Re-engaging with the physical environment: a health-related environmental classification of the UK

Citation for published version:
Shortt, NK, Richardson, EA, Mitchell, R & Pearce, J 2011, 'Re-engaging with the physical environment: a health-related environmental classification of the UK', *Area*, vol. 43, no. 1, pp. 76-87. https://doi.org/10.1111/j.1475-4762.2010.00960.x

Digital Object Identifier (DOI):
10.1111/j.1475-4762.2010.00960.x

Link:
Link to publication record in Edinburgh Research Explorer

Document Version:
Peer reviewed version

Published In:
Area

DOI: 10.1111/j.1475-4762.2010.00960.x

Re-engaging with the physical environment: a health-related environmental classification of the UK

Niamh K. Shortt*, Elizabeth A. Richardson, Richard Mitchell and Jamie Pearce

*Corresponding Author.

Dr Niamh Shortt
Geography Building
Drummond Street
University of Edinburgh
Edinburgh, UK
EH8 9XP

Re-engaging with the physical environment: a health related environmental classification of the UK.

Abstract

This paper presents a health related area-level multiple environmental classification of the UK and examines ecological associations with health. This classification, akin to a geodemographic profile of the environment, classifies small areas across the UK into seven environment types ranging from "Industrial" to "Sunny, Clean and Green". The data for the classification were gathered from a range of agencies, rendered to Census Area Statistic Wards (n=10,654) and processed through a two-stage clustering technique to create a Multiple Environmental Deprivation Classification, or MEDClass. In order to explore the utility of MEDClass this paper presents an empirical investigation into the extent to which the type of physical environment one lives in can influence self-reported health and mortality rates. The findings suggest that whilst physical environment 'type' makes a modest contribution towards our understanding of health inequalities, socioeconomic deprivation remains the most important challenge for those seeking to address these inequalities. In conclusion we suggest that human geographers should embrace a broader conceptualisation of the environment and in particular, re-engage with traditional aspects of the physical environment.

Key words: UK, health inequalities, environmental profile, environmental deprivation, geodemographics, physical environment

Background

In May 2009 Alan Johnson, the then UK Secretary of Health, declared that “there can be no question about the importance of addressing the wider determinants of poor health today” (Johnson, 2009). Yet despite such government rhetoric progress is slow and whilst life expectancy has increased, the gap between the social groups has not narrowed (Department of Health, 2008). Since the early 1980s health has improved at a substantially faster pace in the most advantaged areas of the UK than in the least advantaged. A 10 year gap in female life expectancy between Kensington and Chelsea (87.8 years) and Glasgow City (77.1 years) in 2006 highlights these marked spatial inequalities. Those in the most deprived UK neighbourhoods suffer, on average, 13.6 years more poor health than those in the most affluent neighbourhoods (House of Commons Health Committee, 2009).

Although the drivers of rising health inequalities in the UK are likely to be multi-factorial, it is plausible that the local physical environment plays an important role in determining geographical differences in mortality and morbidity (Jerrett et al., 2004). Geographers have focussed on the effect of ‘place’ and in particular the idea of the ‘locale’ in which various aspects of the social and economic environment converge to influence health outcomes. The premise that place matters for health has led geographers to explore a wide range of area effects and consider the implications for health, and in particular a large body of research has evaluated whether health inequalities are determined by the characteristics of the population who live in the areas (the compositional argument) and/or by the physical or social characteristics of the areas themselves (the contextual argument) (Cummins et al., 2005, Ecob and Macintyre, 2000). Whilst research has been successful in identifying that local context matters for health, much of this body of work has been restricted to examining the influence of area level socio-economic deprivation. True contextual effects, however, are unlikely to be fully captured by an aggregation of individual socio-economic characteristics and exclusion of physical area characteristics shared by the population (Burrows and Bradshaw, 2001, Joshi, 2001)

Curtis and Jones propose three theoretical frameworks that support a contextual effect on health (Curtis and Jones, 1998). Firstly, the spatial patterning and diffusion of physical and biological risk factors, second, the role of space and place in social relations and finally, a sense of place through the interpretation of landscape. It could however be surmised that human geography, as a discipline, has become divorced from the physical environment leaving us with 'two halves of geography'(Johnston, In Press); few of us engage with the first framework proposed by Curtis and Jones and even fewer acknowledge the multi-dimensional nature of the physical environment and its relationship with health. Indeed much research has focussed on 3 aspects of the environment 1) the social environment 2) the economic environment and 3) the cultural environment. However the notion that the physical environment may partly shape health inequalities is supported by the growing evidence that socially disadvantaged groups often reside in areas of poorer physical environments. Using the framework of environmental justice, researchers have often noted that low income communities suffer the burden of environmental disamenities such as air and noise pollution and toxic facilities (Brainard et al., 2002, Evans and Kantrowitz, 2002, Jerrett et al., 2001, Perlin et al., 2001, Sobotta et al., (2007), Walker et al., 2005). Unequal access to a health promoting physical environment may partly account for the variations in health outcomes across areas differentiated by social disadvantage.

Although research into the relationship between the physical environment and health has largely been a tale of 'risky places' (Smith and Easterlow, 2005), thus ignoring the salutogenic aspects of the environment, recently, within a 'new' health geography focus has turned to therapeutic landscapes (Conradson, 2005, Gesler, 2005) and a shift towards seeing the environment as a positive enabler of wellbeing (Fleuret and Atkinson, 2007, Mitchell, 2009). However few have attempted to simultaneously capture both the pathogenic and salutogenic aspects of our exposure to the physical environment . Evidence is thus lacking on the population's exposure to multiple aspects of the physical environment and how this might influence health (Fone and Dunstan, 2006, Kawachi and Subramanian, 2007, Schempf et al., 2009). We propose a framework that moves away from a separation of environmental factors into individual 'risks' towards a convergence of health related environmental factors that represent the *type* of physical environment to which populations are exposed. In doing so we argue that environment and health research should recognise that environmental factors are intertwined, exist simultaneously and variably across space and that these combinations may have differential impacts upon health. In this paper we propose that the health of individuals may be influenced by the *type* of physical environment to which they are exposed, both health damaging and health promoting aspects combined. By focussing on *type* we are suggesting that profiling the local environment may help us to understand how specific combinations of physical environmental factors can influence health inequalities.

This notion of physical environment type is comparable to that of traditional geodemographics which is based on the principle that people living in the same neighbourhood share similar characteristics and thus neighbourhoods can be classified accordingly. Effectively, geodemographics exploits what human geographers understand: place and people construct each other. One of the earliest examples of area classification was Charles Booth's survey into life and labour in London between 1886 and 1903 which included information on levels of poverty, types of occupation, housing, population movements, religion and education (Booth, 1889). Maps of London were colour coded by street according to a classification system which indicated levels of poverty and wealth divided into types such as *'lowest class, visious, semi-criminal'* through *'mixed, some comfortable others poor'* to *'upper middle and upper class'*. More recently tools such as Mosaic, ACORN, Super Profiles and National Statistics Output Area Classification (OAC) have been used by commercial and marketing companies for geographic segmentation of their customer base into customer types (Sleight et al., 2005). Each contains different levels of detail, for example MOSAIC, the most widely used geodemographic data in the UK, uses 400 variables to classify 1.3 million people into 61 types. Furthermore in the analysis of health inequalities such classifications have been used to understand the spatial distribution of mortality (Lawlor et al., 2000, Shelton et al., 2006), heart disease (Manson-Siddle and Robinson, 1998) and health behaviours (Blaxter, 1990).

