Data from the survey 'Understanding Society' was used. Understanding Society is an annual longitudinal survey that collects data on around 40,000 individuals across multiple variables including health. We used the most recent wave of data available for 2015, which introduces temporal mismatch to our index but could not be avoided. LSOA and Data Zone codes were applied for, and a special license was granted for their usage.

We used five outcome variables

1. *Whether an individual had a limiting long-term illness (LLTI) or not (binary)*. The variable was selected to match the ecological health outcome measure. A value of 1 was assigned to individuals with a LLTI, and a value of 0 for those without.
2. *Self-rated health status (binary)*. The variable was categorised as whether the individual reported their health to be poor (average, poor or very poor - 1) or not (good or very good – 0) to match the equivalent ecological measure.
3. *12-item Short Form Health Survey (SF12) Physical Health score (continuous)*. A measure of self-rated general health based on the SF12 survey (Ware et al., 2001). Individuals are asked multiple questions related to their physical functioning and dependent upon their responses a score is computed. Larger values represent better physical health.
4. *SF12 Mental Wellbeing score (continuous)*. A score of mental wellbeing calculated from the SF12 survey (Ware et al., 2001). It includes questions about engagement with social activities, happiness and emotional issues. The score is calculated based on different questions asked in the survey not used in the above measure. Larger values represent better mental health.
5. *General Health Questionnaire score (GHQ) (continuous)*. A measure of psychological distress (i.e. mental wellbeing) compiled from 12 questions (Goldberg and Williams, 1988; Goldberg et al., 1997). Since there are two methods for calculating an individual's score (likert or caseness), we have opted to include both measures to maintain a fair analysis. Larger values represent individuals that are more distressed and have poorer wellbeing.

We adjusted our models by controlling for personal characteristics of individuals including age, sex and ethnicity. These characteristics have been previously demonstrated to be associated with health status. We also controlled socioeconomic status through total monthly gross income to measure an individual's material resources (Pampel, Krueger and Denney, 2010).

Analyses were undertaken using regression models. We explored the potential of using multi-level models, but with few observations per area (mean 2.4) it is difficult to identify area effects since there is little variability between areas (i.e. differentiating between random error). Fitting such a model produced similar results. A logistic regression model was used for the first two outcome variables, and linear regression was used for the wellbeing measures. We fit two types of models; one with just the overall AHAH score, and another including each domain score. Missing data were assumed missing at random and dropped from analyses. Sample weights were used for all models.

3. Results

3.1. Understanding access to healthy assets and hazards in Great Britain

Table 1 present summary characteristics of each input variable. On average, a postcode is located nearest to a pharmacy in comparison to all the other services or outlets measured. Average distance to a GP practice or dentist were also good, both located closer on average than any retail outlet. Pubs, bars and nightclubs were the most accessible retail outlet, although fast food outlets and gambling outlets were also highly accessible. While off-license and tobacconists were located further away on average in comparison to the other outlets, this does not necessarily mean that access to them is poor, since alcohol and tobacco can be purchased in other outlets as well (e.g. supermarkets). Hospitals with A&E were located the furthest away, reflecting their smaller prevalence across Great Britain. The median annual pollution levels are each below UK regulations and to contextualise their values a busy road network would have an annual mean greater than 30 $\mu g\, m^{-3}$ for PM_{10}, or NO_2 (vehicle emissions are not major contributors to SO_2 emissions, however values greater than 5 $\mu g\, m^{-3}$ would be seen in industrial sites).

Fig. 1 presents the spatial distribution of the overall AHAH score. There is a notable urban-rural divide, with urban areas broadly performing better than rural areas. The poor performance of many rural regions is driven by the isolation of communities from health services (preserved by the exponential transformation), and particularly evident for the Scottish Highlands. Lincolnshire also has a concentration of areas in the worst performing decile, partly reflecting the inaccessibility to health services but also the higher levels of pollutants from farming. This rural-urban division does not mean that urban areas always perform well. For example, all of the top ten poorest performing areas were located in Inner London due to the high levels of pollution and density of retail outlets. London Heathrow also stands out on the map demonstrating the fine scale nature of patterns captured by the index. Suburban areas surrounding many cities appear to perform best. This is due to their good environmental scores, as well as being located near to health services and far from retail outlets.

