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A spatial analysis of health status in Britain, 1991–2011

Emily K. Dearden[a,*], Christopher D. Lloyd[b], Gemma Catney[a]

[a] *Department of Geography and Planning, School of Environmental Sciences, University of Liverpool, Roxby Building, Chatham Street, Liverpool, L69 7ZT, United Kingdom*
[b] *School of Natural and Built Environment, Queen's University Belfast, Northern Ireland, United Kingdom*

ABSTRACT

Using Census-derived data for consistent spatial units, this paper explores how the population of Britain in 1991, 2001 and 2011 was spatially structured by self-reported health including exploring the trajectories of change. This paper uses consistent small area units to examine the changing spatial structure of census-derived Limiting, Long-Term Illness (LLTI) in Britain over the twenty year period and utilises the 2011 Office for National Statistics Output Area Classification (OAC) as a geodemographic indicator. The results allow the geography of change to be captured, highlighting how health is inextricably linked to geography, demonstrating quantitatively a complex, yet distinctive, spatial organisation of health inequalities within Britain. Overall decreasing unevenness values, coupled with increased positive spatial association suggests that neighbouring areas have become more similar over time – the distinction between areas characterised by poor health or by good health is decreasing.

1. Introduction

Social and spatial inequalities in health across Britain are well documented, with differences in health found between constituent countries (Young et al., 2010), regions (ONS, 2013; Whitehead, 2014), urban and rural communities (Allan et al., 2017), and deprived and more affluent areas (Benzeval et al., 2014; Livingston and Lee, 2014). Health inequalities are systematic disparities in health status, or in the distribution of health-relevant resources, between individuals and population groups arising from the `conditions in which people are born, grow, live, work and age (World Health Organisation [WHO], 2010; Public Health England [PHE], 2015) and they have been demonstrated for many outcomes (Young et al., 2010). Chronic limiting illness and disability require intensive health and social care resources, and, coupled with increasing life expectancy, have become pertinent global health concerns (Manor et al., 2001; Moon et al., 2018). With the proportion of older adults in Europe expected to grow significantly over the next decades (Sabater et al., 2017) quantifying geographical variations in health needs and understanding the processes that underlie residential health segregation are ever more crucial activities. Many countries now routinely record Limiting Long Term Ilnness [LLTI] information which provides considerable scope for analysis including international comparisons of morbidity prevalence and monitoring health trends over time (Manor et al., 2001). This paper explores the spatial structure of health inequalities in Britain over the twenty year period 1991–2011, examining the trajectories of change in LLTI of small areas with differing demographic and socioeconomic characteristics depicted using an area classification framework.

There is a long tradition of studying health inequalities by examining how the health of populations varies in space, and of making comparative studies of population health in particular places (Livingston and Lee, 2014). This has resulted in a large literature on social and geographical differences in the health of resident populations in different localities. The existence of a health divide is well established but is expressed in two different ways. On the one hand, there is a demonstrable health gradient among socioeconomic groups such that morbidity and mortality increase from the least through to the most deprived groups (Macintyre, 1993; Marmot, 2010; Whitehead, 2014). On the other hand, there is clear geographic patterning to this disadvantage (Riva et al., 2011; Livingston and Lee, 2014; Dutey-Magni and Moon, 2016). Areas within Britain have population compositions, contextual area characteristics, and differing opportunity structures in the physical and social environment, that make them distinct from other locales and contribute to the existence of geographic health inequalities (Marmot, 2010). People and their health shape, and are shaped by, the places in which they live and inhabit on a regular basis. This is in part because people with similar sociodemographic characteristics tend to cluster in space, and in part because individuals living in the same neighbourhood are subject to common contextual influences (Boyle et al., 2004; Smith and Easterlow, 2005). Some local areas have lower unemployment rates than others (Rae et al., 2016), whilst in some places there is a greater mix of ethnic groups than

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* Corresponding author.
  E-mail address: sgedeard@student.liverpool.ac.uk (E.K. Dearden).

elsewhere (Catney, 2016), and research suggests increasing spatial age segregation within the UK (Sabater et al., 2017). Thus, the degree of difference between areas varies geographically and between population sub-groups, with spatial health inequalities problematic because they indicate peripheralisation and marginalisation of certain population groups and places. Geographical inequalities link directly to research on residential segregation where the objective is to assess how members of different population groups may live together or apart. Social and spatial polarisation can be broadly defined as the widening gap between groups of people in terms of their economic and social circumstances and opportunities (Dorling and Woodward, 1996) and being able to measure change in this is crucial in assessing whether the population has become more or less similar over time and how it is geographically organised.

Although the study of geographic variations in health has a long history, exploring the changing spatial structure of health in Britain has previously been limited by inconsistent spatial data which do not allow comparability through time. For the first time, we have available a time series of consistent census-derived data for small spatial units across Britain (PopChange, *introduced below*) which has been utilised to examine the spatial structure of health inequalities over the twenty year period 1991–2011. Developing quantitative knowledge about the spatial development and persistence of poor health is crucial to developing effective ways of tackling inequalities in health. The key issue addressed by this work is the identification of spatial clustering in LLTI and its persistence. Using gridded data to offer the first analysis of the spatialities of LLTI change through time, we hypothesize that the spatial scale of concentrations of poor health and the persistence of LLTI clusters might interact. Specifically, this paper seeks to enhance understanding by examining LLTI changes in small areas and exploring whether such 'events' cluster in space and over time with the analysis framework utilised widely applicable beyond Britain.

2. Methodology and results

Analysis of local-level changes in populations across Britain is hampered by inconsistencies in the geographies used to report counts; exploration of health status is no exception. This paper details a novel analysis of change in Census-based self-reported LLTI over small areas of Britain from 1991 to 2011. Firstly, the data used in the analysis are described. Next, the methods of analysing the changing distribution (evenness and clustering) of poor health over time and the results produced are summarised.

