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Environmental inequity in England: Small area associations between socio-economic status and environmental pollution

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Recent studies have suggested that more deprived people tend to live in areas characterised by higher levels of environmental pollution. If generally true, these environmental inequities may combine to cause adverse effects on health and also exacerbate problems of confounding in epidemiological studies. Previous studies of environmental inequity have nevertheless indicated considerable complexity in the associations involved, which merit further investigation using more detailed data and more advanced analytical methods. This study investigates the ways in which environmental inequity in England varies in relation to: (a) different environmental pollutants (measured in different ways); (b) different aspects of socio-economic status; and (c) different geographical scales and contexts (urban vs. rural). Associations were analysed between the Index of Multiple Deprivation (IMD2004) and its domains and five sets of environmental pollutants (relating to road traffic, industry, electro-magnetic frequency radiation, disinfection by-products in drinking water and radon), measured in terms of proximity, emission intensity and environmental concentration. Associations were assessed using bivariate and multivariate correlation, and by comparing the highest and lowest quintiles of deprivation using Student's *t*-test and Hotelling's T2. Associations are generally weak ($R^2 < 0.10$), and vary depending on the specific measures used. Strongest associations occur with what can be regarded as contingent components of deprivation (e.g. crime, living environment, health) rather than causative factors such as income, employment or education. Associations also become stronger with increasing level of spatial aggregation. Overall, the results suggest that any triple jeopardy for health, and problems of confounding, associated with environmental inequities are likely to be limited.

Introduction

Early studies in the USA as part of the anti-racism movement highlighted the apparent clustering of hazardous and polluting sites in areas inhabited by ethnic minorities (Brown, 1995; Bullard, 1983). Out of this has developed a rapidly growing body of research, under the various banners of environmental (in)equality, environmental (in)equity, environmental apartheid, environmental racism or environmental (in)justice (Anderton, Anderson, Oakes, & Fraser, 1994; Davidson & Anderton, 2000; Jerrett et al., 2001; Jerrett, Eyles, & Cole, 1998; Morello-Frosch, 2002; Morello-Frosh, Pastor, Porras, & Sadd, 2002; Oakes, Anderton, & Anderson, 1996; Ringquist, 1997).

Evidence for such inequities clearly has important implications, for it suggests that people who are socially disadvantaged or marginalised, either deliberately or accidentally, become subject to the additional burden of a more polluted and hazardous living environment (Blowers & Leroy, 1994; Brown, 1995; Morello-Frosch, 2002; Morello-Frosch et al., 2002). These inequities may also translate into a further jeopardy for health. The association between

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deprivation and increased mortality or morbidity is well-established, across a wide range of diseases and areas (Benach, Yasui, Borrell, Sáez, & Pasarin, 2001; Carstairs, 2000; Curtis, Southall, Congdon, & Dodgeon, 2004; Davey Smith, Dorling, Mitchell, & Shaw, 2002; Davey Smith et al., 1998; Krokstad & Westin, 2002). Equally, exposures to environmental pollution represent important risk factors for many diseases. Together, they may thus contribute to what Jerrett et al. (2001) call the 'triple jeopardy' of environmental inequity, and in the UK has been termed multiple deprivation (Carstairs, 1981; Noble et al., 2004): poor socio-economic status, poor living environment and poor health. A simple model of how this triple jeopardy arises, and its implications for research, is offered by Jerrett et al. (2001). This, however, gives only a very partial view of the processes involved in environmental inequities, for it ignores the complex feedback and adaptive processes that may operate within the system. Poor health, for example, may itself feed back to affect employment opportunities, income, mobility and access to power, thereby further constraining people's ability to move away from, or act to mitigate, hazards within their community. Individual risk responses (e.g. closing windows or sleeping at the back of the house to avoid exposure to traffic noise) may also intercede in the link between hazard and exposure, with varied (and sometimes unpredictable) implications for health.

In addition, associations between SES and environmental pollution imply the potential for socio-economic confounding (or, if interactions occur, effect modification) in epidemiological studies, especially where analysis is done at the aggregate scale (Blakely, Kawachi, Atkinson, & Fawcett, 2004; Blakely & Woodward 2000; Dolk et al., 1995; Greenland & Morgenstern, 1989). Inadequate control for such effects is often cited as a reason for caution in interpreting results of epidemiological studies.

How serious these problems are depends on how strong and ubiquitous the association between SES and environmental pollution is. Somewhat surprisingly, this remains uncertain. Results from previous research have been inconsistent and inconclusive (Bowen, 2002). Early studies were criticised on the grounds that they were often anecdotal, and that the relationships with environmental hazards were often described in simplistic and crude terms, while few studies demonstrated that the relationships found actually translated into increased exposures (Bowen, 2002; Holifield, 2001; Maantay, 2002). Many studies have focused on a small number of selected environmental hazards in individual areas or communities; the generalisability of the findings to other areas or other hazards has thus been open to debate, while the possibility of inverse associations with SES (i.e. higher exposures in less deprived communities) has rarely been explored.

More recent studies, using more powerful study designs, have suggested considerable complexity in the associations with SES. In a national survey in the USA, for example, Davidson and Anderton (2000) found that census tracts containing sites handling hazardous materials were generally more industrial, more working class and less well educated than those without. Nevertheless, associations with SES varied to some extent between metropolitan and rural areas, while associations with ethnic minorities (Hispanic and black) were either non-existent or negative. They concluded: "Overall our findings suggest that the siting of [hazardous] facilities does not merit high priority among the potential hazards and burdens to which minorities and the disadvantaged are disproportionately exposed." In the UK, McLeod et al. (2000) found varying associations between air pollution and social class in different regions of England. Pye, Stedman, Adams, and King (2001) reported positive correlations between air pollution and the national index of multiple deprivation (IMD2000) in Greater London, Birmingham and Greater Belfast, but not in Cardiff. Walker, Fairburn, Smith, and Mitchell (2003) compared associations across a wide range of environmental hazards, including proximity to industrial sources, air pollution and flooding: associations were seen to vary depending on the scale of analysis or the precise definition of the hazard, and in several cases were non-linear or even U-shaped.

Against this background, the study presented here assesses geographical associations between potential environmental exposures and socio-economic status in England. It addresses three specific questions: (a) how do these associations differ in relation to different hazards, measured at different points in the environment-exposure chain (proximity to source, emissions, environmental concentrations); (b) how sensitive are the associations to different measures of socio-economic deprivation; (c) to what extent are they sensitive to the spatial scale of analysis and geographic context? Based on the results it then considers the extent to which environmental inequities might also be associated with adverse health status.

Methods

The study was restricted to England because other countries in the British Isles use somewhat different measures of deprivation. Data were compiled, integrated and processed in a geographic information system (ArcGIS), at three levels of analysis: super output areas (SOAs), wards and districts. SOAs are the second tier in the census geography of England, with an average population of about 1500 persons ($n = 32{,}482$). Wards are aggregations of SOAs, with an average population of about 6200 persons ($n = 7{,}932$). Districts are further aggregations, with average populations of about 139,000 persons ($n = 354$). Data sources, methods for data integration and justification for the variables are summarised in Table 1.

Socio-economic data

Socio-economic status was measured using the Index of Multiple Deprivation (IMD2004) and its component domains. IMD2004 is a composite, area-based measure of deprivation, combining seven different dimensions (domains) of deprivation: income, employment, education, health, living environment, barriers to housing and services, and crime (Noble et al., 2004; see Table A1, appendix). Each domain is quantified on the basis of a set of indicators (37 in total), which are aggregated into domains either by direct summation, where variables are solely in the form of counts of people (e.g. in receipt of benefits), or using factor analysis

Table 1
Measures of socio-economic status and environmental quality, and data sources

Theme[a]	Measure	Target characteristics	Computation	Source
1	IMD2004	Socio-economic status	Download from source	Office of Deputy Prime Minister (www.communities.co.uk)
1	IMD domains	Income, employment, education, health, access to housing and services, living environment, crime	Download from source	Office of Deputy Prime Minister (www.communities.co.uk)
2	Proximity to roads	Air pollution, noise	% Population within 500 m of motorway or 150 m of a road	Meridian, Codepoint 2001
3	Proximity to major point emission source	Air pollution	% Population within 1 km of major point emission source	National Atmospheric Emissions Inventory (www.naei.org.uk), Codepoint 2001
3	Density of industrial land	Air pollution, noise	% SOA area classified as industrial	CORINE land cover map (www.eea.europe.eu)
5	Proximity to airports	Noise, air pollution	% Population within 2 km of a major airport	Eurocontrol, Codepoint 2001
4	Proximity to mobile phone masts	EMF radiation	% Population within 500 m of a mobile phone transmitter	Sitefinder (www.sitefinder.ofcom.org.uk), Codepoint 2001
3	Proximity to operating landfill sites	Waste decomposition products (via air and water)	% Population within 2 km of landfill site	Environment Agency, Scottish Environmental Protection Agency, Codepoint 2001
3	Proximity to operating special landfill sites			
3	Proximity to closed landfill sites			
4	Proximity to powerlines	EMF radiation	% Population living with 600 m of a high tension powerline	National Grid, Copepoint 2001
2	NO_x emissions	Air pollution	Total annual emissions of NO_x (tonnes/km^2) - area weighted	NAEI (www.naei.org.uk)
2,3	PM_{10} emissions	Air pollution	Total annual emissions of PM_{10} (tonnes/km^2) - area weighted	NAEI (www.naei.org.uk)
3	VOC emissions	Air pollution	Total annual emissions of VOCs (tonnes/km^2) - area weighted	NAEI (www.naei.org.uk)
3	SO_2 emissions	Air pollution	Total annual emissions of SO_2 (tonnes/km^2) - area weighted	NAEI (www.naei.org.uk)
4	Power output of mobile phone transmitters	EMF radiation	Total power output of mobile phone transmitters (W/km^2) - area weighted	Sitefinder (www.sitefinder.ofcom.org.uk)
2	Atmospheric NO_2 concentration	Air pollution	Mean annual NO_2 concentration (μg/m^3) - population weighted	National Air Quality Archive (www.airquality.co.uk)
3	Atmospheric SO_2 concentration	Air pollution	Mean annual SO_2 concentration (μg/m^3) - population weighted	National Air Quality Archive (www.airquality.co.uk)
2	Atmospheric PM_{10} concentration	Air pollution	Mean annual PM_{10} concentration (μg/m^3) - population weighted	National Air Quality Archive (www.airquality.co.uk)
2	Atmospheric ozone concentration	Air pollution	Mean annual O_3 concentration (μg/m^3) - population weighted	National Air Quality Archive (www.airquality.co.uk)
5	Domestic radon concentration	Air pollution (indoor)	Mean annual domestic radon concentration (Bq/m^3) - population weighted	National Radiological Protection Board
5	THM concentrations in domestic water	Water pollution	Mean annual THM concentration (μg/m^3) - population weighted	Water supply companies

[a] Theme groups variables are as follows: 1 = variables relating to socio-economic status; 2 = road traffic; 3 = industry; 4 = EMF; 5 = other (see text).

for other data types. The seven domains are then weighted (as shown in the appendix) and summed.