In this paper we present a method for classifying small areas according to shared physical environment characteristics. In the remainder of the paper we outline the processes taken to create a Multiple Environmental Deprivation Classification (MEDClass) and demonstrate its utility in investigating small area health differentials.

Methodology

To create our multiple environmental deprivation classification (MEDClass) we began by reviewing published literature to identify a range of physical environmental factors with health relevance. A full discussion of this process is available elsewhere (Richardson et al., Under Review), however we will provide a brief summary here. Our definition of the physical environment included external physical, chemical and biological factors (whether salutogenic or pathogenic) and excluded social and cultural factors. The selected environmental factors had to satisfy four criteria: (i) at least 10% of the UK population should be exposed; (ii) there had to be a plausible association with health; (iii) the association with health had to be robust as evidenced in the literature and (iv) comprehensive, spatially contiguous and contemporary data were available in the UK. The pathogenic factors meeting our criteria were outdoor ambient air pollutants, exposure to certain kinds of industrial facilities and cold climate. The salutogenic factors meeting our criteria were exposure to ultraviolet (UV) radiation and access to green space (see Table 1). The decision to treat UV radiation as salutogenic and not pathogenic was based on the available UK evidence which suggests that although it is the main risk factor for skin cancer (Reichrath, 2006), in the UK a consistent protective effect of UV (via Vitamin D production) has been found against a number of more prevalent cancers (e.g. prostate, breast and ovarian) (van der Rhee et al., 2006) as well as rickets, multiple sclerosis and type 1 diabetes (Kimlin, 2008).

Table 1: Data and data sources included in MEDCLass

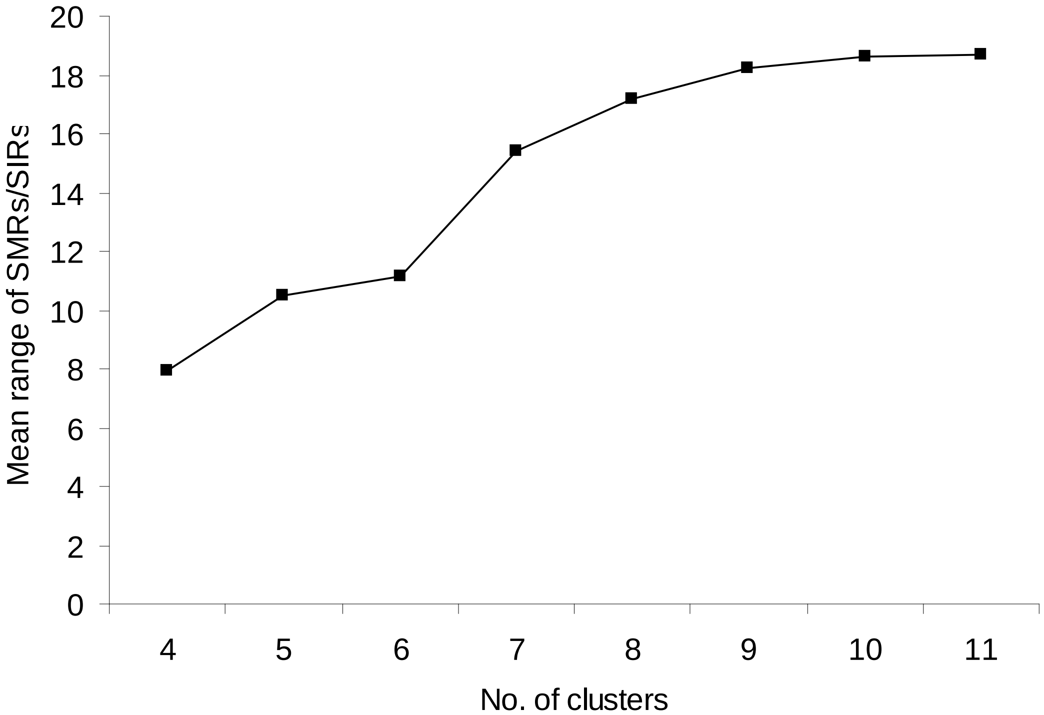
Dimension	Sub-dimensions	Data source
Air pollution	Particulate matter (PM_{10}) Ozone (O_3) Nitrogen dioxide (NO_2) Sulphur dioxide (SO_2) Carbon monoxide (CO)	AEA Technology (1 km grids, annual average concentrations, modelled from National Atmospheric Emissions Inventory (NAEI) data, 1999-2006)
Climate	Average temperature Cooling degree-days Heating degree-days Winter coldwave duration Summer heatwave duration	Meteorological Office UK Climate Impact Programme data (5 km grids, 1996-2003)
UV radiation	-	UVB Index (Mo and Green, 1974) calculated using Meteorological Office monthly cloud cover data (1 km grid, 1991-2000) and latitude
Industrial facilities	Waste management sites Metal production/processing sites	European Pollutant Emission Register (EPER) (grid references, 2001-2002)
Green space	-	Generalised Land Use Database (GLUD, England only, 2001) and Coordination of Information on the Environment (CORINE) Land Cover Data (UK, 2000)

Datasets were gathered from various agencies and rendered to a consistent geographic scale. We chose Census Area Statstics (CAS) wards (n = 10654, mean population size 5518) as our basic unit of analysis as they are small enough to reflect physical environmental difference but large enough to allow compatibility with routinely collected health data.

The next stage was to use the area-level variables to create a single classification of the physical environment for each ward. As air pollution and climate were each represented by more than one variable it was necessary to prevent these characteristics dominating any clustering technique. Principal Components Analysis (PCA) was used to reduce the air pollution and climate variables into single components which would account for the majority of the variance in the input variables. The air pollutant PCA produced one main component (Air_PCA) which accounted for 79% of the variance within the input variables. The climate PCA included UV, as the climate variables and UV were highly correlated and inclusion of both would have meant an even stronger latitudinal influence thus biasing the resulting classification. The climate/UV classification produced a component (Climate_PCA) which accounted for 53% of the variance in the original variables. As such four ward-level variables were used in the clustering procedure; Air_PCA, Climate_PCA, % green space availability, and proximity to industrial facilities.

Two-step cluster analysis in SPSS, a method to 'cluster' a set of observations into *N* number of sub-sets was applied to create the classification. Other clustering methods were considered (such as k-means clustering) and whilst cluster membership between the techniques was similar, the two-step clustering method was chosen as it is designed to handle large datasets and summarises the importance of each variable to each cluster. The clustering procedure produced solutions of varying complexity, which we then assessed to determine the optimal number of clusters for our purposes. There is no universal rule for this assessment, although (De Kluyver and Whitlark, 1986) suggest that a good cluster solution should be efficient (i.e., using as few clusters as possible, thereby minimising complexity) but also effective (i.e., having sufficient clusters to capture the salient differences in the data). In other words, the best solution will minimise intra-cluster difference and maximise inter-cluster differences. We therefore assessed our cluster solutions using the elbow criterion (Bryan, 2006). We calculated standardised mortality and incidence rates (SMRs and SIRs – comparisons of the numbers of observed deaths/illnesses to what would be expected given the underlying population) of selected health outcomes, and plotted the mean range of these rates against the solution's complexity (Figure 1). The 'elbow' of the graph marks the number of clusters at which any gain in information from identifying additional clusters would not justify the increased complexity of the solution. The marginal gain for additional complexity is reduced after the 7-cluster solution, as such seven clusters were declared optimal.