2.1. Data and units of analysis

A limitation for many studies which seek to assess evidence for geographical divides in Britain is that they are generally based on data for large areas, whereas a geographically-refined analysis might be more revealing. The Census is the key source of small area data in Britain and we examine the patterning and distribution of self-reported health in consistent 1 km^2 grid cells across Britain using small-area aggregate Census self-reported LLTI data for 1991, 2001 and 2011.

Fine-scale, spatially aggregated, gridded data allow for a novel perspective on how far the health of populations are becoming more or less similar and offer several advantages over irregular geographies for analyses of change through time. Gridded data are not constructed according to the population structure at any one time point (unlike, for example, output areas) and they arguably allow for a more natural representation of populations, with gaps where there is no population present; empty cells include, for example, large unpopulated areas in the highlands of Scotland. The gridded data utilised were generated as a part of the PopChange project (for more information see https://popchange.liverpool.ac.uk/) by overlaying source zones (Enumeration Districts [EDs] or Output Areas [OAs]) with 1 km grids, using postcode densities to allocate parts of the populations of source zones to grid cells; more details are provided by Lloyd et al. (2017). As grid cells have a constant size, their populations vary markedly, and population estimates can be a fraction. For this reason we experimented with a threshold approach which draws on the Northern Ireland Census grid square product (Shuttleworth and Lloyd, 2009). The analysis was conducted only on cells which are estimated to contain people (in practice, two separate population thresholds – of 0.5 and 25 persons or above - are used, noting that fractions of people are possible when utilising PopChange data). Experimentation suggested that results were robust to changes in thresholds, and that thresholds utilised provide a balance between the uncertainty associated with small counts and retaining the large majority of cells, with 136,175 grid squares across Britain found to be consistently populated at the lowest threshold through all three Census time points.

Variations of 'Limiting Longstanding Illness' are frequently used in Europe and relate to health conditions that limit a person's everyday activities or work and is a commonly-used global indicator of morbidity (Manor et al., 2001; Cooper et al., 2015; Putrik et al., 2015). In Britain, LLTI has been recorded in the decennial census since 1991. We measure poor health by the proportion of people reporting a Limiting Long-Term Illness (LLTI) using ED and OA-level UK Census data allocated to 1 km^2 cells (as outlined above) for England and Wales, and Scotland for 1991, 2001 and 2011. Definitions of LLTI are not consistent across Censuses and the groups used in 2011 have to be aggregated to construct consistent groupings for comparison across the Censuses of 1991, 2001, and 2011 (Table 1). Based on ONS guidelines, LLTI response options for all Census years were dichotomised into 'Limited' or 'Not Limited' (expressed as a percentage of all people) permitting comparisons between areas and over time (ONS, 2013).

2.2. Assessing changing LLTI rates over time

Before considering how the structure of health inequalities has changed over time, national-level geographical distributions and percentage shares of LLTI across Britain over time are provided for context. The percentage of people with activity limiting long-term illness increased between 1991 (12.17%) and 2011 (18.07%) although data reveal that this increase took place over the ten year period between 1991 and 2001, with all constituent countries, and Britain as a whole, reporting small decreases in LLTI rates between 2001 and 2011

Table 1
Limiting long-term illness census questions and responses 1991, 2001, 2011.

	Question	Response Options	Output for Analysis
1991	Does this person have any long-term illness, health problem or handicap which limits his/her daily activities or the work he/she can do?	Yes, has a health problem which limits activities. Has no such problem.	Limited. Not Limited.
2001	Do you have any long-term, illness, health problem or disability which limits your daily activities or the work you can do? Include problems due to old age.	Yes. No.	Limited. Not Limited.
2011	Are your day-to-day activities limited because of a health problem or disability which has lasted, or is expected to last, at least 12 months? Include problems related to old age.	Yes, limited a lot. Yes, limited a little. No.	Limited. Limited. Not Limited.

Table 2
LLTI rates for region and area classification and differences for 1991, 2001 and 2011.

	1991	2001	2011	Difference 1991–2001	2001–2011	1991–2011
Great Britain	12.17	18.41	18.07	6.24	−0.34	5.90
Scotland (S)	12.69	20.34	19.67	7.64	−0.67	6.97
Wales (W)	16.17	23.33	22.76	7.16	−0.57	6.59
North East (NE)	15.32	22.74	21.67	7.42	−1.08	6.35
North West (NW)	13.79	20.73	20.24	6.94	−0.49	6.45
Yorkshire and The Humber (YH)	13.30	19.52	18.84	6.22	−0.69	5.53
East Midlands (EM)	11.73	18.42	18.64	6.70	0.22	6.92
West Midlands (WM)	12.24	18.90	18.99	6.67	0.09	6.76
East of England (EE)	10.21	16.21	16.71	6.00	0.50	6.50
London (L)	11.13	15.49	14.15	4.36	−1.34	3.03
South East (SE)	9.95	15.48	15.72	5.52	0.24	5.76
South West (SW)	11.40	18.12	18.43	6.72	0.32	7.04
Business and Education Centres	13.63	19.55	17.91	5.92	−1.64	4.27
Coast and Heritage	12.87	20.12	20.02	7.25	−0.10	7.15
English and Welsh Countryside	11.67	18.74	19.53	7.07	0.79	7.86
London Cosmopolitan	11.76	15.60	13.75	3.84	−1.85	1.99
Mining Heritage and Manufacturing	14.26	21.33	21.05	7.07	−0.28	6.80
Prosperous England	8.84	13.98	14.55	5.14	0.57	5.71
Scottish Countryside	12.05	19.93	19.83	7.88	−0.10	7.78
Suburban Traits	10.76	16.29	15.87	5.52	−0.42	5.11

Authors calculations using PopChange data derived from ONS and NRS data.