Data on all the constituent indicators of IMD2004 are not available for analysis. Scores for both the overall index and its domains have, however, been computed at SOA and district level, and made available via the Web (www.communities.gov.uk). For this study, therefore, data were downloaded and linked to SOA and district boundaries. Scores for wards were then computed by weighted aggregation on the basis of the SOA populations, as follows:

$$Sward_j = \sum_{i=1}^{n_j} Ssoa_{ij} \frac{Psoa_{ij}}{Pward_j}$$

where $Sward_j$ is the score for ward j, $Ssoa_{ij}$ is the score for SOA i, $i = 1,\ldots,n_j$, lying in ward j, $Psoa_{ij}$ is the population of SOA i lying in ward j and $Pward_j$ is the population in ward j.

Environmental data

Many different environmental hazards merit consideration in the context of environmental inequity. Ideally, those selected should provide an unbiased cross-section of the environmental hazards that people encounter. In practice, however, data availability and quality severely limit the hazards that may be explored, especially at the small area scale. Variables were sought here that could be measured in terms of three different metrics – proximity to source, emissions and environmental concentrations – in order to reflect the different types of measure used in previous studies of environmental inequity, and the range of exposure indicators often used in epidemiological studies. On this basis, 20 variables were selected (Table 1). Other potential environmental variables (including flooding, noise, nuclear radiation, climate and pesticide usage) were considered but excluded because reliable, country-wide data at a sufficient spatial resolution could not be obtained.

Source proximity

Many previous studies have explored environmental inequity in relation to source proximity to toxic release facilities and dumps (Anderton et al., 1994; Davidson & Anderton, 2000; Graham, Beaulieu, Sussman, Sadowitz, & Yi-Chung, 1999; Morello-Frosch, 2002; Morello-Frosch et al., 2002; Oakes et al., 1996). In this study, nine measures of proximity were computed, relating to roads, point emission sources, industrial activities, landfill sites and sources of electro-magnetic fields (EMF). With the exception of industrial land (see below), proximity was measured by computing the percentage of people in each SOA living within a specified distance of the source. Population data were derived from the postcode headcounts from the 2001 census (each postcode comprises a point representing an average of about 12 residential addresses). Proximities were determined by buffering around the source, then intersecting the resulting areas with postcode locations, and selecting the postcodes falling within the buffer zone. These were then further intersected with SOA boundaries, and the headcount data summed and expressed as a percentage of the total SOA population. The results were then further summed to ward and district level. Buffer distances (Table 1) used for this purpose were defined to represent the likely limit of any detectable increase in pollutant concentrations related to the specific source.

Data on roads were obtained from the OS Meridian database, and buffer distances specified on the basis of experimental atmospheric dispersion modelling, using ADMS-Urban, for a set of typical traffic volumes, and by reference to previous monitoring studies (Gilbert, Woodhouse, Stieb, & Brook, 2003; Janssen, van Vliet, Aarts, Harssema, & Brunekreef, 2001; Kingham, Briggs, Elliott, Lebret, & Fischer, 2000; Maheswaran & Elliott 2003). Point emission sources comprised those listed under the Integrated Pollution Control (IPC) legislation, and contained in the National Atmospheric Emissions Inventory (NAEI) maintained by NETCEN (www.naei.org.uk). Dispersion modelling was again undertaken using ADMS-Urban, for a stack height of 50 m (the average of those recorded in the NAEI), and typical emission temperatures, exit velocities and wind conditions to estimate the likely limit of detectable increases in average pollutant concentrations. For airports, buffer distances were defined on the basis of noise data and modelling from the Heathrow airport. Data on landfill locations were derived from the inventories compiled on behalf of the Environment Agency, and subsequently enhanced as part of the previous SAHSU study on landfill sites (Elliott et al., 2001). A buffer distance of 2 km was used in recognition of the likely limit of exposures from landfills suggested by WHO (2000) and uncertainties in the available locational data on waste sites (Elliott et al., 2001). Proximities were estimated to three groups of sites: operational special sites (i.e. those licensed to accept hazardous wastes), all operating sites (special and non-special), and closed sites (special and non-special). Data on the location (and power output) of mobile phone masts were obtained from the four main operators of GSM transmitters (Orange, O2, T-Mobile and Vodafone). The buffer distance of 500 m is based on a combination of results from previous field studies (Mann, Cooper, Allen, Blackwell, & Lowe, 2000) and purpose-designed propagation modelling and monitoring for a selection of typical masts. Proximity to powerlines was calculated using data on the high tension powerline network (270 and 450 kHz) in the year 2001, supplied by the National Grid. The buffer distance of 600 m reflects the limit of potential exposure and accords with the distance used in the study of childhood leukaemias associated with powerlines by Draper, Vincent, Kroll, and Swanson (2005).

For industrial land, a proximity measure was not considered meaningful, since areas of industrial land vary greatly in extent. Densities in each SOA (or ward or district) were instead estimated by selecting the 'industrial and commercial' class from the satellite-derived CORINE land cover map (www.eea.eu.int), then intersecting this with SOA (or ward or district) boundaries.

Emissions

Measures of emissions were available for two pollutant groups: air pollution and radio-frequency radiation. Data on atmospheric emissions by 1 km grid cell are available for the whole of England, from the NAEI. Four pollutants were selected in terms of potential adverse health effects: nitrogen oxides (NO_x), particulate matter of 10 μm or less (PM_{10}), sulphur dioxide (SO_2), and total volatile organic compounds (VOCs). Nationally, NO_x derives mainly from road traffic sources; PM_{10} comes more-or-less equally from transport, industrial/energy production and other (e.g. natural) sources; SO_2 is primarily generated from industry and energy production, and VOCs from industrial sources (www.naei.org.uk). These pollutants have been implicated in a range of health effects, including respiratory and cardio-vascular morbidity and mortality and a number of cancers (Bernstein, 2004; Brunekreef & Holdgate, 2002; Katsouyanni, 2003; Pope & Dockery, 2006).

Estimates for each pollutant in each area were made by intersecting the 1 km NETCEN grid with administrative boundaries, and area weighting as follows:

$$Esoa_j = \sum_{g=1}^{n} Egrid_g Agrid_{gj}$$

where $Esoa_j$ is the emissions in $SOA\, j$, $Egrid_g$ is the emission total from grid cell $g = 1,\ldots,n$, and $Agrid_{gj}$ is the proportion of the area of grid cell g intersecting with $SOA\, j$.

Power output from mobile phone masts was computed on the basis of the reported maximum licensed power outputs (in dBi) included in the Sitefinder database. Total output in each SOA (or ward or district) was computed by intersecting all sites with the relevant administrative boundaries and summing the reported outputs (converted to W/m). Outputs were then summed to W/km^2 for the purpose of analysis.

Environmental concentrations

Estimates of concentrations were made for ambient nitrogen dioxide (NO_2), PM_{10}, SO_2, VOCs and ozone (O_3), indoor radon and trihalomethanes (THMs) in drinking water. O_3 is a secondary pollutant, derived from interactions between NO_2 and oxygen. Evidence for associations with increased risks of acute respiratory illness and mortality is relatively strong (Samet, Zeger, & Dominici, 2000; Thurston & Ito, 2001), though the contribution to chronic effects is more equivocal (Katsouyanni, 2003; McDonnell, Abbey, Nishino, & Lebowitz, 1999). Radon is a known carcinogen (Darby et al., 1998; Lubin & Boice, 1997) and is associated with granitic rocks. Concentrations in indoor environments tend to be greatest where these lie close to the surface, or where radon can reach the surface via fissures in the overlying strata. THMs are a by-product of chlorination of drinking waters and have been tentatively associated with a range of health effects, including birth defects and cancers (Gallagher, Nuckols, Stallones, & Savitz, 1998; Toledano et al., 2005; Waller, Swan, DeLorenze, & Hopkins, 1998).

Area weighting of concentration data leads to biased estimates of potential exposure, especially in rural areas, since they will be dominated by concentrations in the often large zones of low population density. To avoid this problem, mean concentrations for each SOA (or ward or district) were estimated using postcode headcount weighting. By placing greater emphasis on the average concentration at the locations where people live, rather than over the whole area, these measures thus give an approximation of exposures for local residents. The population weighted average concentrations were calculated as follows:

$$Xsoa_j = \sum_{s=1}^{n} C_s \cdot \frac{P_{sj}}{P_j}$$

where $Xsoa_j$ is the population-averaged concentration in *SOA j*, C_s is the average pollutant concentration in source area *s*, P_{sj} is the population in source area *s* lying in *SOA j* (estimated as the sum of all headcount populations at postcodes in source area *s* lying in SOA *j*), and P_j is the total population in *SOA j*.