A correlation matrix between our indicators, as well as the domain scores, is provided in Appendix D.

Table 1
Summary characteristics for each input variable per area.

Domain	Indicator	Median value	Interquartile range
Retail Environment	Accessibility to Fast food outlets (km)	1.30	0.66–2.61
	Accessibility to Gambling outlets (km)	1.21	0.70–2.39
	Accessibility to Off-licenses (km)	2.58	1.26–6.13
	Accessibility to Tobacconists (km)	3.08	1.69–6.29
	Accessibility to Pubs, bars and nightclubs (km)	1.12	0.64–1.99
Health Services	Accessibility to GP practices (km)	1.05	0.65–1.79
	Accessibility to Accident & Emergency hospitals (km)	7.45	4.22–14.40
	Accessibility to Pharmacies (km)	0.85	0.56–1.36
	Accessibility to Dentist practices (km)	1.05	0.62–1.82
	Accessibility to Leisure services (km)	2.45	1.33–4.98
Physical Environment	Accessibility to Green spaces (km^2)	0.55	0.30–0.95
	Nitrogen Dioxide (NO_2) ($\mu g\, m^{-3}$)	10.60	8.24–13.35
	Particulate Matter 10 ($\mu g\, m^{-3}$)	12.74	10.95–14.11
	Sulphur Dioxide (SO_2) ($\mu g\, m^{-3}$)	1.15	0.96–1.42