(Table 2). Given that the magnitude of increase between 1991 and 2001 was largely uniform across all areas, it has been suggested that higher prevalence in 2001 may be attributable to a change in the LLTI question wording between Censuses (Wright et al., 2014). As Table 1 displays, in contrast to 1991, the 2001 Census specification includes problems which are related to old age, possibly leading to wider reporting of age-related LLTI in 2001 that was not captured in 1991. Additionally, the use of the word 'handicap' in 1991 was replaced by 'disability'. It has been suggested that the stigma associated with the word 'handicap' may have previously led to a systematic bias and underreporting of LLTI (Bajekal et al, 2004). This increase in prevalence, set within a trend of increasing life expectancy, may also reflect increased expectations people have about their health (Wright et al., 2014).

Differences between the constituent countries of Britain are noticeable and have persisted through time. Wales consistently has the highest prevalence of activity limitations, a rate that was five percentage points higher than in England in 2011, with similar differences recorded in other Census years. All regions increased their percentage share of LLTI over the two decade period (Table 2), however regions in the north have similarities in their health profiles and trajectories that make them distinct from the southern regions of England; distinctions between the regions are noticeable and have persisted through time. There is a pronounced concentration of small percentages of LLTI in central and southern England and higher rates in northern urban areas and Wales, with health improving in line with a southerly and easterly direction of travel. Rates remain highest in regions where heavy industry was formally most concentrated, specifically in coal mining areas. Outside of Wales (22.76%), the North East region of England (21.67%) had the highest percentage of activity limitations in 2011. London (14.15%) had the lowest LLTI rate in 2011. A difference of 8.61 percentage points is observed between the top and bottom ranked regions in 2011, a gap which appears to have widened over time from 6.22% in 1991 and 7.85% in 2001, suggesting growing regional health inequality. Exploring how English regions, Scotland and Wales in 2011 compare with 2001 reveals a variable picture; those regions with the highest rates of LLTI saw their rates fall between 2001 and 2011, while regions with the lowest rates of LLTI in 2001 saw increases. London is an exception to this trend and experienced decreases over this decade from already comparatively low rates, becoming the region with the most favourable health in 2011. Furthermore, rates have risen most

slowly in London (+3.03%) where economic in-migration is likely to have affected the sociodemographic structure towards a more trained and skilful workforce and younger age structure resulting in more favourable health status (ONS, 2013). Although regional disparities require addressing, evidence for variation in the spatial structure of the poor health at a local level is presented, which a regional-only focus would fail to tackle.

We also investigate the spatial variation of health segregation using a detailed district classification. By examining health inequalities though an area classification framework we can obtain new insights into health inequalities in different demographic and socioeconomic contexts and, correspondingly, the potential causes of local health inequalities. We grouped small area grid squares using the 2011 ONS Output Area Classification (OAC) for Local Authorities (ONS, 2014a). This classification is a three-tier system comprising of Supergroups, Groups and Subgroups on the basis of 59 demographic and socioeconomic variables drawn from the 2011 Census and has been used extensively in academic research (Lymperopoulou and Finney, 2016) to provide descriptive characterisations of geographic areas. We use the top tier classification comprising 8 Supergroups of areas in the UK.

It should be noted that the OAC used refers to the most recent period and consequently, may not be fully applicable to all cells across all periods. Since this work seeks to chart how the same areas changed over time it was not possible to apply separate classifications for each time point and results should be interpreted in consideration of this. However, it has been demonstrated that area deprivation, whilst not static, does tend towards persistence of advantage and disadvantage (Norman, 2016). Furthermore, this classification covers the whole of the UK but in the present study has been applied only to Britain, therefore the ONS classification of 'Scottish and Northern Irish Countryside' applies only to Scotland and will, hereafter, be referred to as 'Scottish Countryside'. Table 3 illustrates changes in health segregation across small areas by district type in Britain since 1991. All area classification types experienced increased LLTI rates over the twenty year period but with a large amount of variation. All regions, excluding English and Welsh Countryside (+0.79%) and Prosperous England (+0.57%) experienced a decrease in LLTI rates between 2001 and 2011, suggesting that these two, more rural, area types are key locations for worsening health over time, albeit at a comparatively low level. Mining, Heritage and Manufacturing (21.05%) and Coast and

Table 3
Segregation index (D) values for region and area classification and differences for 1991, 2001 and 2011.

	1991	2001	2011	Difference 1991–2001	2001–2011	1991–2011
Great Britain	14.10	13.59	13.70	−0.51	0.11	−0.40
Scotland (S)	16.99	14.70	13.33	−2.30	−1.37	−3.66
Wales (W)	14.22	13.05	12.28	−1.17	−0.77	−1.94
North East (NE)	12.83	11.50	11.29	−1.33	−0.21	−1.54
North West (NW)	12.00	11.19	11.03	−0.81	−0.16	−0.97
Yorkshire and The Humber (YH)	12.66	11.62	11.77	−1.04	0.15	−0.89
East Midlands (EM)	12.44	12.09	12.34	−0.34	0.25	−0.09
West Midlands (WM)	11.57	10.25	9.72	−1.32	−0.52	−1.84
East of England (EE)	12.77	12.44	12.90	−0.33	0.46	0.13
London (L)	8.79	7.55	7.77	−1.24	0.23	−1.02
South East (SE)	13.82	13.29	13.44	−0.53	0.15	−0.38
South West (SW)	11.88	11.97	12.42	0.09	0.45	0.54
Business and Education Centres	12.38	12.84	13.55	0.46	0.71	1.17
Coast and Heritage	11.2	11.71	12.38	0.50	0.67	1.17
English and Welsh Countryside	12.97	12.37	12.12	−0.60	−0.26	−0.85
London Cosmopolitan	7.96	7.63	8.09	−0.33	0.46	0.13
Mining Heritage and Manufacturing	13.51	11.92	10.77	−1.60	−1.14	−2.74
Prosperous England	12.51	11.54	11.67	−0.98	0.14	−0.84
Scottish Countryside	16.39	13.49	12.04	−2.90	−1.45	−4.36
Suburban Traits	10.98	9.84	9.85	−1.14	0.01	−1.13

Authors calculations using PopChange data derived from ONS and NRS data.