For the ambient pollutants, data were obtained from the national air quality archive (www.airquality.co.uk/archive/index.php). This provides data on concentrations for background locations (i.e. unaffected by nearby emission sources) for a 1 km grid across Great Britain, modelled using empirical regression-based methods (Stedman, 1998). Data on average domestic radon concentrations were derived from the national radon atlas (Green, Miles, Bradley, & Rees, 2002). This reports average radon concentrations by postcode sector from sampling in 40,000 homes in England and Wales, in areas considered to have a significant risk of excess exposure. Areas not covered by the programme (ca. 78% of postcode sectors) were here assigned a random concentration between 0 and half the lowest reported concentration (to reflect random variation below the likely detection limit). Data on THMs in domestic water supplies were obtained from water supply companies, as part of a separate SAHSU study (Toledano et al., 2005). Average annual concentration data, from sample monitoring, were used for the years 2000–2001, by water supply zone. Data were available only for 12 water companies, covering about 85% of England and about 86% of the population.

Statistical analysis

All variables were initially mapped, histograms constructed to assess normality, and semiovariograms produced using the kriging function in ArcGIS to explore spatial structure. Covariation in the environmental variables was also explored using bivariate correlation analysis and principal components analysis (PCA). For PCA, variables were standardised by their *z*-score, and analysis was done with Varimax rotation, and retention of the first two components. Associations between IMD2004 and its individual domains and the environmental variables were explored using boxplots (with SES as quintiles) and scattergrams (with SES as a continuous variable), and by bivariate regression analysis (with data transformed as appropriate). Both Spearman rank correlation and Pearson product moment correlation were used to analyse bivariate associations, and the results compared. Quintiles of IMD2004 scores were also computed, and multivariate as well as univariate comparisons of the environmental hazards were made between the highest and lowest quintiles, using Hotelling's T2 and Student's *t*-test, respectively, in order to assess evidence for multiple environmental inequities.

For the multivariate analysis, the environmental hazards were grouped into four themes: road traffic, industry, EMF and others (as shown in Table 1). The first three of these were analysed as groups of variables, using both multivariate and univariate techniques; variables in the 'other' category (proximity to airports and radon concentration) were analysed individually using univariate methods. THM concentrations were omitted from the multivariate analysis because of the incompleteness of the data. Multiple regression analyses using generalised additive models (Hastie & Tibshirani, 1990) were also carried out to explore the extent to which variations in potential environmental exposures could be 'explained' by the income, employment and education domains, when adjusting for spatial autocorrelation. To do so, the *x*,*y*-coordinates of the area (ward, district or SOA) centroids were included as non-parametric terms; SES domains were included as parametric regression variables. In addition, associations between these three domains and the health domain, and between the health domain and environmental variables, were investigated, post hoc, using generalised additive linear (GAM) models, in order to explore possible relationships with general health status.

All analyses were conducted at three geographic levels: SOA, ward and district. For analyses at the SOA level, additional analyses were also carried out for urban and rural SOAs separately; rural SOAs were defined as those containing less than 25% built-up land.

Results

Univariate analysis

Table 2 presents summary statistics at the SOA level for all the variables used. Statistical distributions are highly varied, and often highly skewed, and for many of the environmental variables, there are a large number of very low or zero values. Distributions at ward level (not shown) are similar; those at district level are much attenuated, with relatively few zero values and generally more symmetrical distributions.

Many of the variables also show evidence of local and long-range spatial structure: examples of maps for IMD2004 and selected environmental variables at ward level are given in Figs, 1 and 2, respectively. It should be noted in interpreting these maps that, while wards have a generally uniform population (ca. 6200 people), they vary greatly in surface area. The maps are therefore visually dominated by the larger, more rural areas and tend to mask the more finely granulated patterns in urban areas. (Maps of all variables, at all scales, are available on request from the authors.) Socio-economic status tends to be lower and pollution worse in the north compared to the south of England: a simple linear trend, on the x and y coordinates, explains between 7% (at SOA level) and 13% (at district level) of the spatial variation in IMD2004, and similar levels of variation are shown by most of the environmental variables. Trends persist at ward level, and are especially strong at district level, where they account for up to 34% of the spatial variation in the variables examined. More local clustering is also seen in urban areas. Two factors are at work here: urban (especially inner city) areas tend to be more deprived, and to have higher levels of pollution, while urban administrative areas tend to be smaller, so spatial associations operate over shorter distances. Kriging at the SOA level thus shows only a weak association between distance (lag) and the semivariance, while the fitted curve levels off (the so-called 'sill') at a range of about 5–10 km, indicating the limit of any spatial structure in the data. Amongst urban SOAs (i.e. those with more than 25% built-up land), this short-range variation typically explains ca. 15–20% of the variation in the measures of SES and pollution. As might be expected, this short-range spatial variation becomes weaker as the level of analysis is expanded to ward and then to district level.

Associations between domains of IMD2004

Associations between the seven domains of IMD2004 at the SOA level are summarised in Table 3. The income, employment, education and health domains show

Table 2
Summary statistics for socio-economic and environmental variables at SOA level

	Units	Mean	Skewness	Min	P5	P25	P50	P75	P95	Max
IMD2004		21.67	1.14	0.59	4.19	9.62	17.02	30.02	53.9	86.36
Income	% Population[a]	0.14	1.38	0	0.02	0.05	0.1	0.19	0.38	0.96
Employment	% Population[a]	0.11	1.56	0	0.03	0.05	0.08	0.14	0.25	0.69
Health		0	0.09	−3.26	−1.44	−0.63	−0.02	0.61	1.5	3.87
Education		21.69	1.32	0.03	1.96	7.46	16.12	30.4	61.91	99.22
Housing		21.69	0.57	0.28	6.14	13.3	20.29	28.66	42.17	66.98
Crime		0	0.03	−3.46	−1.36	−0.6	0	0.59	1.39	3.13
Living environment		21.69	1.06	0.14	2.95	8.54	16.81	31.37	55.42	93.52
Proximity to roads	% Population[b]	24.66	0.94	0	0	0	15.39	42.86	80.41	100
Proximity to point sources	% Population[b]	5.44	3.87	0	0	0	0	0	52.22	100
Percentage industrial land	% Population[b]	1.76	6.13	0	0	0	0	0	9.25	100
Proximity to airports	% Population[b]	0.28	18.94	0	0	0	0	0	0	100
Proximity to mobile phone masts	% Population[b]	37.46	0.5	0	0	0.29	26.1	70.75	100	100
Proximity to open landfill sites (all)	% Population[b]	25.62	1.11	0	0	0	0	53.43	100	100
Proximity to open landfill sites (special)	% Population[b]	3.52	5.02	0	0	0	0	0	7.57	100
Proximity to closed landfill sites (all)	% Population[b]	78.82	-1.4	0	0	74.35	100	100	100	100
Proximity to powerlines	% Population[b]	3.70	4.82	0	0	0	0	0	25.06	100
PM_{10} emissions	Tonnes/km^2/year	3.05	73.94	0.02	0.32	1.36	2.46	3.71	6.7	941.16
VOC emissions	Tonnes/km^2/year	46.56	9.29	0.24	2.73	16.39	38.04	61.59	121.07	1790.6
SO_2 emissions	Tonnes/km^2/year	5.69	95.28	0.02	0.14	0.44	0.99	1.95	6.26	22,769.49
NO_x emissions	Tonnes/km^2/year	32.45	38.87	0.2	2.27	12.34	24.3	39.23	80.94	5222.69
EMF emissions from mobile phone masts	Watts/km^2	3507.03	12.38	0	0	0	0	413.51	18,401.31	616,187.4
NO_2 concentration	μg/m^3	28.33	−0.06	0	14.97	22.13	29.01	34.53	40.17	60.28
PM_{10} concentration	μg/m^3	20.81	−0.19	0	16.69	19.19	20.87	22.52	24.66	34.47
SO_2 concentration	μg/m^3	4.15	2.34	0.36	2.08	2.94	3.92	4.9	7.38	30.97
O_3 concentration	μg/m^3	41.99	0.82	23	34.46	38.01	40.34	45.39	53.19	67.54
Radon concentration	dB/m^3	10.58	4.8	0	1	3	5.42	8	40	339
THM concentration	μg/m^3	30.63	0.44	1.39	6.05	15.77	28.87	43.55	62.85	94.08

[a] Refers to the percentage of the SOA population in social benefit programmes due to lack of income of employment (see appendix).
[b] Refers to the percentage of the population in each SOA living within certain distance from the source (see Table 1).