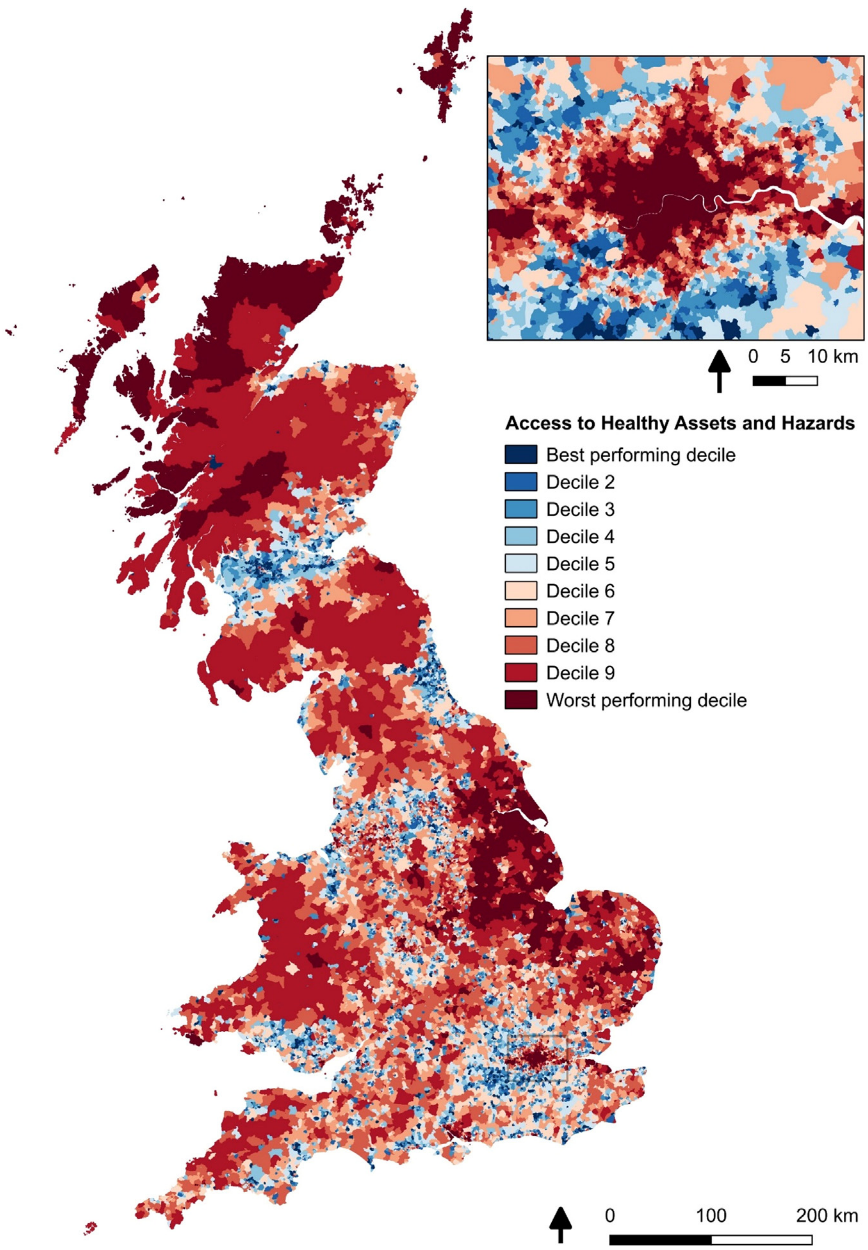

Fig. 1. The geographical distribution of the index of Access to Healthy Assets and Hazards (AHAH) for Great Britain (deciles split by rank values).

3.2. Exploring the association of AHAH to ecological measures

The first piece of analysis was to examine how AHAH and its constituent domains were associated to key ecological measures (Table 2). The overall AHAH score was positively associated to population density in England and Wales, suggesting that areas which were identified as having poor health-related features were more common in urban areas. This would imply that Fig. 1 is somewhat misleading.

There was little correlation of the overall index to population density in Scotland. Disaggregating the index into the domain scores explains this variation, suggesting that the domain scores are cancelling each other out in Scotland. The retail domain score was for each country positively correlated to population density (i.e. higher population density (urban) areas were associated with poorer environments), reflecting the concentration of retail outlets in urban environments. The health domain was negatively associated to population density demonstrating the greater accessibility to health services in urban environments. The environment domain was positively

Table 2
Pearson's Correlation analysis of AHAH and the domain scores to ecological measures by country.

AHAH	Country	Population density	Limiting long term illness	Poor health	Overall IMD rank	Income domain rank
Overall Index	England	0.48	−0.15	−0.08	−0.26	−0.17
	Scotland	0.00	−0.20	−0.21	0.10	0.17
	Wales	0.26	−0.28	−0.23	−0.01	0.09
Retail Domain	England	0.65	−0.09	0.00	−0.33	−0.30
	Scotland	0.56	0.02	0.08	−0.12	−0.15
	Wales	0.66	−0.13	−0.07	−0.15	−0.16
Health Domain	England	−0.56	−0.01	−0.10	0.30	0.37
	Scotland	−0.51	−0.16	−0.23	0.18	0.27
	Wales	−0.59	−0.05	−0.11	0.20	0.30
Environment Domain	England	0.55	−0.11	0.00	−0.31	−0.29
	Scotland	0.27	−0.13	−0.09	0.03	0.03
	Wales	0.60	−0.18	−0.08	−0.17	−0.18

Table 3
Examining the association between AHAH, each domain and three measures of an individual's physical health.

	Outcome variable		
	Long-standing illness *logistic* (1)	Poor Self-Rated Health *logistic* (2)	SF12 Physical health *OLS* (3)
(A) AHAH as overall index only			
AHAH score	0.0002 (−0.002, 0.003)	0.003 (−0.001, 0.006)	−0.008 (−0.022, 0.006)
(B) Domain scores			
Health Domain	−0.003*** (−0.005, −0.002)	−0.005*** (−0.007, −0.003)	0.022*** (0.015, 0.030)
Environment Domain	0.001 (−0.001, 0.002)	0.003*** (0.001, 0.004)	−0.013*** (−0.020, −0.006)
Retail Domain	0.0004 (−0.001, 0.002)	0.0001 (−0.002, 0.002)	0.005 (−0.003, 0.013)
Observations (n)	36,176	33,137	32,907

Note: We report log odds for the logistic models (models 1 and 2), beta coefficients for the OLS models (model 3) and 95% Confidence Limits for these estimates. Results are adjusted for age, sex, ethnicity and income level. * = $p < 0.05$, ** = $p < 0.01$ and *** = $p < 0.001$.

correlated to population density suggesting that urban environments performed poorly.