Heritage (20.02%) areas had the highest rates of LLTI of all the area types, these area types have had consistently comparatively high rates of LLTI over the twenty year period, but have also experienced large increases over the period 1991 to 2011.

Fig. 1 shows LLTI rates for 1 km grid cells for Britain in 2011 and demonstrates distinctive spatial variability. Intrinsic geographical differences in health inequalities across residential contexts are revealed; Wales, western Scotland, north-east England and many coastal areas have distinctly higher rates of LLTI whilst eastern Scotland and many inland areas (predominantly in southern England) have very low LLTI rates. Maps of 1991 and 2001 LLTI percentages [not presented] show broadly similar geographic trends.

An analysis of the percentage change in LLTI between 1991 and 2011 (Fig. 2) also reveals distinctive geographic patterning. Large decreases in the percentage share of LLTI in some urban centres especially in central London, Edinburgh, Cardiff, Manchester, Leeds and Sheffield are observed with small increases in LLTI in surrounding suburban areas during this period. Increases in the percentage share of LLTI are found in cells which are predominantly in coastal locations including Lincolnshire and areas along its coastline, south-western Scotland and the north Scottish coast, areas along the coast of East Anglia and the coastline of south east England. Coastal communities tend to have an older age profile than others across Britain (ONS, 2014b). Disproportionate patterns of internal and inward migration, remoteness, lack of investment in infrastructure, high levels of socioeconomic deprivation and seasonal employment have also been highlighted as factors that threaten wellbeing and health in coastal communities (Depledge et al., 2017).

2.3. Measuring segregation and unevenness with the index of dissimilarity

Measures of segregation are essential tools for the evaluation of social equality, allowing complex structural patterns over time to be described by single measures. The dissimilarity index, hereafter D (Duncan and Duncan, 1955), is applied to assess the distribution (evenness) of people who report LLTI relative to those who do not:

$$D = 50 \sum_{i=1}^{n} \left(\left| \frac{x_i}{X} - \frac{y_i}{Y} \right| \right),$$

where x_i and y_i are counts of population in two groups for areal unit i

and there are n units. X and Y are the total population counts across the whole of the study area. Multiplying by 50 expresses the share as a percentage where D takes a value between 0 (completely even spread of the two groups) and 100 (all grid cells are 100% LLTI or non-LLTI). Thus, the more the population has spread out, the greater the decrease in segregation.

In 1991 D was 14.10 for Britain (25 persons population threshold). Over the following two decade period, the distributions of those with a LLTI and those reporting no LLTI have become more even. Although Britain as a whole was less segregated by health status in 2011 than it was in 1991, it was very slightly more segregated in 2001 (+0.11%) than in 2011. While global measures demonstrate a trend of decreasing health segregation across small areas, they hide considerable heterogeneity at the sub-national level. To examine this, we explored variations in residential health segregation within regions across Britain. Table 2 presents the segregation index (D) values for 1991, 2001 and 2011 and the differences over time (Fig. 3 displays dissimilarity index change over time for regions 1991–2011).

The observed changes in health segregation are small but trends are consistent (albeit with some local differences). Health segregation at a regional level generally declined rapidly in the 1990s and further decreased in the 2000s, albeit to a lesser degree, but this change is complex and not uniform across regions. Between 1991 and 2001, all regions, with the exception of the South West (+0.09%), reported decreasing segregation. Outside of London, the regions least segregated by health are located in the north. In contrast, slight increases in segregation values in the decade 2001–2011 are reported predominantly in the southern regions of England. There has been a large reduction in segregation by LLTI status in Scotland over time (−3.66%), however, it still has one of the highest segregation levels by region in 2011 (13.33%). Levels of segregation in the South East have stayed consistent through the decades, but this region has the highest levels of segregation in 2011 ($D = 13.44\%$).