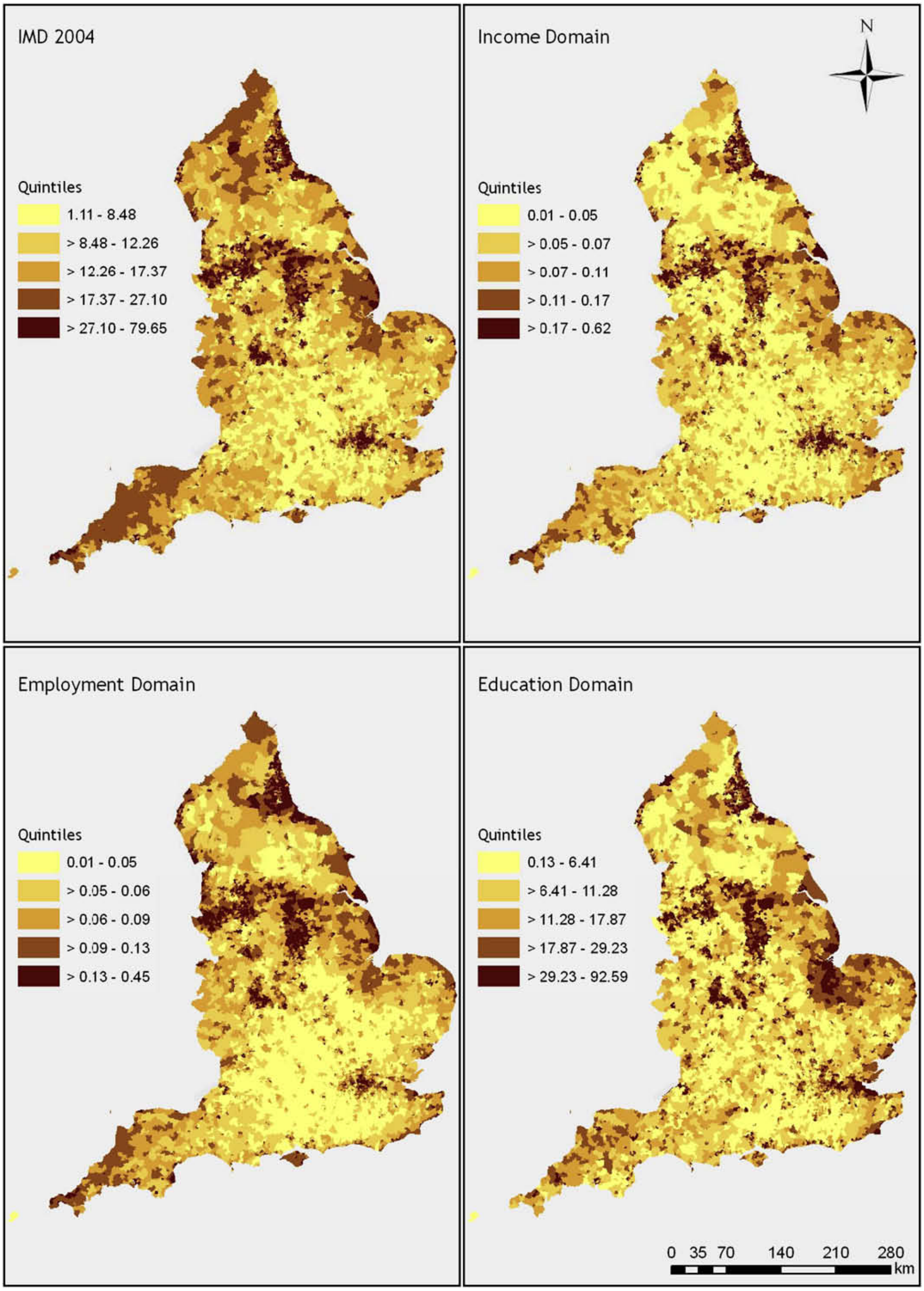

Fig. 1. Geographic distributions of the IMD2004 and three primary domains (income, employment, education) in England: ward level.

relatively strong correlations ($r > 0.7$), and are also strongly associated with the overall IMD2004 and, to a lesser extent, with the health domain. Associations between these measures and the living environment and crime domains are somewhat weaker ($r = 0.3$–0.6). The housing domain is very weakly correlated with the other domains, and negatively so in several cases, indicating an essentially independent spatial pattern. Correlations for ward and district levels (not shown) are slightly higher, but depict similar patterns.

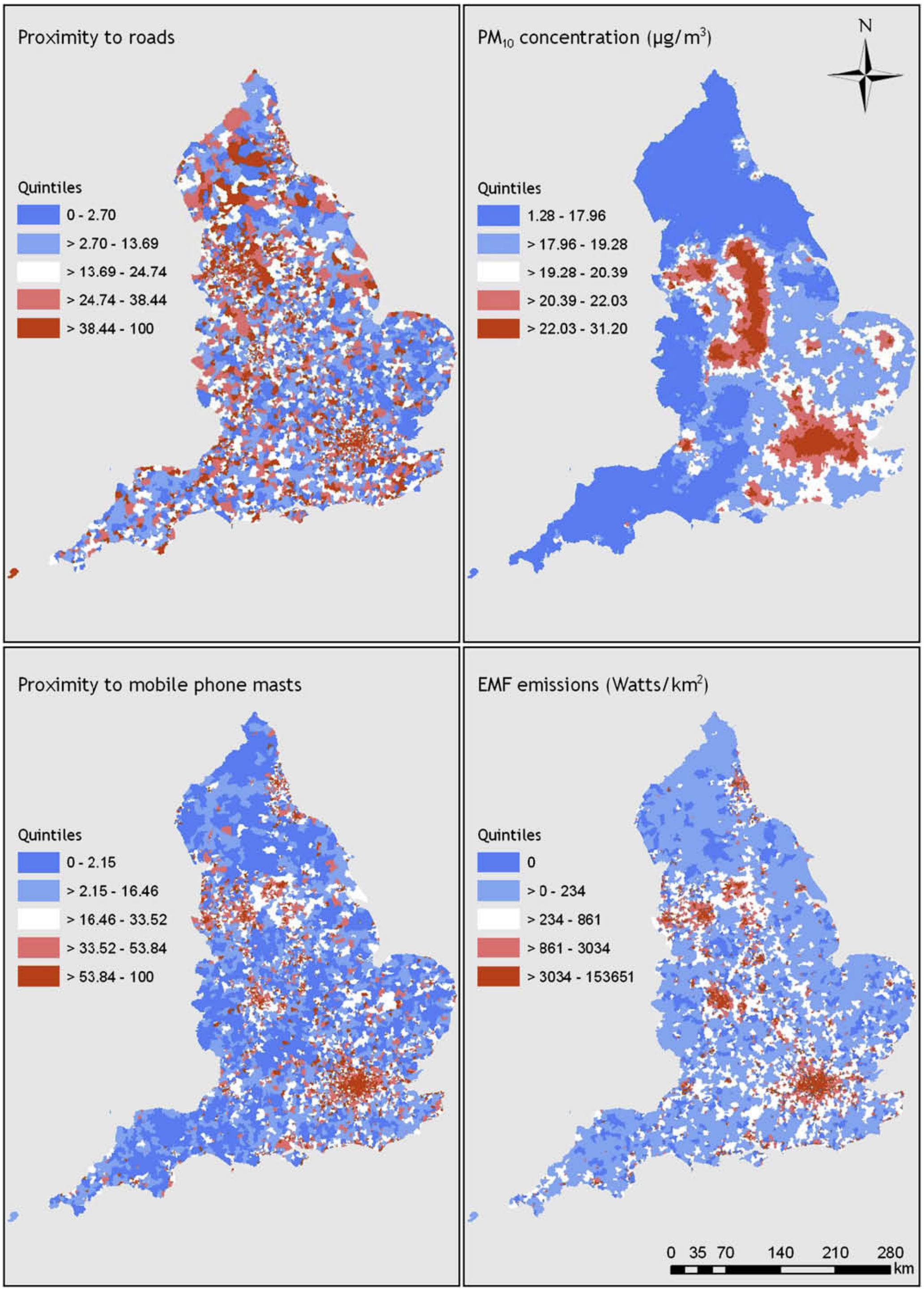

Fig. 2. Geographic distributions of selected environmental variables in England (ward level): proximity to roads, mean annual background PM10 concentration, proximity to mobile phone masts and total EMF emissions from mobile phone masts.

Associations between environmental variables

Bivariate correlations between the environmental variables at SOA level are shown in Table A2, appendix (correlations for ward and district levels are similar, though strength of correlation tends to increase with increasing level of aggregation). Associations between measures of proximity to source (together with power output from mobile phone masts and THM concentrations) are generally weak (<0.1) and in some cases negative. Correlations

Table 3
Bivariate correlations between domains of the IMD2004: SOA level ($n = 32,482$)

	IMD2004	Income	Employment	Health	Education	Housing	Crime
Income	0.957						
Employment	0.937	0.896					
Health	0.877	0.804	0.883				
Education	0.819	0.795	0.760	0.702			
Housing	0.057	0.032	−0.106	−0.115	−0.148		
Crime	0.689	0.608	0.560	0.617	0.503	−0.048	
Living environment	0.615	0.515	0.461	0.507	0.338	0.066	0.565

between the measures of atmospheric emissions and concentrations, and between these two sets of variables, however, tend to be greater (typically 0.4–0.85). Both O_3 and radon concentrations show moderate negative correlations with the other air pollutants, reflecting their different geographies and processes of formation. As noted, for example, O_3 is a secondary pollutant and is created mainly by chemical reaction of daylight ultraviolet rays with NO_2 as it disperses away from urban (especially traffic) sources; unlike most other air pollutants it thus tends to show highest concentrations in suburban, peri-urban and rural areas. Radon is associated with the distribution of source rock types (mainly granites), especially where these lie close to the surface or are overlain by permeable rocks such as limestone or sandstone. While rapidly dispersed and deposited in the ambient environment, it can accumulate to high concentrations when released directly into buildings. Historical urban development has tended to concentrate in lowland, and often alluvial, sites, where radon levels are low; highest concentrations are thus often found in buildings in more rural areas.