There was little association of the overall index or the individual domains to either health variable. Many of these weak correlation values suggest that the index was negatively associated with poor health outcomes, contrary to the hypothesised direction.

Finally, there was little association of the overall index or the domain scores to the deprivation rank of an area. There was little difference in the results between the overall IMD rank and the income domain rank. Although the association was slightly stronger in England, this may partly reflect differences in how the measures were constructed.

3.3. Examining whether AHAH predicts individual-level health

The final piece of analysis was to examine whether AHAH and its corresponding components are associated to individual-level health and wellbeing. Table 3 presents analyses examining their associations to our three physical health measures. We found no associations of the overall AHAH score across each of these outcomes.

Disaggregating by the individual domain scores of AHAH (larger domain values represent areas with poorer health-related environments for each domain), we detect some associations to each of our measures. The health domain is independently associated to each measure of physical health, although the direction of the associations do not fall in the expected direction. The health domain score was negatively associated with the odds of having a limiting long-term illness or poor self-rated health (i.e. individuals who lived in areas located further away from health services were less likely to report poorer health outcomes across the two measures). A positive association was detected for the SF12 physical health measure, suggesting that as the health services domain become poorer, individuals were more likely to report good health.

The physical environment domain also displays associations to two of our measures and these were both in the expected directions. The domain score was positively associated to an individual's risk of rating their health as poor, so that individuals who resided in areas with poorer environmental quality were more likely to rate their health as poor. It was also negatively associated to the risk of physical functioning as captured by the SF12 measure, with a decline in physical

Table 4
Examining the association between AHAH, each domain and three measures of an individual's mental health.

	Outcome variable		
	SF12 Mental health *OLS* (1)	General health questionnaire (Likert) *OLS* (2)	General health questionnaire (Caseness) *OLS* (3)
(A) AHAH as overall index only			
AHAH score	−0.023*** (−0.036, −0.010)	0.008** (0.001, 0.015)	0.005** (0.001, 0.009)
(B) Domain scores			
Health Domain	0.015*** (0.008, 0.022)	−0.006** (−0.009, −0.002)	−0.002* (−0.004, −0.0002)
Environment Domain	−0.007* (−0.013, −0.001)	0.003 (−0.001, 0.006)	0.002 (−0.0001, 0.004)
Retail Domain	−0.015*** (−0.023, −0.008)	0.005* (0.001, 0.010)	0.002* (0.00003, 0.005)
Observations (n)			

Note: All models are OLS regression models. We report beta coefficients and 95% Confidence Limits for these estimates. Results are adjusted for age, sex, ethnicity and income level.
* = $p < 0.05$.
** = $p < 0.01$.
*** = $p < 0.001$.

health as measured on the SF12 index with increasing domain score (i.e. areas that had poorer environments). No association was found for the risk of having a long-standing illness and the physical environment domain. We detected no associations for the retail domain at all.

Table 4 repeats the same analysis but for the mental wellbeing indicators. We find consistent evidence for the AHAH score being associated to an individual's wellbeing. Individuals who lived in areas with poorer AHAH scores (i.e. higher values representing poorer health-related environments) were more likely to have poorer mental health across all the measures. It was negatively associated to SF12 mental wellbeing score (i.e. larger values represent better wellbeing), and positively associated to both GHQ measures where larger values represent poorer wellbeing.