It is, however, important to interpret changes in segregation within the context of LLTI percentage values. Over the study period, LLTI % and D decreased in northern regions whilst southern regions of England experienced increased LLTI % and D. Furthermore, observed D values in the south of England are larger than in north suggesting geographical inequalities are greater in the south than in the north. Overall whilst LLTI levels are higher in the north of England, Wales and Scotland, differences between neighbourhoods are greater in southern regions of
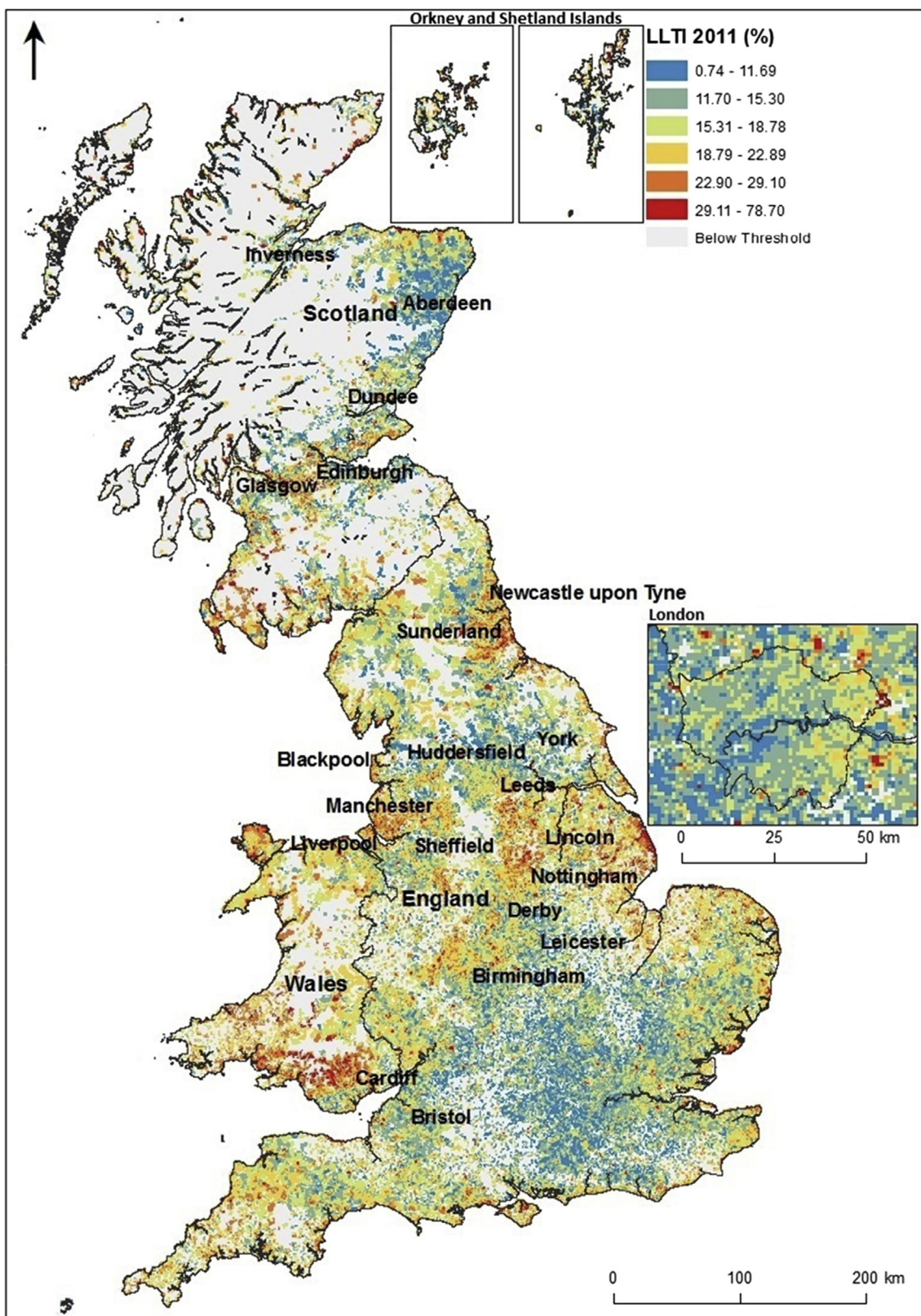
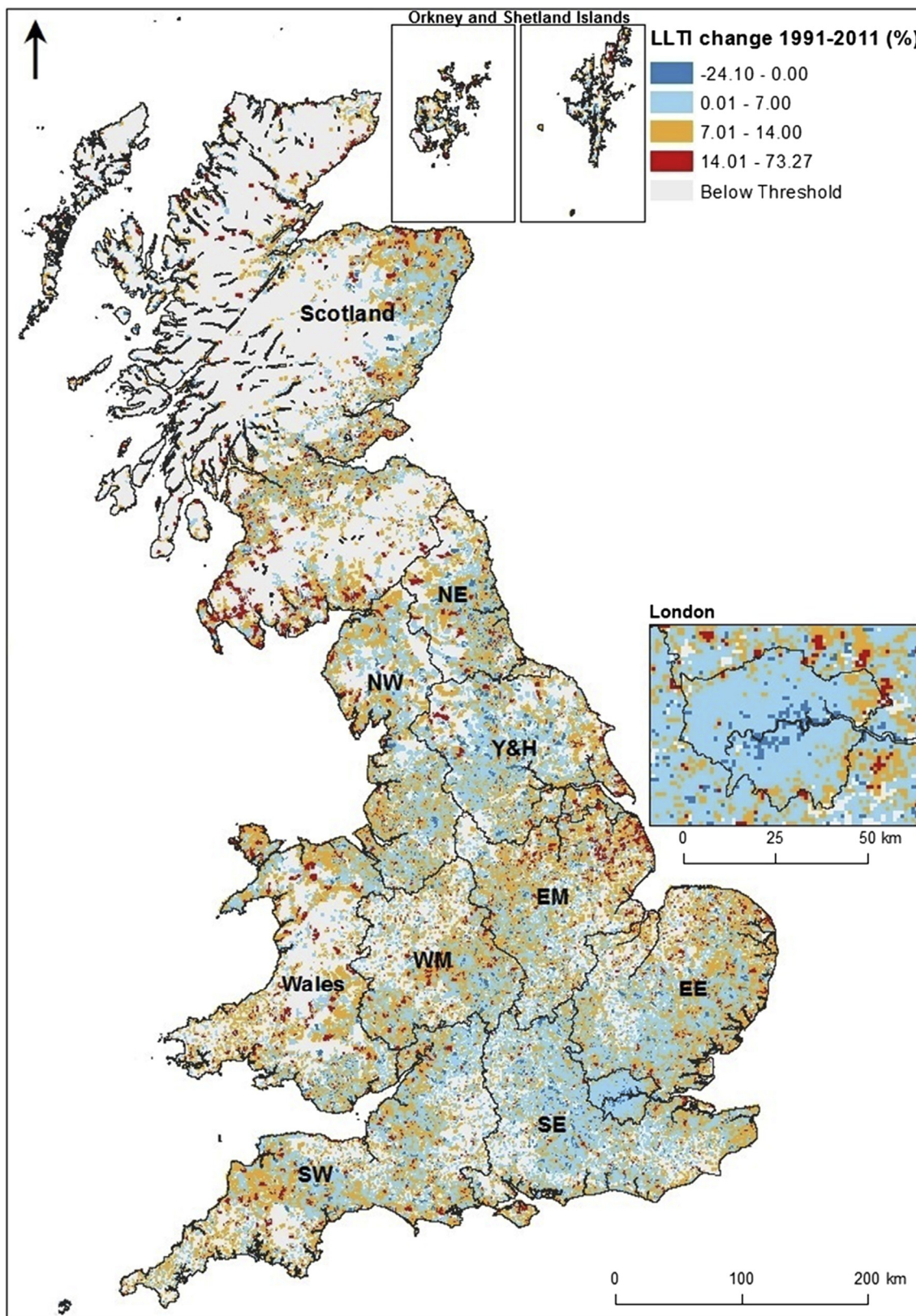**Fig. 1.** LLTI (%) 2011 (population threshold of 0.5 person's).
Authors calculations using PopChange data derived from ONS and NRS data.