Principal components analysis revealed two main components amongst these variables, explaining, respectively, 31% and 8% of the total variation in the environmental data at the SOA level (increasing to 41% and 11% at district level). The first component is characterised by positive loadings from NO_x, VOCs and PM_{10} emissions and concentrations of NO_x, NO_2 and PM_{10}, together with power output from mobile phone masts; ozone concentration has a negative loading. The second has high negative loadings from proximity to landfill sites, point emission sources, powerlines, the density of industrial land, SO_2 emissions, and SO_2 concentrations, while loadings for proximity to mobile phone masts and EMF emissions are positive Fig. 3. The first seems to represent the urban distribution of pollutants, with systematic marked gradients between inner city and suburban areas. The second component

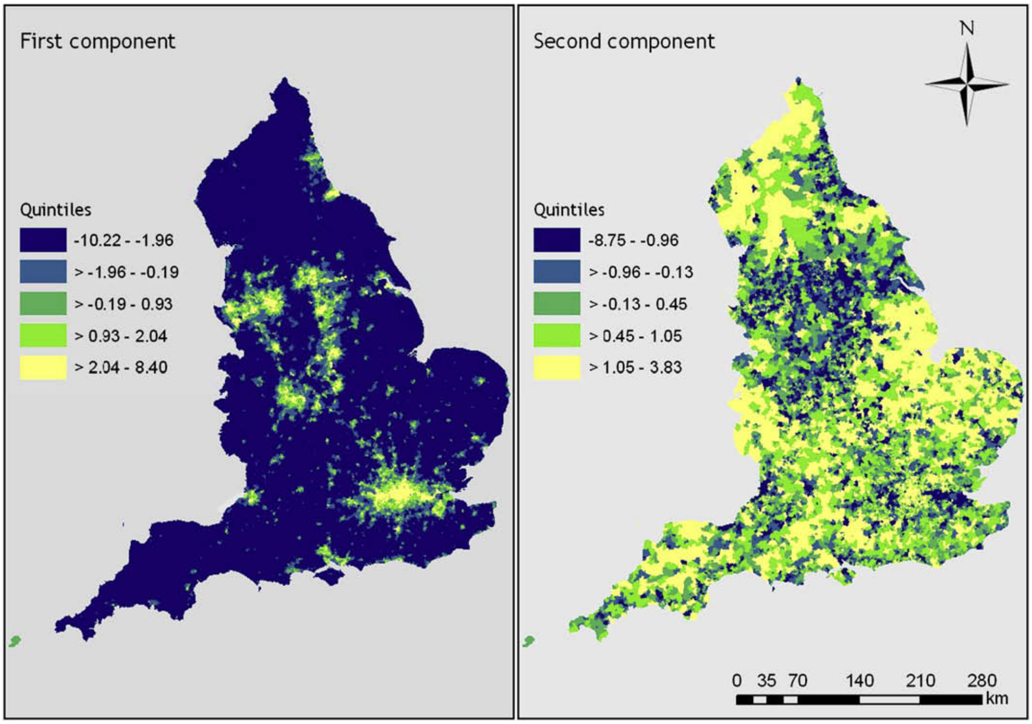

Fig. 3. Geographic distribution of the first two components from the PCA.

reflects the more haphazard, and less finely granulated, distribution of environmental hazards in rural areas.

Associations with IMD2004

Bivariate associations of IMD2004 with the various environmental measures are summarised in Table 4, and selected relationships at ward level are shown as loess plots in Fig. 4. Spearman correlation coefficients tend to be slightly higher than those for Pearson correlation, and are markedly so for atmospheric emissions, reflecting non-linearity in the associations. Positive correlations (increasing deprivation associated with higher potential exposure) are seen with all environmental hazards except proximity to powerlines, atmospheric ozone concentration and radon concentration. Overall, the strength of the association tends to increase from measures of source proximity to emissions to environmental concentration. At SOA level, the strongest associations are with VOC emissions (Pearson $r = 0.32$), NO_2 concentrations ($r = 0.32$) and ozone concentrations ($r = -0.35$). For proximity to roads, point sources and industrial land (the main sources of these pollutants), associations are weaker ($r = 0.09$–0.16). Associations with proximity to closed landfill sites are stronger than those for operating sites. Correlations with SO_2 and EMF emissions are also weak. With the exception of proximity to powerlines (Pearson) and special landfill sites (Spearman), both at district level, the direction of association is in every case consistent across the different scales. For proximity to source, correlations also generally increase from SOA through to ward and district level; for emissions and concentrations effects of scale are more variable.

Multivariate comparisons between the areas ranked in the lowest and highest quintiles of IMD2004 showed differences in all three mean vectors of road traffic, industry and EMF related environmental hazards at all geographical levels. At the SOA level, Hotelling's $T2 = 0.52$, 0.54, and 0.13, respectively ($p < 0.0001$ in all cases); at the ward level $T2 = 0.63$, 0.54, and 0.27, respectively ($p < 0.0001$); at the district level, $T2 = 1.11$, 1.66, and 0.51, respectively ($p < 0.0001$). Table 5 shows univariate comparisons for each environmental hazard at SOA level. For most hazards, significantly higher values are seen in the most deprived quintile, except for both ozone and radon concentrations for which significantly higher values occur in the least deprived quintile.

Comparisons between urban and rural areas, at SOA level, are summarised in Table 5. Generally, associations in urban areas are stronger than those in rural SOAs, quite markedly so for some measures of emissions and environmental concentrations. For proximity to powerlines, EMF emissions from mobile phone masts, NO_2 concentrations, PM_{10} concentrations and radon concentrations, the associations are also reversed between urban and rural areas.

Associations with domains of IMD

Relationships between each of the environmental variables and the seven individual domains of IMD2004 show broadly similar patterns to those of the overall index (Table 6). Income and employment have rather weak associations with most variables. Education and health provide the highest correlations with point sources, landfill sites and industrial land. For most of the other environmental variables, the strongest associations are with access to housing/services, crime and living environment, the first of which often gives opposite directions of association.

Table 7 presents the parametric regression coefficients from GAM models for multivariate analyses of the relationship between each environmental hazard and scores on the employment, income and education domains at SOA level. These models also include non-parametric terms on the *x*,*y*-coordinates of the SOA centroids, to control for the spatial autocorrelation. The first column shows the R^2 coefficients when only the *x*,*y*-coordinates are included; the

Table 4
Bivariate correlations between IMD2004 and environmental hazards, at SOA, ward and district levels

Environmental hazard	SOA		Ward		District	
	Pearson	Spearman	Pearson	Spearman	Pearson	Spearman
Proximity to roads	0.129	0.106	0.182	0.175	0.353	0.335
Proximity to point sources	0.164	0.151	0.192	0.201	0.327	0.358
Percentage industrial land	0.087	0.086	0.203	0.197	0.416	0.400
Proximity to airports	0.030	0.014	0.044	0.010	0.070	0.032
Proximity to mobile phone masts	0.278	0.269	0.363	0.308	0.453	0.388
Proximity to open landfill sites (all)	0.068	0.041	0.099	0.058	0.13	0.115
Proximity to open landfill sites (special)	0.021	0.009	0.037	0.034	0.06	−0.002
Proximity to closed landfill sites (all)	0.132	0.184	0.172	0.224	0.228	0.303
Proximity to powerlines	−0.014	−0.062	−0.018	−0.053	0.03	−0.070
PM_{10} emissions	0.101	0.415	0.163	0.400	0.403	0.446
VOC emissions	0.319	0.449	0.025	0.303	0.498	0.466
SO_2 emissions	0.007	0.199	0.186	0.343	0.081	0.426
NO_x emissions	0.129	0.373	0.414	0.421	0.358	0.372
EMF emissions from mobile phone masts	0.143	0.021	0.279	0.284	0.304	0.411
NO_2 concentration	0.324	0.328	0.308	0.217	0.063	0.239
PM_{10} concentration	0.260	0.273	0.236	0.165	0.027	0.130
SO_2 concentration	0.174	0.197	0.221	0.195	0.024	0.190
O_3 concentration	−0.348	−0.380	−0.392	−0.386	−0.421	−0.421
Radon concentration	−0.126	−0.120	−0.130	−0.141	−0.109	−0.234
THM concentration	0.199	0.195	0.243	0.242	0.297	0.313

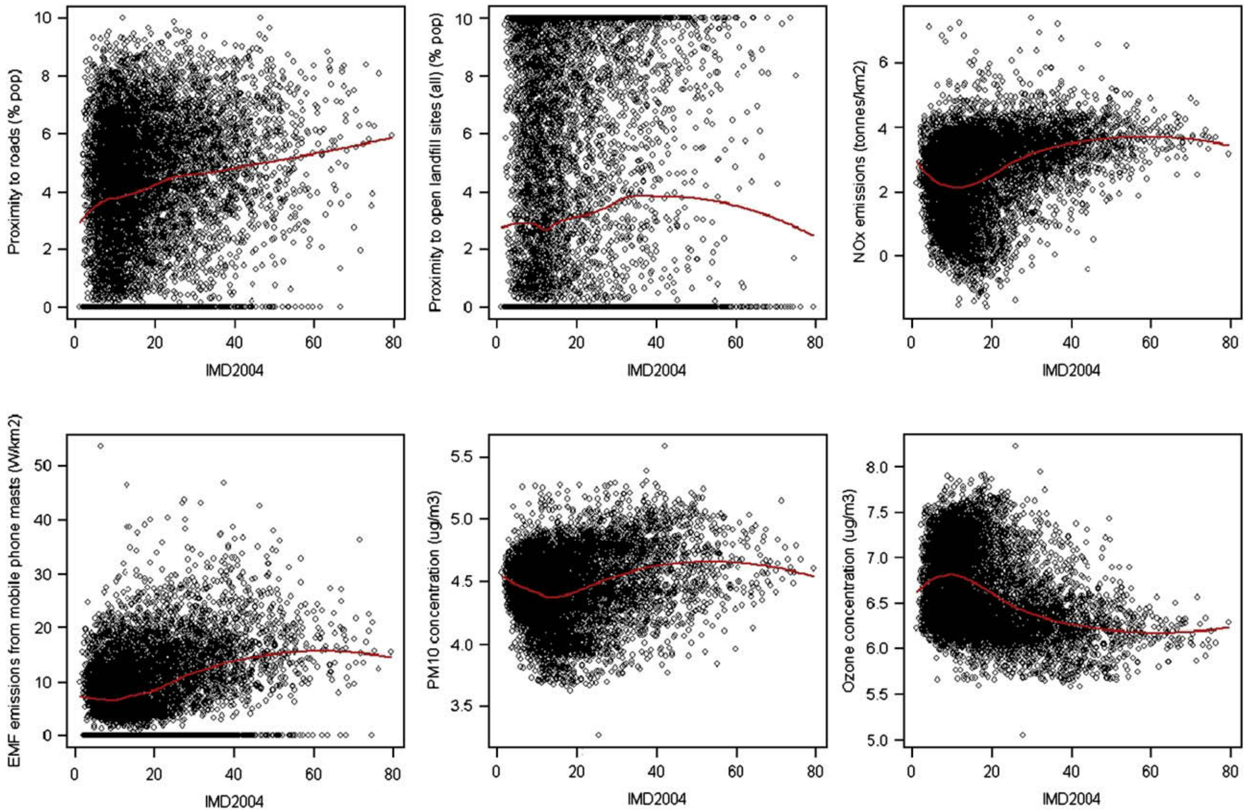

Fig. 4. Loess plots of associations between IMD2004 and selected environmental variables. Top (left to right): proximity to roads, proximity to open landfill sites, EMF emissions from mobile phone masts. Bottom (left to right): NO_x emissions, PM^{10} concentrations, O_3 concentrations. *Note:* Some variables have been transformed to achieve normality before plotting.

last column displays the R^2 after further including the SES domains (standardised to ease comparison between regression coefficients). The resulting models also vary considerably, and with no clear pattern. Directions of effect differ for individual domains, and in some models one of the domains is non-significant ($p > 0.05$), reflecting high levels of collinearity and competition between the explanatory variables. In every case, also, small increases in the goodness of fit (R^2) can be seen when the SES domains are included in the model, which suggests that only a small amount of variation in the environmental indicators can be explained by the SES variables. Increments of 0.1 or more in the R^2 coefficient can only be seen for O_3 concentration and PM_{10} and VOC emissions. Results from the models that include only the *x*,*y*-coordinates (second column in Table 7) suggest that spatial trends are smoother for concentrations than for emissions, and, in turn, that those based on emissions are smoother than models using proximity to source.