Figure 1: Plot of a solution's complexity (i.e., number of clusters) against its mean range of SMRs and SIRs.



Another practical criterion applied when selecting the most appropriate cluster solution was ease of naming: the individual clusters should be sensibly named and differentiated from other clusters (based on the environments that they typify) otherwise the solution was deemed to be capturing too coarse or too fine a level of detail. When naming the clusters we returned to the output from the Two-Step clustering procedure and explored the dominant environmental characteristics of each of the seven clusters. The cluster names therefore refer to the physical environmental characteristics which defined them and, to some extent, their geographical spread. Addressing all the criteria the seven-cluster solution remained relatively easy to name, displayed the largest range of health effects, was fine enough to determine health differences and according to the elbow criterion any further division would have resulted in little marginal gain.

Health data

Individual level mortality records (including age, sex, cause of death, and area of residence at death) for the leading causes of death in the UK were obtained from the Office for National Statistics for England and Wales, General Registers Office for Scotland and the Northern Ireland Statistics and Research Agency. Causes of death included in the analysis were all causes excluding external causes (International Classification of Disease: ICD-9 codes <800, ICD-10 codes A00–R99), all cancer (ICD-9 140-239; ICD-10 C00–D48), lung cancer (ICD-9 162; ICD-10 C33-C34), colorectal cancer (ICD-9 153-154; ICD-10 C18-C20), female breast cancer (ICD-9 174; ICD-10 C50), prostate cancer (ICD-9 185; ICD-10 C61), oesophageal cancer (ICD-9 150; ICD-10 C15), cardiovascular disease (ICD-9 390-459; ICD-10 I00-I99), and respiratory disease (ICD-9 460-519; ICD-10 J00-J99). We extracted measures of self-reported health from the 2001 census. We selected the Carstairs Deprivation Index (based on the prevalence of overcrowding, unemployment among men, low social class, and not having a car) as our area-level measure of socio-economic deprivation (Carstairs and Morris, 1991).

Analyses

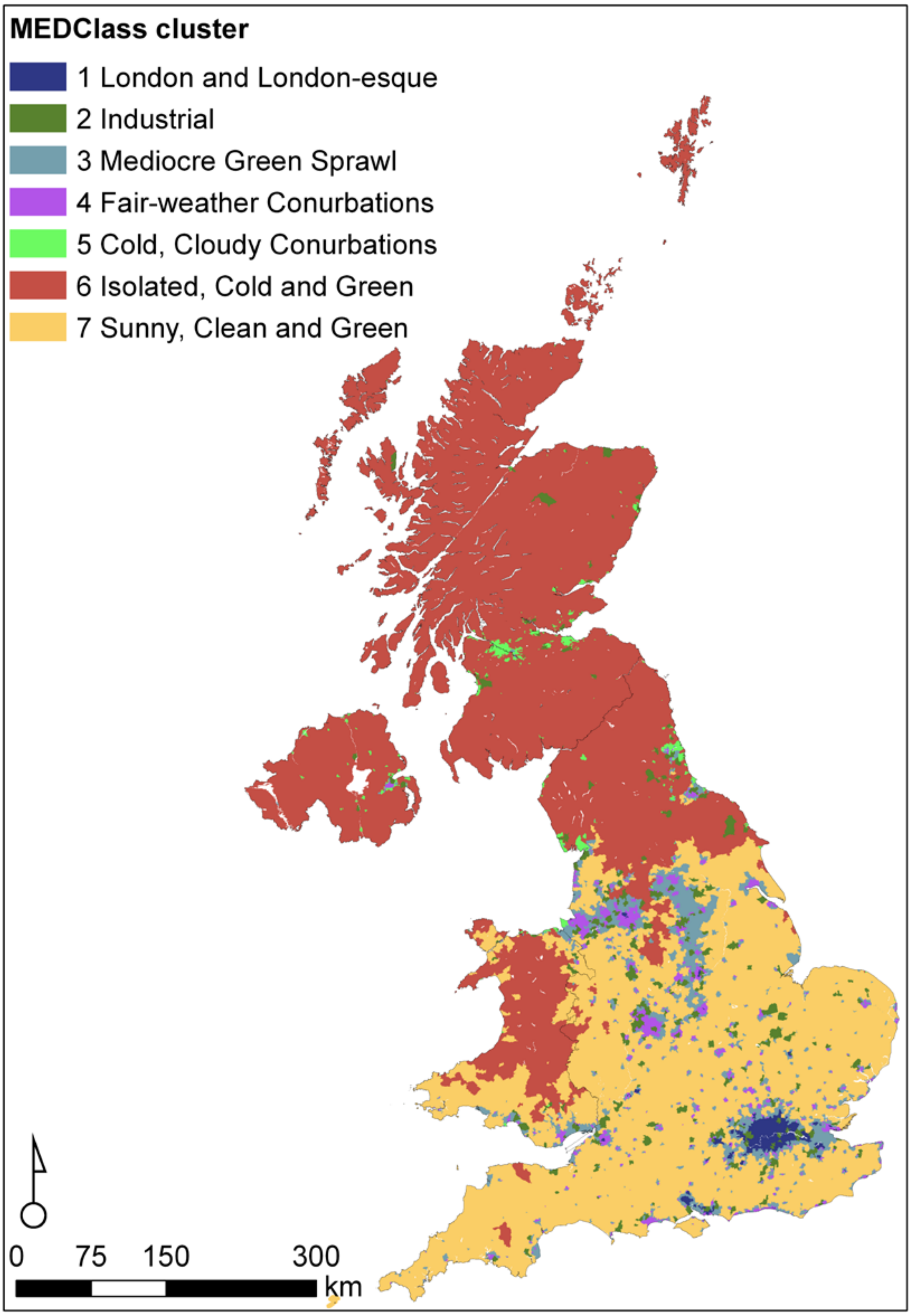
Negative binomial regression models that adjusted for age-group and sex were applied to investigate the relationship between MEDClass and risk of mortality and morbidity. Such models take into account the over-dispersed mortality and self-reported health count data. Two models were used. The first, controlling for Carstairs score as a continuous variable and the second running individual models for each combination of MEDClass cluster (n=7) and Carstairs deprivation quintile (i.e. 35 models for each health outcome), enabling us to explore associations between each deprivation quintile and each environmental cluster. This allowed us to examine the level of association between MEDClass score and health within deprivation quintiles and to determine whether the health of those at either end of the deprivation spectrum was equally affected by environment type.

Results

The final seven cluster solution is presented in Figure 2. An inspection of the geographical patterning of MEDClass demonstrates the dominance of cluster seven, 'Sunny, clean and green', in rural England and South Wales with wards in this cluster having large amounts of green space, low levels of air pollutants and high UV levels. On the other hand cluster five, 'Cold, cloudy conurbations', covers the major urban centres of Scotland (Glasgow, Edinburgh and Aberdeen) as well as Newcastle and urban areas of Northern Ireland. Wards in this cluster are dominated by a cold climate, low UV levels, and a low percentage of green space. The remaining clusters are spread throughout the UK with some predominating in certain areas cluster six ('Isolated, cold and green) accounting for the majority of rural Scotland, Northern

England, Northern Ireland and Wales and cluster one (London and London-esque) accounting for most of London and other urban centres of England).