Britain.

The results confirm that the geographical separation between LLTI and no LLTI groups is varied but small across district types, although important changes over time are revealed. Separation has decreased predominantly in rural settings. Scottish countryside has seen the biggest decrease in D (-4.36%) indicating that those with poor health and those with good health are becoming geographically less separate. Similarly, English and Welsh countryside has seen a decrease in health

Fig. 2. Difference Map, LLTI (%) 2011–1991 (population threshold of 0.5 persons).
Authors calculations using PopChange data derived from ONS and NRS data.

segregation over time (−0.85). London Cosmopolitan has the lowest degree of health segregation (8.09% in 2011) but the separation between LLTI and no LLTI has increased marginally over time (+0.13% between 1991 and 2011). Coast and Heritage (+1.17%) and Business

and Education Centres (+1.17%) also show fairly consistent increases in segregation over the two decade period and are the most highly segregated area types in 2011. In Suburban Traits (−1.13%) and Prosperous England (−0.84%) there was an overall decrease in
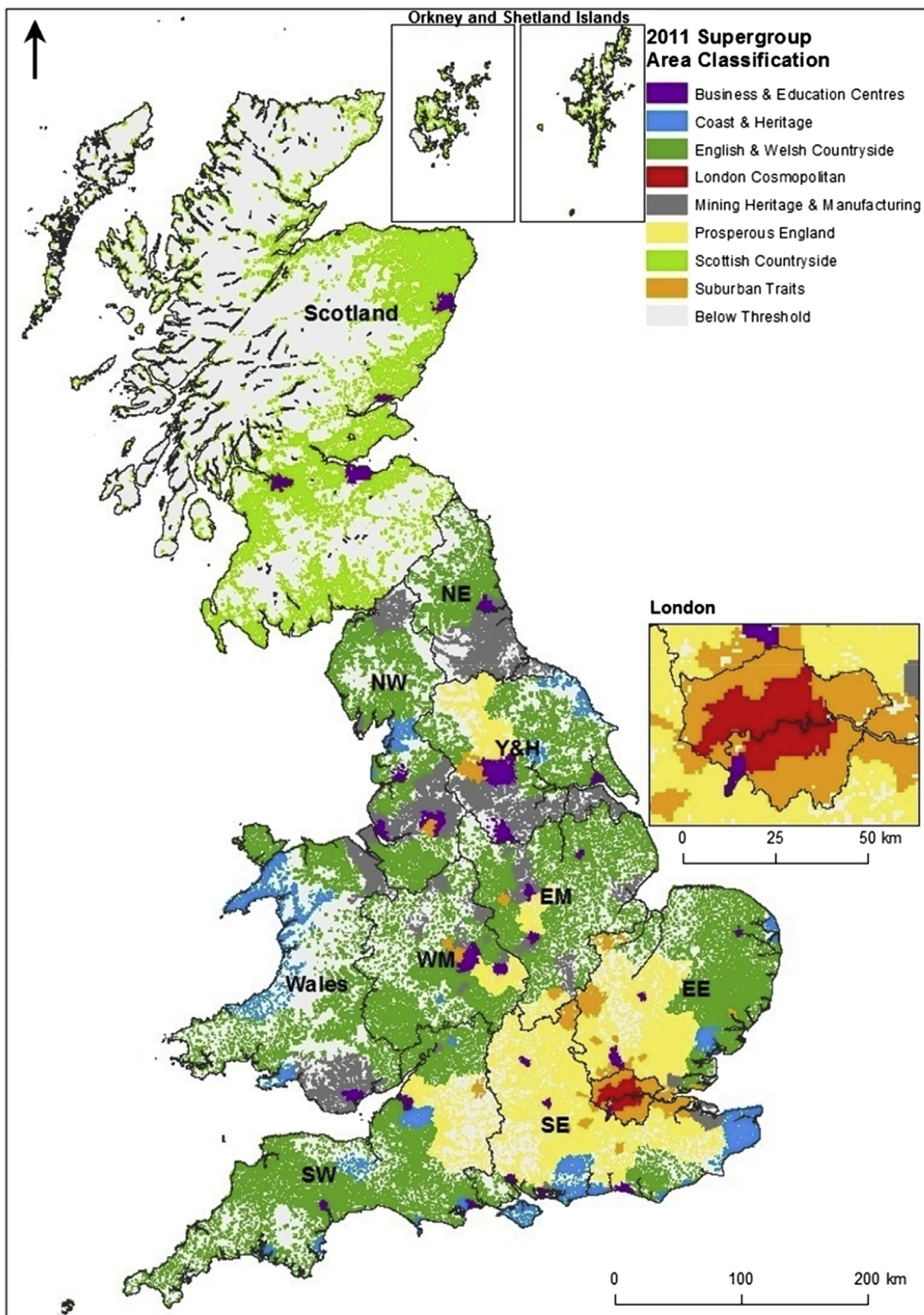
Fig. 3. ONS area classification for Local Authorities (population threshold of 0.5 person's).
Authors calculations using PopChange data derived from ONS and NRS data.

segregation, with small increases (0.01% and 0.14% respectively) in segregation between 2001 and 2011. Mining Heritage and Manufacturing areas have experienced the largest decrease in segregation over time (−2.74%). This decline has occurred consistently over

the decades to become one of the least segregated area types by 2011 (10.77%).