Associations of the health domain with the other domains and the environmental indicators

Multivariate GAM models showed significant positive associations (i.e. increased deprivation in health with increased deprivation in the other domains) between the health domain and the income (regression coefficient $\beta = 0.231$; $p < 0.001$), employment ($\beta = 0.454$; $p < 0.001$) and education ($\beta = 0.041$; $p < 0.001$) domains. The model including *x*,*y* coordinates of SOA centroids to adjust for spatial autocorrelation explained 83% of the variability of the health domain (compared to a 32% explained by a model with just the *x*,*y*-coordinates).

The use of a multivariate GAM (adjusting for spatial autocorrelation) at the SOA level again gave significant ($p < 0.001$) positive associations between the health domain and proximity to point emission sources ($\beta = 0.043$), percentage of industrial land ($\beta = 0.019$), proximity to airports ($\beta = 0.018$), proximity to mobile phone masts ($\beta = 0.067$), VOC emissions ($\beta = 0.249$), SO_2 emissions ($\beta = 0.023$), total power output from mobile phone masts ($\beta = 0.018$), and PM_{10} concentrations ($\beta = 0.310$). Significant ($p < 0.001$) negative associations were found with proximity to powerlines ($\beta = -0.011$), emissions of NO_x ($\beta = -0.115$), and concentrations of NO_2 ($\beta = -0.036$), O_3 (-0.090) and THM ($\beta = -0.017$). This model explained 51.1% of the geographical variability of the health domain.

Discussion

Strengths and limitations

The research presented here provides probably the most detailed and comprehensive analysis of environmental inequity in Great Britain conducted to date, and has attempted to address some of the weaknesses recognised

Table 5
Results of Student's *t*-test of differences between lowest and highest quintiles of IMD2004 at SOA level (columns 2–5)

Environmental hazard	*t*-Tests[a]				Correlations	
	Mean		*t*	*p*	IMD2004	
	Lowest quintile	Highest quintile			Rural	Urban
Proximity to roads	18.73	29.26	−17.12	0.000	0.05	0.11
Proximity to point sources	1.84	10.71	−25.58	0.000	0.08	0.15
Percentage industrial land	0.79	2.76	−15.33	0.000	0.07	0.06
Proximity to airports	0.07	0.46	−4.04	0.000	0.01	0.03
Proximity to mobile phone masts	25.48	53.43	−41.41	0.000	0.09	0.21
Proximity to open landfill sites (all)	22.97	30.38	−8.40	0.000	0.08	0.07
Proximity to open landfill sites (special)	2.88	4.12	−3.14	0.002	0.04	0.02
Proximity to closed landfill sites (all)	74.29	86.30	−19.10	0.000	0.07	0.09
Proximity to powerlines	3.53	3.61	2.08	0.038	0.04	−0.01
PM_{10} emissions	2.11	4.39	−68.09	0.000	0.05	0.07
VOC emissions	27.08	72.59	−77.51	0.000	0.12	0.24
SO_2 emissions	3.68	10.13	−27.62	0.000	0.05	0.00
NO_x emissions	21.24	47.21	−61.53	0.000	0.04	0.09
EMF emissions from mobile phone masts	1152.73	7366.44	−19.41	0.000	0.06	0.12
NO_2 concentration	26.12	32.87	−56.43	0.000	−0.01	0.27
PM_{10} concentration	20.26	21.91	−43.25	0.000	−0.04	0.20
SO_2 concentration	3.83	4.61	−28.88	0.000	0.14	0.12
O_3 concentration	44.24	38.87	64.77	0.000	−0.09	−0.25
Radon concentration	11.21	6.44	22.35	0.000	0.02	−0.08
THM concentration	26.09	35.32	−30.35	0.000	0.17	0.20

Bivariate correlation coefficients (Pearson's *r*) for relationships between IMD2004 and potential exposures to environmental hazards in rural and urban SOAs (columns 6 and 7)

[a] *t*-Tests were carried out using variables transformed to normality but means are displayed on the original scale to ease interpretation.

in previous studies. In particular, it has involved the analysis of geographic associations between a wide range of independently derived measures of environmental quality and different measures of SES, at a range of spatial scales, across an entire country. This helps to assess the robustness of the associations found and the generalisability of the concept of environmental inequity. Use of both univariate and multivariate statistical analyses (including GAM models allowing for spatial autocorrelation) also enabled some of the complexities of the associations to be explored, while the further association with the health domain from the IMD2004 provided opportunity to test for evidence of the triple jeopardy on health.

Nonetheless, the limitations of the research need to be recognised. As in almost all previous studies, for example, none of the measures used here represents an explicit measure of exposure – rather they are all proxies from different points in the source-exposure chain. The aggregate level of analysis also inevitably means that the results are prone to the ecological fallacy (Blakely & Woodward, 2000): the group-level associations between SES and environmental hazards seen here cannot be assumed to translate into individual experiences. This type of bias is expected to be lower at SOA level than at district level, since the within-area heterogeneity that is behind this bias source decreases with the size of the area. In addition, as a cross-sectional study it provides no direct indication of the causal mechanisms that lie behind environmental inequities; longitudinal study designs would be essential to elucidate these processes.

Variations across different environmental hazards, and the choice of exposure metric

The results reported here show that associations between SES and environmental pollution tend to vary depending on the choice of pollutant and the way in which it is characterised. In general, associations were strongest for measures related to ambient air pollution (as defined in Table 1), compared to EMF, radon or waste, and tended to be weaker for measures of proximity compared to emission intensity or concentration.

Table 6
Bivariate associations (Pearson's *r*) between each environmental hazard and the seven individual domains of IMD2004 (SOA level, all areas)

	Income	Employment	Education	Health	Housing/services	Crime	Living environment
Proximity to roads	0.10	0.09	−0.03	0.11	0.07	0.19	0.27
Proximity to point sources	0.16	0.15	0.17	0.16	−0.05	0.12	0.12
Percentage industrial land	0.08	0.07	0.10	0.10	−0.01	0.06	0.06
Proximity to airports	0.03	0.01	0.02	0.02	0.03	0.03	0.01
Proximity to mobile phone masts	0.27	0.21	0.10	0.23	0.03	0.35	0.37
Proximity to open landfill sites (all)	0.05	0.09	0.15	0.11	−0.17	0.06	0.00
Proximity to open landfill sites (special)	0.01	0.03	0.05	0.05	−0.05	0.02	−0.03
Proximity to closed landfill sites (all)	0.12	0.15	0.14	0.18	−0.20	0.17	0.09
Proximity to powerlines	−0.01	−0.02	0.01	0.00	0.03	−0.01	−0.05
PM_{10} emissions	0.10	0.08	0.08	0.09	−0.02	0.11	0.12
VOC emissions	0.31	0.23	0.16	0.27	0.03	0.36	0.40
SO_2 emissions	0.01	0.01	0.02	0.01	0.00	0.00	−0.01
NO_x emissions	0.12	0.09	0.06	0.11	0.03	0.16	0.17
EMF emissions from mobile phone masts	0.14	0.10	0.02	0.10	0.11	0.15	0.2
NO_2 concentration	0.30	0.21	0.15	0.27	0.05	0.50	0.41
PM_{10} concentration	0.26	0.12	0.14	0.16	0.13	0.44	0.35
SO_2 concentration	0.15	0.17	0.21	0.19	−0.19	0.25	0.11
O_3 concentration	−0.35	−0.27	−0.21	−0.33	0.11	−0.50	−0.40
Radon concentration	−0.13	−0.11	−0.11	−0.13	0.13	−0.23	−0.08
THM concentration	0.15	0.25	0.13	0.32	−0.15	0.09	0.16

Table 7
Parametric regression coefficients from GAM models for multivariate associations between each environmental hazard and the three 'primary' domains of the IMD2004 at SOA level adjusting for spatial autocorrelation