Figure 2: Map of the MEDClass clusters



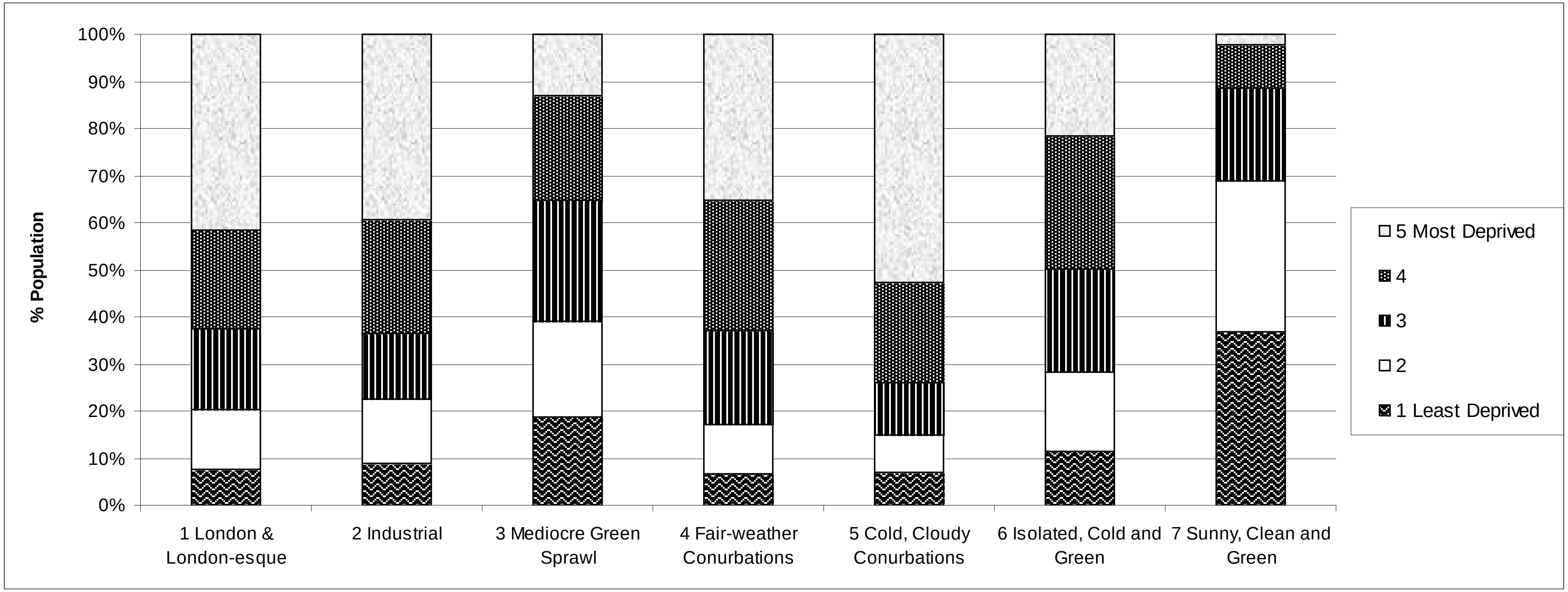
The distribution of population, wards and Carstairs deprivation scores across the clusters is shown in Table 2, whilst Figure 3 presents the percentage of population assigned to each Carstairs Quintile within each environmental cluster. It is evident that there was a broad distribution of population across each cluster with no combination of cluster and deprivation quintile having a particularly small population that would compromise any health based analysis. However, as Carstairs scores varied across the clusters it was important to control for the possible confounding effect of socio-economic deprivation on health outcomes in subsequent analysis.

Table 2: Distribution of population, wards and mean Carstairs score across clusters

Cluster	**Population**	**n wards**	**Mean Carstairs Score***
1 London & London-esque	8402313	840	1.681
2 Industrial	4876759	673	0.890
3 Mediocre Green Sprawl	12276454	1955	-0.644
4 Fair-weather Conurbations	13393659	1649	1.226
5 Cold, Cloudy Conurbations	4659367	988	2.784
6 Isolated, Cold and Green	5348830	1691	0.185
7 Sunny, Clean and Green	9831812	2858	-2.043

* Higher Carstairs score = more deprived in socio-economic terms

Figure 3: Percentage of population assigned to each Carstairs Quintile within each environmental cluster



Negative binomial regression yields Incidence Rate Ratios (IRRs) which can be interpreted as the risk of mortality/illness in a particular cluster relative to the rest of the UK (IRR 1.0) (e.g., an IRR of 1.2 among a specific population represents a 20% increased risk of death/illness for that population, compared to the rest of the country). Figure 4, for example, shows the elevated risk of all-cause mortality within 'Cold, cloudy conurbations' relative to the rest of the UK (IRR = 1.05). A similar elevated risk in this cluster was seen for all cancers (1.08), lung cancer (1.19) and oesophageal cancer (1.17). In comparison 'London and London-esque' wards had the lowest mortality risk for all-cause (0.93), all cancer (0.92), cardiovascular disease (0.90), colorectal cancer (0.89), oesophageal cancer (0.83) and lung cancer (0.90). Respiratory disease IRRs showed quite a different pattern, being higher in more southern clusters (one, three and four) and lower in more northern clusters (five and six), perhaps reflecting high levels of urban air pollution in the south, particularly in 'London and London-esque' (cluster one) wards (Figure 5).

Figure 4: IRR for all cause mortality by MEDClass cluster, adjusted for age, sex and area-level Carstairs deprivation.

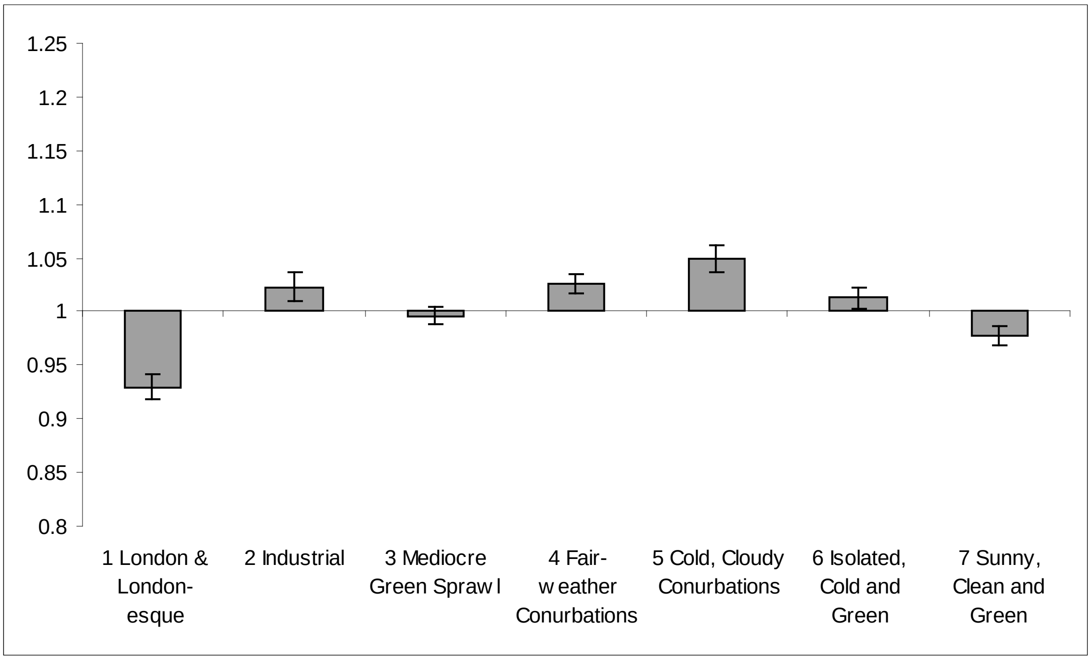


Figure 5: IRR for respiratory disease mortality by MEDClass cluster, adjusted for age, sex and area-level Carstairs deprivation.