The results discussed so far are aspatial and make no reference to the spatial configuration of values which could be geographically
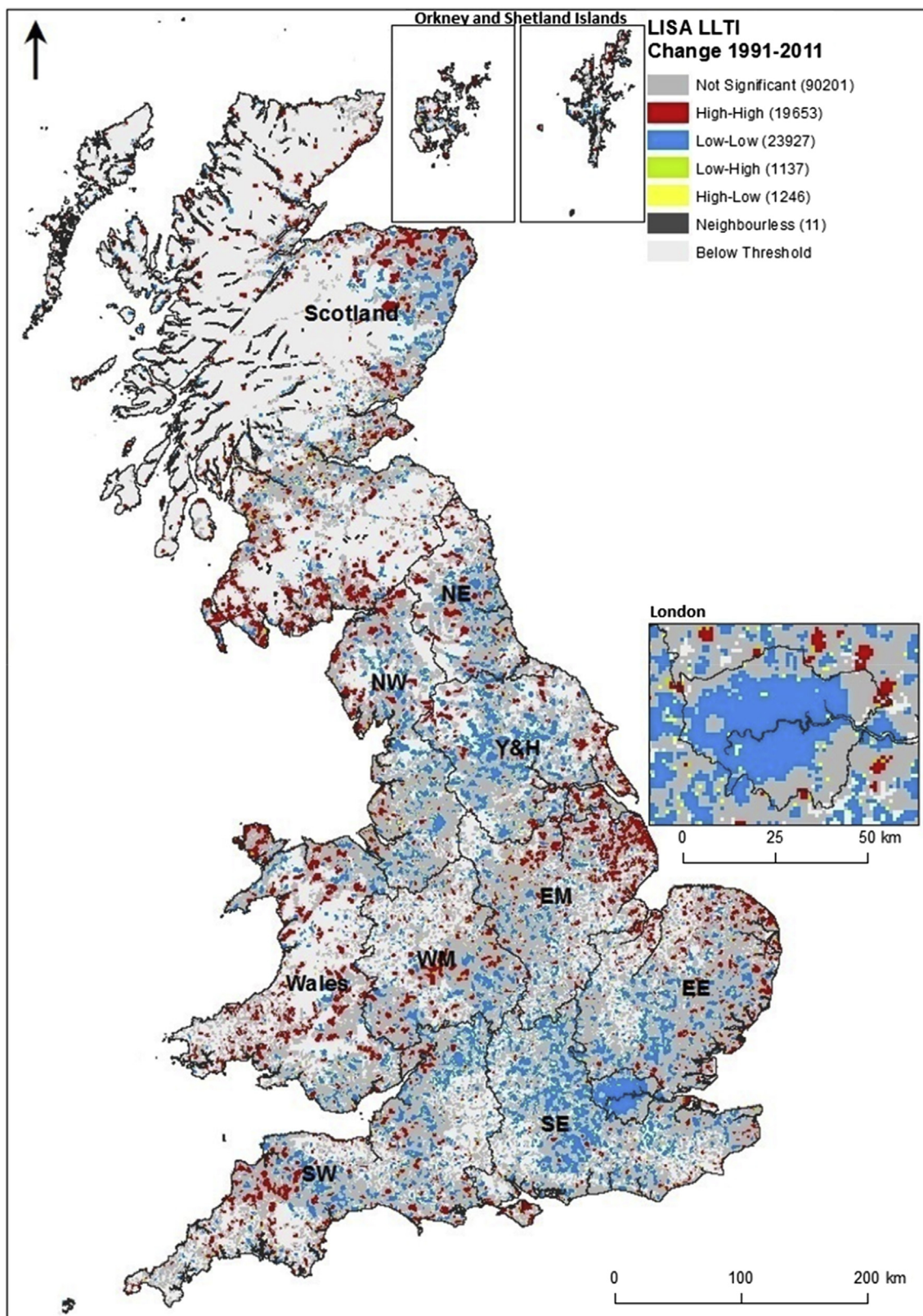
Fig. 4. Local Indicators of LLTI (%) change 1991–2011 (population threshold of 0.5 person's).
Authors calculations using PopChange data derived from ONS and NRS data.

clustered or dispersed across Britain. The remainder of the analysis focuses on the spatial structure of poor health, and an assessment of clustering using the Moran's *I* spatial autocorrelation coefficient is discussed next.