Environmental hazard	R^2 (semi-parametric terms of x,y coordinates)	Slope coefficient (and p value)			R^2 (including standardised SES domains)
		Income	Employment	Education	
Proximity to roads	0.038	0.417 (0.000)	0.524 (0.000)	−0.864 (0.000)	0.064
Proximity to point sources	0.026	0.071 (0.042)	0.061(0.077)	0.252 (0.000)	0.050
Percentage industrial land	0.023	0.012 (0.296)	−0.03(0.008)	0.081 (0.000)	0.032
Proximity to airports	0.002	0.017 (0.000)	−0.015 (0.000)	0.003 (0.306)	0.003
Proximity to mobile phone masts	0.092	0.821 (0.000)	0.667 (0.000)	−0.644 (0.000)	0.153
Proximity to open landfill sites (all)	0.104	−0.621 (0.000)	−0.109 (0.080)	0.886 (0.000)	0.118
Proximity to open landfill sites (special)	0.028	−0.082 (0.000)	0.015 (0.271)	0.069 (0.000)	0.030
Proximity to closed landfill sites (all)	0.111	−0.672 (0.231)	−0.539 (0.328)	4.944 (0.000)	0.122
Proximity to powerlines	0.014	−0.101(0.001)	−0.127 (0.000)	0.132 (0.000)	0.019
PM_{10} emissions	0.117	0.106 (0.000)	0.166 (0.000)	0.067 (0.000)	0.223
VOC emissions	0.193	0.263 (0.000)	0.123 (0.000)	0.048 (0.000)	0.314
SO_2 emissions	0.036	−0.337 (0.000)	0.327 (0.000)	0.322 (0.000)	0.096
NO_x emissions	0.186	0.214 (0.000)	0.125 (0.000)	−0.007 (0.461)	0.268
EMF emissions from mobile phone masts	0.016	0.852 (0.000)	1.829 (0.000)	−1.618 (0.000)	0.040
NO_2 concentration	0.552	1.419 (0.000)	0.883 (0.000)	−0.366 (0.000)	0.601
PM_{10} concentration	0.585	0.291 (0.000)	0.375 (0.000)	−0.029 (0.046)	0.641
SO_2 concentration	0.563	−0.107 (0.000)	0.089 (0.000)	0.082 (0.000)	0.593
O_3 concentration	0.233	−0.133 (0.000)	−0.025 (0.000)	0.022 (0.000)	0.326
Radon concentration	0.411	0.060 (0.006)	−0.107 (0.000)	−0.195 (0.000)	0.426
THM concentration	0.461	0.248 (0.000)	−0.131 (0.000)	−0.088 (0.000)	0.464

These differences nevertheless need to be interpreted with care, for simple linear correlations mask some of the complexities in the associations seen. More detailed examination shows that the associations are in some cases non-linear, and J- or U-shaped relationships are seen for concentrations of PM_{10}, NO_2 and ozone, broadly replicating the associations reported by Walker et al. (2003). More fundamentally, associations vary in direction, as well as strength: while most hazards show a positive association with deprivation, those relating to ozone and radon concentrations, and proximity to powerlines, tend to be negative (i.e. to have higher levels of potential exposure in less deprived communities). Such reverse associations have rarely been recognised in previous studies, to some extent because they have explicitly sought evidence of injustice. Overall, it is therefore clear that environmental inequities are not one thing, but many. Areas of poor environmental quality in relation to one hazard are not necessarily adverse in relation to others, and associations with SES cannot easily be generalised. This emphasises the need to see environmental inequities in a much more balanced and holistic manner than has sometimes been the case.

Choice of SES metric

Similar issues arise in relation to the way in which SES is characterised. Previous studies have employed a range of different measures of SES. In the USA, the tradition has been to use independent measures of SES, such as income, education and ethnicity (Brown, 1995). Strongest associations have often been found with ethnicity, with the result that explanation has tended to focus on some form of environmental racism, either through the deliberate targeting of hazardous activities in ethnic minority areas, or because of the reduced power of such communities to resist the pressures for such developments (Morello-Frosh et al., 2002; Pastor, Sadd, & Hipp 2001). This contrasts with studies in the UK, where composite measures of SES have generally been used, such as the Carstairs score (Carstairs, 2000; Carstairs & Morris, 1989), Jarman Deprivation Score (Jarman, 1983), Townsend Index (Townsend, Phillimore, & Beattie, 1988) or, more recently, the Index of Multiple Deprivation (Noble et al., 2004). Here, environmental inequities tend to be explained in terms of broader disadvantages of multiple or economic deprivation.

In the attempt to bridge the gap between these two approaches, we analysed associations between the geographical distribution of environmental hazards and the seven individual domains that make up the IMD2004 (income, employment, education, living conditions, access to housing and services, health and crime). Environmental associations with these different domains vary substantially, both for any specific hazard and between different hazards. The immediate implication is that environmental inequities cannot readily be characterised by any single aspect of SES. On the other hand, nor does a compound measure such as the IMD2004 seem to provide a complete and consistent basis for analysis since it brings together, and averages across, different elements of SES which show different spatial patterns and have differing associations with the environment. Instead, if deeper insight is sought of environmental inequities, it would seem more helpful to analyse them in a multivariate framework, using a number of different measures of SES.

In this context, a distinction can perhaps be made between two groups of the domains analysed here. While it has to be emphasised that neither the indicators nor the domains that make up IMD2004 are intended to represent the causes of deprivation (Noble et al., 2004), those relating to income, employment and education can be interpreted as primary factors which act directly to limit people's ability to avoid, resist or escape from more polluted environments (e.g. through influences on the affordability of housing, mobility or employment opportunity). Domains representing health, crime, access to housing and services, and living environments, on the other hand, can be regarded as secondary – consequences of where people live and the conditions found there (albeit with reciprocal effects on affluence, education and mobility).

Here, notably, correlations with domains representing income, employment and education tend to be relatively weak; the strongest association was in fact the negative one with ozone concentration. Multivariate analysis also showed that these three domains together 'explain' only a small proportion of the variation in potential exposures to environmental hazards (<15% at the SOA level), and often produce counter-intuitive associations in multivariate models. Even in combination, therefore, these factors seem to be only limited predictors of environmental inequity. Stronger associations are seen with the 'secondary' domains, implying that environmental inequity may in fact be an essentially contingent phenomenon – reflecting the geographic clustering of environmental and social problems in particular communities and neighbourhoods. Economic disadvantage almost certainly plays a role in influencing this clustering, but on the evidence of this study cannot be regarded as the over-riding force. Other social and political processes leading to geographical stratification of society, as well as the influences of historical inertia, thus need to be considered.

Geographical factors

The Modifiable Areal Unit Problem (MAUP), in which results of spatial analyses are sensitive to the choice of zone design system, is widely recognised in geographical studies (Nakaya, 2000; Openshaw, 1984). Related to this, the spatial scale of analysis is also known to affect geographic patterns and associations (Haining, 1990). In the past, relatively little attention has been given to these issues in environmental inequity research, though in recent years a number of authors have begun to highlight their importance (Jerrett et al., 2001; McLeod et al., 2000). In this study, we explored these effects by comparing associations between SES and hazard intensity at three different scales of analysis: super output area, ward and district. We also explored spatial structure in the data using kriging, and compared associations between urban and rural areas.

Results suggest that associations are sensitive both to the scale of analysis and geographical context of the study. Correlations between SES and hazard intensity, for example, tended to increase in strength from SOA to ward to district level of analysis, as previously suggested in Great Britain by Walker et al. (2003). The main exceptions relate to measures of atmospheric PM_{10}, SO_2 and NO_2 concentrations, and indoor radon concentrations, where the effect of scale is less consistent. Like Davidson and Anderton (2000), we also found differences in the associations between urban and rural areas, with stronger correlations in urban areas. In addition, as reported by Jerrett et al. (2001) from Ontario, there is evidence of spatial autocorrelation in the data. GAM models revealed an increasingly smooth spatial behaviour in the environmental indicators from proximities to emissions to concentrations. This behaviour is expected, but may be partly due to the way in which data on emissions, and especially concentrations, are derived for each type of geographical area (districts, wards and SOAs). Kriging also suggested the presence of two levels of structure, at local and regional scales. The latter relates to the general north–south trend in both SES and pollution across England – a product to a large extent of the historical concentration of heavy industry in the north of the country. At the local level, scales of spatial autocorrelation are seen to differ between urban and rural areas, perhaps because of the differing sizes of their administrative areas. These results again emphasise the complexities inherent in environmental inequities. There is, especially, a need to take account of the spatial structure of the data, and of spatial autocorrelation specifically, in environmental inequity studies, which we did here by including non-parametric functions on the *x*,*y*-coordinates of the area centroids in GAM models.

The triple jeopardy

Geographical concordance between socio-economic deprivation and environmental pollution is clearly an issue of considerable concern both for local communities and for policy. More serious still, however, is the possibility that these combine to produce a third form of disadvantage, in terms of impaired health (Jerrett et al., 2001; Northridge, Stover, Rosenthal, & Sherard, 2003). The potential for such a triple jeopardy can certainly be envisaged. Positive associations between socio-economic deprivation and health have been previously shown for a wide range of health outcomes, including mortality, cancer incidence, hospitalisation, birth defects and many different mental disorders (Batty & Leon, 2002; Byrne, Agerbo, Eaton, & Mortensen, 2004; Carstairs, 2000; Eachus et al., 1996; Mäkelä, 1999; Vriheid et al., 2000). All the environmental hazards studied here are also known (or strongly suspected) to be significant risk factors for health. If more deprived people are more likely to be exposed to these hazards, then their health will be even more seriously compromised. There is also some evidence to suggest that deprivation might exacerbate the effects of environmental exposures in some cases, by making those exposed more susceptible to environmental factors, perhaps because of their impaired prior health status or because of their poorer access to health care (Marmot & Wilkinson, 2006; O'Neill et al., 2003). In this case, the combined effects of deprivation and environmental exposures are likely to be more complex than additive. Spatial correlations between the different environmental hazards also imply that exposures will rarely occur singly, and that more deprived populations are likely to be subject to complex exposure mixtures, though the health effects of such exposure mixtures are not well understood. These same associations would indicate possibilities of spatial confounding both by socio-economic factors and by other environmental hazards in epidemiological studies, making it difficult to unravel the independent effects of individual pollutants or sources using area-level study designs.