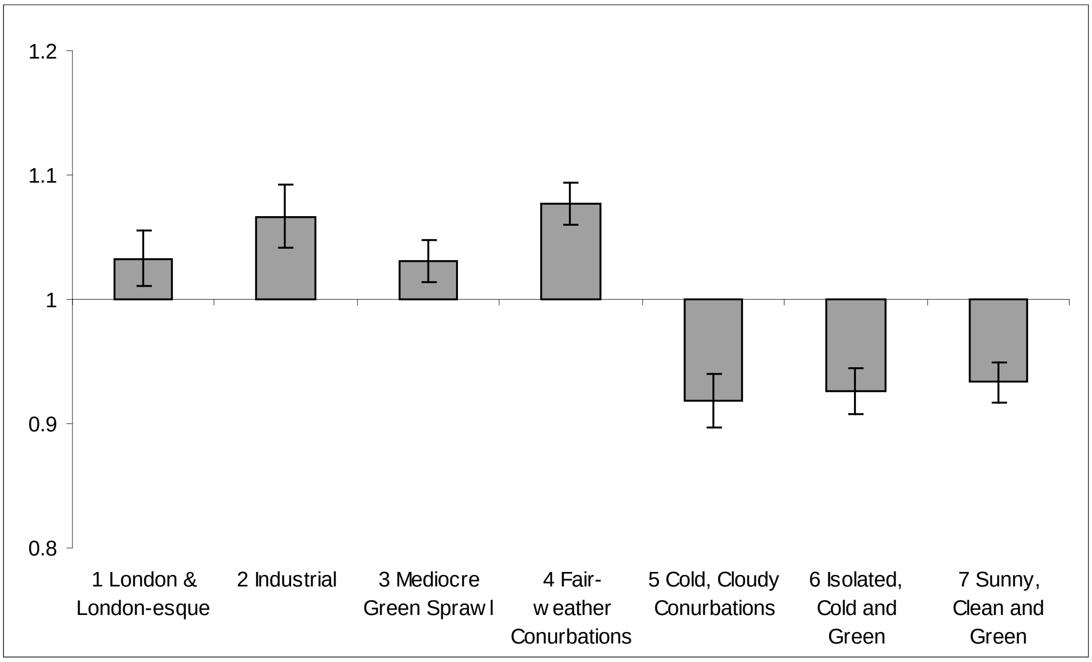


Table 3 presents associations between MEDClass and health within populations who experience approximately the same levels of socioeconomic deprivation but different types of physical environment. These are the results of the individual models for each combination of MEDClass cluster and deprivation quintile to explore the effects of particular combinations of environment type and socio-economic deprivation. Notably the type of environment has a relatively small effect on population health in the most affluent quintiles (one and two) suggesting that affluent areas enjoy health that is significantly better than the UK average regardless of physical environment type. In contrast those in the most socio-economically deprived quintiles experienced the greatest variation (though still not large) in health outcomes by physical environment type, most notably between clusters one and five. Of the most deprived wards (quintile five), those in 'Cold, cloudy conurbations' (cluster five) had significantly greater risk of all cause (IRR = 1.38), all cancer (1.27) and lung cancer (1.80) than any other cluster (e.g., lung cancer, Figure 6). At the other end of the spectrum wards in 'London and London-esque' (cluster one) were at a significantly reduced risk of limiting long term illness (0.655), all cancer mortality (0.856) and cardiovascular mortality (0.784). It should be noted at this point that health related behaviours were not controlled for in our analysis. Whilst such behaviours are strongly related to socioeconomic deprivation we did not have individual level data. Such behavioural data may be especially important in specific causes of death, such as lung cancer and cardiovascular disease.

Table 3. Incidence rate ratios (+ 95% confidence intervals) for the association between MEDClass and selected health outcomes. The IRRs are presented relative to the rest of the UK (IRR = 1.0). Models stratified by Carstairs deprivation quintiles and adjusted for age-group and sex.