Disaggregating AHAH into the individual domains also demonstrates some associations. The health domain once again produced associations contrary to those expected, being positively associated with SF12 mental wellbeing score (i.e. as areas became located further from health services, people were more likely to report better wellbeing) and negatively associated to both GHQ measures (i.e. individuals residing in areas with poorer access to health services had better wellbeing). A negative association was detected for the environment domain score to the SF12 measure of mental health, showing that individuals living in areas with poorer environmental quality were also associated with poorer mental wellbeing. The domain was not associated to the GHQ measures though. The retail domain was associated to all variables, with each relationship suggesting that individuals who lived in areas with greater access to the retail outlets were associated with poorer mental wellbeing. A negative association was observed for SF12 mental wellbeing, and a positive association for both GHQ measures.

4. Discussion

4.1. Key Results

Our study details the creation and analysis of an open source multidimensional index of accessibility to health-related features for Great

Britain. Our index is constructed from data on accessibility to retail outlets, health services and the wider environmental quality. We detect distinct urban-rural inequalities, with remote rural regions and inner-city areas identified as urban environments with poor health-related features. While AHAH was not associated to the ecological measures of health patterns, we found some association of AHAH to individual-level measures of wellbeing. There were mixed associations in the relevance of the domain scores to physical and mental health.

4.2. Interpretation

Our study contributes to the literature through the development of a multidimensional measure of health-related features of the environment. Past research has focused on teasing out whether individual factors (i.e. unidimensional characteristics) are associated to health outcomes. Such an approach relies on a framework that features can be separated out from multiple competing processes and therefore fails to account for the inherent complexity of society (Diez-Roux, 2001; Gatrell, 2005). Rather individual's may interact with multiple features of environments simultaneously and therefore we need to account for this in how we design indicators (Cummins et al., 2007; Pearce et al., 2010; Richardson et al., 2010). Incorporating this approach into our index helps policy makers target areas that display numerous poor health-related characteristics within environments. The co-occurrence of particular environmental features may have a larger effect on health than compared to individual characteristics. It may also help to identify common underlying mechanisms that may not be identified through focusing on each characteristic separately. While our measures do not fully remedy the issue of added complexity in measuring environmental features, they provide a conceptual framework closer towards measuring the holistic environment that influences health, as well as allow future studies to explore the interactions between specific features through our openly available indicators.

Our analyses revealed a consistent association between our overall AHAH index and three measures of individual-level mental wellbeing. These findings follow previous research that has demonstrated how neighbourhoods (and multiple characteristics of them) are associated to several mental health and wellbeing outcomes (Mair et al., 2008; Pampel et al., 2010). It suggests that our index may be useful for understanding the determinants of wellbeing, as well as measuring the environmental quality of areas. Policy makers could use the index to target neighbourhoods to focus the delivery of interventions aimed at improving wellbeing and mental health related outcomes. While we demonstrate an association, we are unable to show *why* the index is associated to wellbeing. Future research will need to understand what is driving this association, which will be key for demonstrating the importance of using the index for targeting purposes.

We did not find any associations of the index to our physical health measures, which suggests that the utility of the index may be limited. However, this result may not be unsurprising. An individual's physical health will be influenced by longer-term environmental influences (Diez-Roux, 2001), and therefore may be less likely to be affected by purely the current characteristics of the environment alone. Constructing life course measures of neighbourhood-related features is difficult due to data accessibility limitations, however offer potential for exciting analyses and stronger investigations into the role of environmental features (Cherrie et al., 2018). With AHAH we were unable to construct historical measures, however we are aiming to update the measure annually to allow for such analyses in the future.