Here, we explored these potential effects by analysing associations with the health domain of the IMD2004. This includes measures relating to both mortality and disability/morbidity, and as such can be regarded as a general index of health status. Results show that the health domain is strongly associated with other domains in the IMD004, especially the 'primary' domains of income, employment and education. Indeed, in a post hoc analysis using multivariate models, these three measures explained ca. 50% of the variation after adjusting for spatial autocorrelation ($R^2 = 0.32$ when including only the x,y-coordinates, and $R^2 = 0.83$ when further including the SES domains) in the health domain at SOA level, and a similar fraction at district level ($R^2 = 0.45$ with x,y-coordinates only vs. $R^2 = 0.94$ with x,y-coordinates and SES domains). General health status in England would thus seem to be broadly a reflection of material deprivation. By the same token, as suggested by Adams and White (2006), exclusion of this domain from the index when it is being used in health-related studies, to avoid health being represented in both the explanatory and dependent variables, is likely to have little effect on the results, though it will avoid the impression of tautology in the analysis. Health status is also significantly associated with many of the environmental variables analysed here, and in multivariate models environmental variables together explain between 19% at SOA level ($R^2 = 0.32$ when including only the x,y-coordinates and $R^2 = 0.51$ when all the environmental variables are added) and 31% at district level ($R^2 = 0.45$ and $R^2 = 0.76$, respectively) of the variation in the health domain after adjusting for spatial trend. Nevertheless, associations with environmental variables are in some cases negative (notably for EMF emissions, ozone and radon concentrations in univariate models and for proximity to powerlines, NO_x emissions, and NO_2, ozone and THM concentrations in the multivariate GAM model). Moreover, incorporation of both the primary domains of IMD2004 and environmental variables together, in models with health status, adds only 4–5% to the explanation offered by the socio-economic variables alone. Whilst the triple jeopardy of deprivation, increased potential for exposures to environmental pollution and impaired health certainly exists therefore, the additive effects of deprivation and environment on general health status are usually not strong, and not always negative. As noted earlier, complex adaptive and feedback effects may also operate at individual and community levels, either amplifying or damping down any environmental inequities. Further, more detailed research, focusing on specific diseases, exposures and measures of SES, is needed to explore these associations more rigorously.

Socio-economic confounding

By the same token, these results have relevance in terms of attempts to control for socio-economic confounding in epidemiological studies. The associations involved are potentially complex. Socio-economic status, for example, may influence health via a number of different pathways: by specific risk-taking behaviours such as smoking, by more general lifestyle effects such as diet or exercise, and by access to and the quality of available health care – as well as by its influence on levels of exposure to environmental hazards. These factors may operate either independently or jointly at both individual and neighbourhood level. Difficulties in allowing for confounding are further exacerbated by the problems in obtaining relevant data on these various risk factors, especially at individual scale.

In the face of these uncertainties, much emphasis has been placed on the potential for confounding in the interpretation of epidemiological results (Blakely & Woodward, 2000; Blakely et al., 2004; Dolk et al., 1995; Greenland & Morgenstern, 1989). The argument can nevertheless be made that concerns about socio-economic confounding are in some cases over-stated (Christenfeld, Sloan, Carroll, & Greenland, 2004; Day, Byar, & Green, 1980). Breslow and Day (1980), for example, demonstrated that, unless the association between socio-economic status and environmental exposures is strong, the potential for significant effects of confounding will be limited. Blair, Stewart, Lubin, and Forastiere (2007) show that even smoking (a well-known risk factor in its own right) is rarely sufficiently strongly correlated with other environmental exposures significantly to confound associations with health, and conclude (p. 203): "If tobacco does not confound lung cancer risks in occupational studies, it is even less likely that more modest risk factors for various diseases with no known association with the exposure of interest would have a substantial effect". On this basis, the weak associations between environmental conditions and SES found here suggest that problems of area-level confounding may indeed be less than often assumed. Several caveats nevertheless need to be made. First, this study was an area-level analysis, and as such says nothing about the potential for confounding at individual level. The national scale of this analysis may also mask the presence of stronger effects in specific, local areas. In addition, the generalized measures of deprivation used here may not adequately represent the particular aspects of behaviour, lifestyle and economic circumstances that actually impinge on health outcome in specific situations. As Blair et al. (2007) note, misclassification of the confounder leaves open the possibility of residual confounding, though the size of the residual is likely to be broadly proportional to the amount of the effect previously removed in the adjustment process.

Conclusions

This study has confirmed the existence of environmental inequities associated with socio-economic deprivation in England. Stronger associations tend to be found with measures of air pollution than other types of hazard, and with environmental concentrations rather than proximity to source or emissions. The associations found, however, are generally weak, subtle and complex, and the IMD2004 accounts for only a small proportion of the observed variation. Associations also differ to some extent between urban and rural areas, at different scales of analysis, and from one type of hazard to another, while relationships vary between the different domains that make up the IMD2004, implying that there is no universally consistent system of environmental inequity. These complexities have three important implications. They highlight, first, the need for greater methodological sophistication and specificity in investigating environmental inequities, and for greater caution in interpreting the results of such studies. They imply, secondly, that we need to understand these associations in much more detail, and be able to use more explicit measures of socio-economic status, if we are properly (but not overly) to control for potential confounding in epidemiological studies. They suggest, thirdly, that the combined effects of environmental exposures and socio-economic status on health are likely also to be complex, variable and subtle. We therefore need to delve beneath the somewhat simple assumptions that have often been inherent in questions of environmental inequity if we are to move beyond merely decrying its existence and begin, instead, to understand how it is structured, what its implications are, and how best to intervene.

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Appendix

Table A1
Scope and composition of IMD2004 domains

Domain (and weight)	Description	Component indicators
Income (0.225)	Proportions of the population experiencing income deprivation	Income support Income-based job seekers allowance Working families tax credit Disabled person's tax credit Asylum seekers support
Employment (0.225)	Involuntary exclusion of the working age population from the world of work	Unemployment claimants Incapacity benefit claimants Severe disablement allowance claimants New deal for 18–24s participants New deal for 25+ participants New deal for lone parents
Education, skills and training (0.135)	Lack of attainment among children and young people and lack of qualifications and skills	Average points score at key stage 2 Average points score at key stage 3 Average points score at key stage 4 Proportion of children leaving school by age 16 Secondary school absence rate Proportion of under 21s not entering higher education Proportion of working age adults with no or low qualifications
Health and disability (0.135)	Areas with relatively high rates of people who die prematurely or whose quality of life is impaired by poor health or who are disabled	Years of potential life lost Comparative illness and disability ratio Emergency admissions to hospital Adults suffering from mood or anxiety disorders
Barriers to housing and services (0.093)	(a) Geographical barriers to housing and key local services	Road distance to GP premises Road distance to supermarket or convenience store Road distance to primary school Road distance to post office
	(b) Wider barriers to housing and key local services	Household overcrowding Assisted homeless persons Difficulty of access to owner-occupation
Living environment (0.093)	(a) Deprivation associated with indoor living environment (b) Deprivation associated with outdoors living environment	Housing in poor condition Houses without central heating Air quality Road traffic accidents
Crime (0.093)	Occurrence of personal and material victimisation by crime	Burglary Theft Criminal damage Violence

Source: Noble et al. (2004).

Table A2
Bivariate correlations between environmental variables: SOA level ($n = 32,482$)

	Proximity to roads	Proximity to point sources	% Industrial land	Proximity to airports	Proximity to mobile phone masts	Proximity to open landfill sites (all)	Proximity to open landfill sites (special)	Proximity to closed landfill sites (all)	Proximity to powerlines	PM_{10} emissions	VOC emissions	SO_2 emissions	NO_x emissions	EMF emissions from mobile phone masts	NO_2 concentration	PM_{10} concentration	SO_2 concentration	O_3 concentration	Radon concentration
Point sources	0.051																		
Industry	0.040	0.133																	
Airports	0.002	0.022	0.015																
Phone masts	0.235	0.058	0.053	−0.003															
Open landfill	−0.012	0.111	0.065	0.003	−0.065														
Special landfill	−0.023	0.043	0.038	−0.010	−0.033	0.338													
Closed landfill	0.056	0.090	0.056	0.016	0.061	0.212	0.079												
Powerlines	0.035	0.016	0.036	0.047	−0.025	0.072	0.026	0.041											
PM_{10}emissions	0.066	0.061	0.095	0.001	0.100	0.015	0.015	0.032	0.033										
VOC emissions	0.208	0.148	0.105	0.011	0.352	−0.049	−0.025	0.061	−0.021	0.186									
SO_2emissions	0.000	0.017	0.060	−0.001	−0.009	0.013	0.012	0.000	0.043	0.882	0.044								
NO_xemissions	0.161	0.095	0.104	0.003	0.161	0.006	0.021	0.042	0.045	0.730	0.277	0.673							
EMFemissions	0.145	0.005	0.008	−0.004	0.321	−0.054	-.021	-0.016	−0.022	0.058	0.198	-0.004	0.101						
NO_2concentration	0.169	0.064	0.071	0.021	0.273	0.012	0.031	0.125	0.048	0.092	0.316	0.000	0.179	0.151					
PM_{10}concentration	0.058	0.026	0.026	0.009	0.105	−0.001	0.007	0.045	0.017	0.048	0.126	0.002	0.075	0.061	0.854				
SO_2concentration	0.012	0.014	0.018	0.008	0.026	0.026	0.017	0.042	0.013	0.029	0.036	0.011	0.034	0.008	0.738	0.958			
O_3concentration	−0.206	−0.092	−0.097	−0.035	−0.428	0.040	0.007	−0.152	0.014	−0.145	−0.486	−0.003	−0.226	−0.190	−0.466	−0.178	−0.065		
Radon concentration	−0.067	−0.049	−0.045	−0.019	−0.185	−0.032	−0.019	−0.117	−0.046	−0.055	−0.195	−0.007	−0.093	−0.059	−0.296	−0.110	−0.054	0.424	
THM concentration	0.034	0.009	0.043	0.023	0.080	0.019	0.032	−0.014	0.010	0.020	0.102	0.003	0.039	0.040	0.163	0.045	0.043	−0.108	0.034

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