Health outcome	Carstairs deprivation quintile	MEDClass cluster: 1 London & London-esque	2 Industrial	3 Mediocre Green Sprawl	4 Fair-weather Conurbations	5 Cold, Cloudy Conurbations	6 Isolated, Cold and Green	7 Sunny, Clean and Green
All-cause mortality	1 (least)	0.80 (0.77 to 0.83)***	0.84 (0.81 to 0.88)***	0.80 (0.78 to 0.81)***	0.79 (0.77 to 0.81)***	0.82 (0.78 to 0.86)***	0.84 (0.82 to 0.87)***	0.82 (0.80 to 0.83)***
	2	0.87 (0.84 to 0.89)***	0.89 (0.87 to 0.92)***	0.86 (0.85 to 0.88)***	0.88 (0.86 to 0.90)***	0.90 (0.86 to 0.94)***	0.89 (0.87 to 0.92)***	0.86 (0.85 to 0.87)***
	3	0.93 (0.91 to 0.95)***	0.98 (0.95 to 1.01)	0.94 (0.93 to 0.95)***	0.96 (0.95 to 0.98)***	0.99 (0.96 to 1.03)	0.96 (0.94 to 0.97)***	0.92 (0.91 to 0.94)***
	4	1.02 (1.00 to 1.05)	1.11 (1.08 to 1.13)***	1.06 (1.05 to 1.08)***	1.09 (1.07 to 1.11)***	1.12 (1.09 to 1.15)***	1.06 (1.05 to 1.08)***	1.03 (1.00 to 1.05)*
	5 (most)	1.14 (1.12 to 1.17)***	1.25 (1.23 to 1.28)***	1.23 (1.21 to 1.26)***	1.33 (1.31 to 1.35)***	1.38 (1.35 to 1.41)***	1.23 (1.20 to 1.26)***	1.17 (1.13 to 1.22)***
All cancer mortality	1 (least)	0.86 (0.83 to 0.88)***	0.88 (0.85 to 0.90)***	0.84 (0.83 to 0.86)***	0.87 (0.85 to 0.88)***	0.92 (0.89 to 0.96)***	0.87 (0.85 to 0.90)***	0.86 (0.85 to 0.87)***
	2	0.91 (0.89 to 0.94)***	0.93 (0.90 to 0.96)***	0.92 (0.91 to 0.93)***	0.91 (0.89 to 0.93)***	0.95 (0.91 to 0.99)*	0.92 (0.90 to 0.94)***	0.89 (0.88 to 0.90)***
	3	0.95 (0.93 to 0.97)***	0.98 (0.95 to 1.01)	0.97 (0.95 to 0.98)***	0.98 (0.97 to 1.00)*	1.04 (1.01 to 1.07)**	0.98 (0.97 to 1.00)	0.94 (0.92 to 0.95)***
	4	1.00 (0.97 to 1.02)	1.08 (1.06 to 1.10)***	1.06 (1.05 to 1.07)***	1.06 (1.05 to 1.08)***	1.11 (1.09 to 1.13)***	1.05 (1.03 to 1.07)***	1.01 (0.99 to 1.03)
	5 (most)	1.03 (1.01 to 1.05)*	1.15 (1.12 to 1.17)***	1.15 (1.13 to 1.17)***	1.19 (1.17 to 1.21)***	1.27 (1.25 to 1.29)***	1.17 (1.14 to 1.19)***	1.14 (1.10 to 1.18)***
Lung cancer mortality	1 (least)	0.68 (0.63 to 0.74)***	0.72 (0.67 to 0.78)***	0.64 (0.62 to 0.66)***	0.63 (0.59 to 0.66)***	0.72 (0.66 to 0.80)***	0.73 (0.68 to 0.77)***	0.62 (0.60 to 0.64)***
	2	0.83 (0.79 to 0.87)***	0.79 (0.74 to 0.85)***	0.79 (0.76 to 0.81)***	0.77 (0.74 to 0.80)***	0.84 (0.78 to 0.91)***	0.81 (0.77 to 0.85)***	0.69 (0.68 to 0.71)***
	3	0.91 (0.87 to 0.96)***	1.00 (0.94 to 1.06)	0.91 (0.88 to 0.94)***	0.93 (0.90 to 0.96)***	1.06 (1.00 to 1.13)	0.99 (0.95 to 1.03)	0.79 (0.76 to 0.81)***
	4	1.02 (0.98 to 1.07)	1.15 (1.10 to 1.21)***	1.11 (1.08 to 1.14)***	1.12 (1.09 to 1.15)***	1.31 (1.26 to 1.36)***	1.10 (1.06 to 1.14)***	0.94 (0.90 to 0.99)*
	5 (most)	1.17 (1.13 to 1.22)***	1.39 (1.33 to 1.44)***	1.42 (1.37 to 1.48)***	1.55 (1.50 to 1.60)***	1.80 (1.75 to 1.86)***	1.46 (1.39 to 1.52)***	1.29 (1.18 to 1.41)***
Limiting long-term illness	1 (least)	0.66 (0.64 to 0.67)***	0.74 (0.72 to 0.76)***	0.69 (0.68 to 0.70)***	0.71 (0.69 to 0.73)***	0.74 (0.72 to 0.76)***	0.78 (0.76 to 0.79)***	0.70 (0.70 to 0.71)***
	2	0.75 (0.74 to 0.76)***	0.85 (0.83 to 0.87)***	0.82 (0.81 to 0.83)***	0.81 (0.80 to 0.83)***	0.85 (0.82 to 0.87)***	0.86 (0.84 to 0.87)***	0.81 (0.80 to 0.81)***
	3	0.84 (0.82 to 0.85)***	0.99 (0.96 to 1.01)	0.94 (0.93 to 0.95)***	0.94 (0.93 to 0.95)***	0.98 (0.95 to 1.00)	0.98 (0.97 to 1.00)*	0.96 (0.95 to 0.98)***
	4	0.95 (0.93 to 0.97)***	1.13 (1.10 to 1.16)***	1.14 (1.12 to 1.16)***	1.11 (1.09 to 1.12)***	1.13 (1.11 to 1.15)***	1.14 (1.12 to 1.15)***	1.18 (1.15 to 1.21)***
	5 (most)	1.15 (1.13 to 1.17)***	1.34 (1.32 to 1.37)***	1.41 (1.38 to 1.44)***	1.41 (1.39 to 1.43)***	1.47 (1.45 to 1.49)***	1.42 (1.39 to 1.45)***	1.47 (1.39 to 1.55)***

* $0.01 \le p < 0.05$; ** $0.001 \le p < 0.01$; *** $p < 0.001$

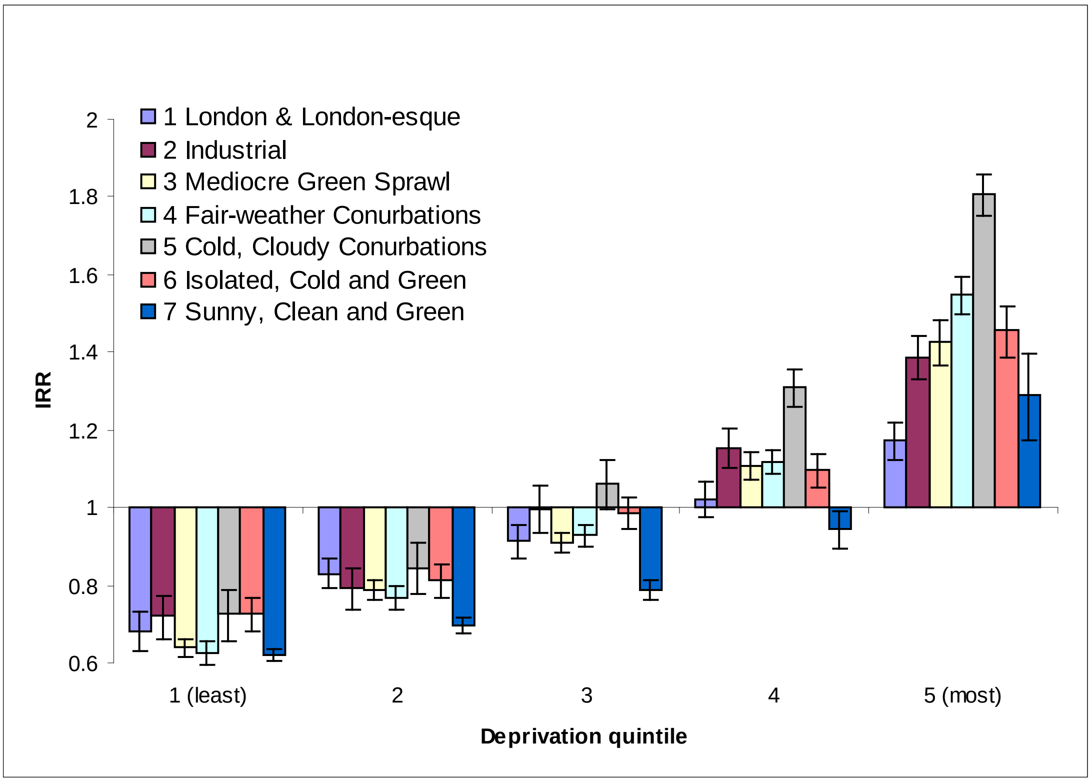


Figure 6: Lung Cancer mortality IRRs by MEDClass cluster 'stratified' by Carstairs area-level deprivation

Discussion

This paper has described the development of an area level classification of the physical environment and demonstrated its utility in researching health inequalities. The approach presented here has allowed us to characterise areas based on the *type* of environment experienced rather than on one or two environmental factors. However, the classification does not infer quality or a rank order on any of the environment types. In further work we created a Multiple Environmental Deprivation Index (MEDIx) which can be used to identify areas in which the environmental burden might be relatively higher or lower (Richardson et al., Under Review).