It is probably no surprise that the individual domains are stronger predictors of health and wellbeing than the overall index. They each represent specific aspects of the environment that may become masked when combined together into a single indicator. The physical environment domain was associated to both physical and mental health measures. Given that each constituent component of the domain have been widely demonstrated to be associated with health and wellbeing (Wheeler and Ben-Shlomo, 2005; Mitchell and Popham, 2008; Shah et al., 2015; Cherrie et al., 2018), such a result gives validity to the construction of the domain. The retail domain was found to be associated to mental health, but not physical health. This finding contrasts with the wider literature which has placed greater focus on physical health outcomes or health behaviours (Fraser and Edwards, 2010; Shortt et al., 2016; Shrek et al., 2018). However, there has been little study into how such outlets may influence wellbeing and the possible mechanisms for how it may operate, demonstrating the need for further investigation. Finally, we detected associations between the health domain and both physical and mental health. However, the direction of association was the opposite of what was expected with individuals who lived further away demonstrating poorer health and wellbeing. Such findings have been observed elsewhere and often reflect compositional issues, with individuals who live further away tending to be of high socioeconomic status and therefore at lower risk of ill health or poor wellbeing (Lovett et al., 2002; Haynes et al.,2003).

Irrespective of whether the associations between our indicators and health/wellbeing detected have wider validity for understanding the determinants of health, the whole suite of open access measures have wider applicability to researchers and policy makers. To our knowledge, there is no other comprehensive small-scale set of health-related indicators openly available for Great Britain. We hope that through releasing the data openly we can minimise data access issues (e.g. availability of data, costs of data, limited skills to process data) and help encourage greater investigation into geographical determinants of health. Importantly, we offer a data set for the whole of Great Britain. Given that data availability issues often restrict studies to undertake local level analyses, our data offer the ability to conduct national level analyses which can feed into national level decision making. Being able to openly measure aspects of the environment or target those areas that perform poorly on the overall measure can be powerful for policy makers. For example, IMD is used widely for allocating funding or targeting neighbourhoods (Smith et al., 2015). The potential of AHAH has seen it become incorporated by Public Health England within their 'FingerTips' system as an indicator of the wider determinants of health (Public Health England, 2018). This was following stakeholder embedding in the development of the index, helping to maintain the policy relevance focus of the project.

4.3. Limitations

There are several limitations of AHAH which can be broadly divided into conceptual and data issues. While the development of a multidimensional index that incorporates multiple environmental characteristics is important, it assumes a framework that environments can be separated into a linear scale of positive or negative environments. Such a framework is simplistic and ignores that different combinations of neighbourhood features may create positive or negative environments (Green et al., 2014). Richardson et al. (2010) extended their index through developing a classification to examine the complexity in neighbourhood features and extending AHAH accordingly will be important.

The input measures included in AHAH do not constitute all features of environments that may influence health. We focused on environmental aspects that we had data on and where the direction of association to health was clear. For example, we avoided incorporating other measures of the food environment such as access to convenience stores or supermarkets since such outlets sell both positive and negative foods/drinks. For these reasons, measures such as off-licenses and tobacconists will underestimate the issues they intend to measure, since alcohol and tobacco can be purchased wider than purely specialist outlets.

It may have been useful to also incorporate features of the social environment (e.g. poverty level, housing quality, access to good schools) as well given the wide literature demonstrating it to be an important determinant of health (Pampel et al., 2010; Sampson, 2012). We opted to avoid such incorporating the social environment within AHAH since we did not wish to replicate common deprivation measures. Table 2 demonstrates that AHAH was not correlated to IMD, and therefore exploring the interaction between these measures presents an exciting opportunity for future research.

Each input measure and the overall domain scores were weighted equally, however they may not contribute equally towards influencing health. We selected equal weightings because there was no agreement across the literature over how to fairly weight each input. Identifying the relative contributions of each domain and input would not only be useful both to refine AHAH to accurately reflect healthy environments, but would also aid policy makers to prioritise which aspects of environments to tackle. Through making all of the inputs openly available, users can also alter and refine how the index is constructed to reflect their needs.

5. Summary

Our open source suite of measures offers a useful resource for understanding the accessibility of small areas to positive and negative features of the built and physical environment. We extend previous approaches towards designing health-related indicators through creating a multidimensional measure incorporating information from 14 health-related features of the environment. All data including the index, domain scores and input values are available to downloaded freely via the interactive web mapping tool http://maps.cdrc.ac.uk (the postcode level inputs are also available upon request via the Consumer Data Research Centre).

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.healthplace.2018.08.019.

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