It should be noted that although each ward has been allocated to a MEDClass cluster based on their *environmental* characteristics it should not be assumed that every ward in a particular cluster will have identical physical environments. This is because there will be some variation in environmental characteristics among areas labelled within the same ‘class’. Whilst some environment types are widely represented across the UK others are restricted to relatively small geographical areas.

We have presented empirical evidence to suggest that the physical environment has some power to explain health inequalities, independent of socio-economic deprivation. However, as shown in the final models this effect is relatively weak and the results emphasise the very strong relationship that exists between health outcomes and deprivation. Nevertheless, there appears to be a threshold effect of socio-economic deprivation: at low levels of socio-economic deprivation there does not appear to be a large effect of the physical environment but at higher levels the physical environment becomes more important. This interaction effect suggests that over and above socio-economic deprivation and individual level characteristics the physical environment matters for sections of the population. The fact that it does so more for those in more deprived areas is in line with literature suggesting that those of lower socio-economic status may be more susceptible to environmental effects, both pathogenic (e.g. (Jerrett et al., 2004) and salutogenic (e.g. (de Vries et al., 2003). Environmental exposure measured for residential locations may be more appropriate for more socially deprived groups who are likely to be less mobile (Scott and Kanaroglou, 2002) and thus exposed at a greater degree to their home environment (Maas et al., 2006). In a further paper we explored the relationship between MEDIx, socioeconomic deprivation and health outcomes. Whilst different results were found, this highlights the distinction between the use of a classification or an index and the importance of exploring alternative measurements in our analysis (Pearce et al., under review).

Our study is however subject to a number of limitations and assumptions. Two factors that we considered as important for inclusion were excluded due to data unavailability (drinking water quality and noise pollution). Our choice of spatial unit and our attribution of environmental data to this unit could also be criticised, however CAS Wards were carefully chosen for the reasons previously outlined. We acknowledge that adopting alternative geographical units may have yielded different results. Finally, our study relies on cross sectional data, hence we were not able to infer causality and we could not control for health selective migration. It is widely acknowledged that health selective migration may partially explain spatial health inequalities; healthier (and wealthier) people may be able to choose to live in more health enabling environments (Boyle, 2004). A further limitation was our inability to control for individual level health behaviours, such as smoking, alcohol intake, diet and physical activity. We are aware that each of this may have an impact upon the relationships found, however, we did control for socioeconomic deprivation which is strongly related to health behaviours. In a further funded project we will begin to explore individual level behaviours and multiple environmental deprivation in England.

Despite these limitations, MEDClass offers an innovative framework for exploring the relationship between the physical environment and health inequalities. The relationship between a poor physical environment and a poor socioeconomic environment may go some way to explaining spatial inequalities in health outcomes but existing evidence is lacking on the specific causal pathways by which the physical environment might influence health (Fone and Dunstan, 2006, Kawachi and Subramanian, 2007, Schempf et al., 2009). We suggest two pathways for further exploration: health behaviours and a psychosocial pathway. There is a small but a growing body of literature suggesting health related behaviours may be a pathway through which the environment impacts upon health outcomes (Diehr et al., 1993, Duncan et al., 1993, Duncan et al., 1996, Ellaway and Macintyre, 1996, Blaxter, 1990). Returning to the theoretical framework proposed by (Curtis and Jones, 1998) further questions could be asked of “the role of space and place in social relations”, in particular how the physical environment influences the processes that operate at the individual level and in turn resulting health behaviours. Furthermore research could explore the psychosocial dimensions of the physical environment and the extent to which aspects of the physical environment (both individually and in a classification such as this) correlate with related outcomes. Previous research has indicated the importance of the physical environment on psychosocial outcomes, with some arguing that it could be as important as characteristics of the socio-cultural environment (Brogan and James, 1980). An important aspect of this could be a person’s perception of local environmental risk (most notably from polluting facilities) and their psychosocial status.

The empirical evidence presented in this paper suggests that whilst physical environment ‘type’ makes a modest contribution to health inequalities, socio-economic deprivation remains the irrefutable driving force behind spatial inequalities in health in the UK. This study demonstrates the utility of classifying the physical environment for spatial health research and acknowledges the fact that the physical environment is an important aspect of the contextual environment. By ignoring the physical environment human geographers risk detachment from the core of the discipline and health geographers in particular have much to offer in rekindling this relationship through a re-engagement with exploring environment and health relationships. This idea is neither conventional, nor outdated (Smith and Easterlow, 2005), but rather critical and urgent given the recent call by UK medical professionals to focus on the health effects of climate change and our rapidly changing physical environment (Costello et al., 2009). Health geographers should therefore embrace a broader conceptualisation of environment, to include not just the social, economic and cultural environments but also a re-engagement with the physical.

References

BLAXTER, M. 1990. *Health and Lifestyles,* London, Routledge.

BOOTH, C. 1889. *Life and Labour of the people. First Series (i) East, Central and South London,* London, Macmillan.

BOYLE, P. 2004. Population geography: migration and inequalities in mortality and morbidity. *Progress in Human Geography,* 28**,** 767-776.

BRAINARD, J. S., JONES, A. P., BATEMAN, I. J. & LOVETT, A. A. 2002. Modelling environmental equity: access to air quality in Birmingham, England. *Environment and Planning A,* 34**,** 695-716.

BROGAN, D. R. & JAMES, L. D. 1980. Physical environment correlates of psychosocial health among urban residents *American Journal of Community Psychology,* 8**,** 507-522.

BRYAN, B. A. 2006. Synergistic techniques for better understanding and classifying the environmental structure of landscapes. *Environmental Management,* 37**,** 126-140.

BURROWS, R. & BRADSHAW, J. 2001. Evidence-based policy and practice. *Environment and Planning A,* 33**,** 1345-1348.

CARSTAIRS, V. & MORRIS, R. 1991. Deprivation and health in Scotland. Aberdeen: Aberdeen University Press.

CONRADSON, D. 2005. Landscape, care and the relational self: Therapeutic encounters in rural England. *Health & Place,* 11**,** 337-348.

COSTELLO, A., ABBAS, M., ALLEN, A., BALL, S., BELL, S., BELLAMY, R., FRIEL, S., GROCE, N., JOHNSON, A., KETT, M., LEE, M., LEVY, C.,

MASLIN, M., MCCOY, D., MCGUIRE, B., MONTGOMERY, H., NAPIER, D., PAGEL, C., PATEL, J., ANTONIO, J., DE OLIVEIRA, P., REDCLIFT, N., REES, H., ROGGER, D., SCOTT, J., STEPHENSON, J., TWIGG, J., WOLFF, J. & PATTERSON, C. 2009. Managing the health effects of climate change. *Lancet,* 373**,** 1693-1733.

CUMMINS, S., STAFFORD, M., MACINTYRE, S., MARMOT, M. & ELLAWAY, A. 2005. Neighbourhood environment and its association with self rated health: evidence from Scotland and England. *Journal of Epidemiology and Community Health,* 59**,** 207-213.

CURTIS, S. & JONES, I. R. 1998. Is there a place for geography in the analysis of health inequality? *Sociology of Health & Illness,* 20**,** 645-672.

DE KLUYVER, C. A. & WHITLARK, B. A. 1986. Benefit segmentaion for industrial products. *Industrial Marketing Management,* 15**,** 273-286.

DE VRIES, S., VERHEIJ, R. A., GROENEWEGEN, P. P. & SPREEUWENBERG, P. 2003. Natural environments–healthy environments? An exploratory analysis of the relationship between greenspace and health. *Environment and Planning A,* 32**,** 1717-1731.

DEPARTMENT OF HEALTH 2008. Tackling Health Inequalities: 2007 Status Report on the Programme for Action. London: Department of Health.

DIEHR, P., KOEPSELL, T., CHEADLE, A., PSATY, B. M., WAGNER, E. & CURRY, S. 1993. Do Communities Differ in Health Behaviors. *Journal of Clinical Epidemiology,* 46**,** 1141-1149.

DUNCAN, C., JONES, K. & MOON, G. 1993. Do Places Matter - a Multilevel Analysis of Regional Variations in Health-Related Behavior in Britain. *Social Science & Medicine,* 37**,** 725-733.

DUNCAN, C., JONES, K. & MOON, G. 1996. Health-related behaviour in context: A multilevel modelling approach. *Social Science & Medicine,* 42**,** 817-830.

ECOB, R. & MACINTYRE, S. 2000. Small area variations in health related behaviours; do these depend on the behaviour itself, its measurement, or on personal characteristics? *Health & Place,* 6**,** 261-274.

ELLAWAY, A. & MACINTYRE, S. 1996. Does where you live predict health related behaviours?: a case study in Glasgow. *Health Bull (Edinb),* 54**,** 443-6.

EVANS, G. W. & KANTROWITZ, E. 2002. Socioeconomic status and health: the potential role of environmental risk exposure. *Annu Rev Public Health,* 23**,** 303-31.

FLEURET, S. & ATKINSON, S. 2007. Wellbeing, health and geography: A critical review and research agenda. *New Zealand Geographer,* 63**,** 106-118.

FONE, D. & DUNSTAN, F. 2006. Getting strategic about environment and health. *Public Health,* 120**,** 904-906.

GESLER, W. 2005. Therapeutic landscapes: An evolving theme. *Health & Place,* 11**,** 295-297.

HOUSE OF COMMONS HEALTH COMMITTEE 2009. Health Inequalities. London: The Stationary Office.

JERRETT, M., BURNETT, R. T., BROOK, J., KANAROGLOU, P., GIOVIS, C., FINKELSTEIN, N. & HUTCHISON, B. 2004. Do socioeconomic characteristics modify the short term association between air pollution and mortality? Evidence from a zonal time series in Hamilton, Canada. *Journal of Epidemiology and Community Health,* 58**,** 31-40.

JERRETT, M., BURNETT, R. T., KANAROGLOU, P., EYLES, J., FINKELSTEIN, N., GIOVIS, C. & BROOK, J. R. 2001. A GIS - environmental justice

analysis of particulate air pollution in Hamilton, Canada. *Environment and Planning A,* 33**,** 955-973.
JOHNSON, A. 2009. Health Inequalities Speech at the Fabian Society, 7 May 2009.
JOHNSTON, R. In Press. *Sixty Years of Change in Human Geography*, Cambridge University Press.
JOSHI, H. 2001. Is there a place for area-based initiatives? *Environment and Planning A,* 33**,** 1349-1352.
KAWACHI, I. & SUBRAMANIAN, S. V. 2007. Neighbourhood influences on health. *Journal of Epidemiology and Community Health,* 61**,** 3-4.
KIMLIN, M. G. 2008. Geographic location and vitamin D synthesis. *Molecular Aspects of Medicine,* 29**,** 453-461.
LAWLOR, D. A., HARVEY, D. & DEWS, H. G. 2000. Investigation of the association between excess winter mortality and socio-economic deprivation. *Journal of Public Health Medicine,* 22**,** 176-181.
MAAS, J., VERHEIJ, R. A., GROENEWEGEN, P. P., DE VRIES, S. & SPREEUWENBERG, P. 2006. Green space, urbanity, and health: how strong is the relation? *Journal of Epidemiology and Community Health,* 60**,** 587-592.
MANSON-SIDDLE, C. J. & ROBINSON, M. B. 1998. Super Profile analysis of socioeconomic variations in coronary investigation and revascularisation rates. *Journal of Epidemiology and Community Health,* 52**,** 507-512.
MITCHELL, R. 2009. Health, Risk and Resilience. *In:* SMITH, S. J., PAIN, R., MARSTON, S. A. & JONES, J. P. I. (eds.) *The SAGE Handbook of Social Geographies.* London: Sage.
MO, T. & GREEN, A. E. S. 1974. A climatology of solar erythema dose. *Photochemistry and Photobiology,* 20**,** 483-496.
PERLIN, S. A., WONG, D. & SEXTON, K. 2001. Residential proximity to industrial sources of air pollution: interrelationships among race, poverty, and age. *Journal of the Air and Waste Management Association,* 51**,** 406-21.
REICHRATH, J. 2006. The challenge resulting from positive and negative effects of sunlights: how much solar UV exposure is appropriate to balance between risks of vitamin D deficiency and skin cancer. *Progress in Biophysics and Molecular Biology,* 92**,** 9-16.
RICHARDSON, E. A., MITCHELL, R. M., SHORTT, N. K., PEARCE, J. & DAWSON, T. P. Under Review. Developing summary measures of multiple environmental deprivation for epidemiological research: a pilot study. *Environment & Planning A.*
SCHEMPF, A., STROBINO, D. & O'CAMPO, P. 2009. Neighborhood effects on birthweight: An exploration of psychosocial and behavioral pathways in Baltimore, 1995-1996. *Social Science & Medicine,* 68**,** 100-110.
SCOTT, D. M. & KANAROGLOU, P. S. 2002. An activity-episode generation model that captures interactions between household heads: development and empirical analysis. *Transportation Research Part B-Methodological,* 36**,** 875-896.
SHELTON, N. J., BIRKIN, M. H. & DORLING, D. 2006. Where not to live: a geo-demographic classification of mortality for England and Wales, 1981-2000. *Health & Place,* 12**,** 557-569.
SLEIGHT, P., HARRIS, R. & WEBBER, R. 2005. *Geodemographics, GIS and Neighbourhood Targeting,* Chichester, Wiley.
SMITH, S. J. & EASTERLOW, D. 2005. The strange geography of health inequalities. *Transactions of the Institute of British Geographers,* 30**,** 173-190.

SOBOTTA, R. R., CAMPBELL, H. E. & OWENS, B. J. (2007). Aviation noise and environmental justice: The barrio barrier *Journal of Regional Science,* 47**,** 125-154.

VAN DER RHEE, H. J., DE VRIES, E. & COEBERGH, J. W. 2006. Does sunlight prevent cancer? A systematic review. *European Journal of Cancer,* 42**,** 2222-2232.

WALKER, G., MITCHELL, G., FAIRBURN, J. & SMITH, G. 2005. Industrial pollution and social deprivation: Evidence and complexity in evaluating and responding to environmental inequality *Local Environment*, 10**,** 361-377.