2.4. Measuring clustering using Moran's I

With traditional aspatial segregation measures, the index values obtained will be identical if the values attached to the grid cells are
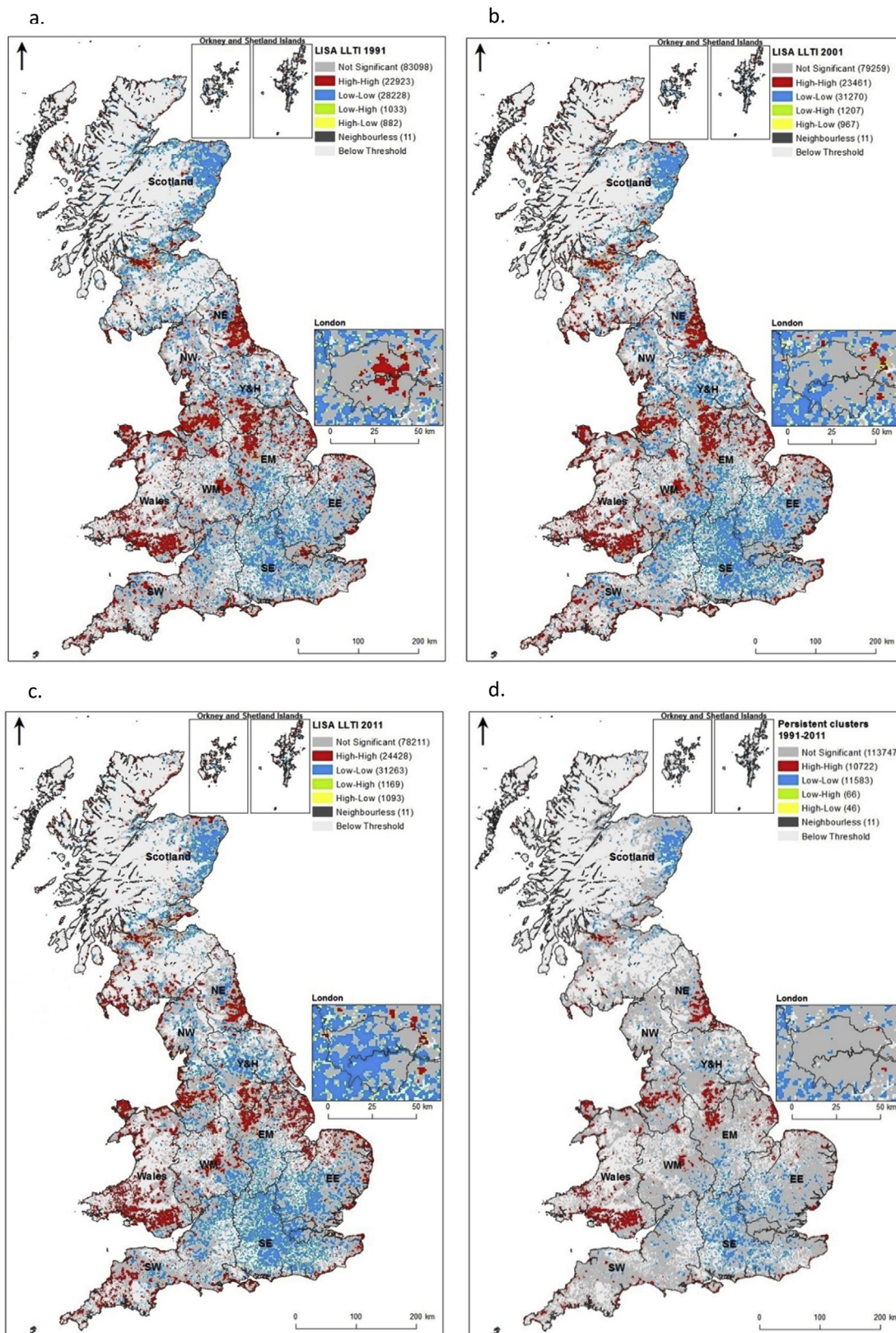
a.

b.

c.

d.

Fig. 5. Local Indicators of LLTI (%) (a) 1991, (b) 2001, (c) 2011 and (d) persistent clusters across all three time points (population threshold of 0.5 person's). Authors calculations using PopChange data derived from ONS and NRS data.

randomly reallocated to other grid cells. Local measures of spatial autocorrelation have been applied that enable the exploration of local variations in residential health segregation across Britain. Previous studies have treated neighbourhoods as independent geographical units, however, the wider spatial context in which a neighbourhood is situated is increasingly recognised as influential for health (Zhang et al., 2011) but known to be spatially variable (Livingston and Lee, 2014). In this section, global and local spatial autocorrelation is measured using

variants of Moran's *I* in order to identify temporally consistent spatial clusters of LLTI across Britain and examine how this patterning has changed over time (1991–2011).

Global spatial autocorrelation has been employed to measure how LLTI rates in each small area compare with its neighbours and with more distant areas, giving an indication of the degree of spatial concentration of health status across Britain. There are a variety of spatial autocorrelation (and thus spatial dependence) measures. One of the most widely applied measures of autocorrelation is the *I* coefficient developed by Moran (1950):

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \left(y_i - \bar{y} \right) \left(y_j - \bar{y} \right)}{\left(\sum_{i=1}^{n} (y_i - \bar{y})^2 \right) \left(\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \right)}$$

Where the values of y_i (of which there are n) have the mean $\bar{y}$ and the proximity between locations i and j is given by w_{ij}. Here, this is a geographical weight set to one when locations i and j are neighbours and 0 when they are not; this is termed queen contiguity. The *I* coefficient measures covariation in LLTI at the multiple small-area locations across the entire study area. A randomised simulation procedure was used to estimate the statistical significance of *I*; the process was based on 9999 random spatial reconfigurations of the data values. Moran's *I* was then computed for each of these randomised data values and the observed value of *I* was compared to the distribution of the *I* values derived from the randomised data. Autocorrelation analyses were conducted using the freely available software package GeoDa™ (Anselin et al., 2006). The Moran's *I* values generated for LLTI rates for 1991 (0.633), 2001 (0.636) and 2011 (0.653) were highly significant (P < 0.001) and indicate quite a strong degree of positive spatial association; small areas with similar rates of LLTI tend to occur next to each other (i.e., they form spatial clusters). Furthermore, there is little change over the decades with LLTI Moran's *I* increasing slightly, but steadily, over time. This trend is fairly weak but it suggests that the degree of spatial clustering of LLTI rates may be growing.

In global tests for autocorrelation, it is assumed that the relationship between nearby or connected observations will remain stationary across the study area (Lloyd, 2010). However, such an approach masks any variation in the spatial structure of the variable of interest. For this reason, a spatially explicit variant of Moran's *I* which assesses the degree of similarity of values to neighbouring values is implemented (one of a set of local indicators of spatial association; LISAs) detailed by Anselin (1995):

$$= z_i \sum_{j=1}^{n} w_{ij} j \neq i$$

Where z_j are differences of variable y from its global mean $(y_i - \bar{y})$. The weighting scheme is queen contiguity, as applied in computing global *I*. Spatial clustering techniques have been applied in many epidemiological studies (Flynt and Daepp, 2015). The significance of local clusters was determined using the same randomisation approach as employed to assess the significance of global *I*. The grid cells with significant values of *I* are then classified according to the nature of the cluster, as detailed below. Fig. 4 displays the local indicators of spatial autocorrelation reported for change in LLTI status between 1991 and 2011 and reveals distinctive geographic patterning of poor health that is masked when assessing global indicators. Positive associations (i.e. association between similar values) are observed in areas labelled high-high (i.e. high rates of LLTI in an area surrounded by high values of the weighted average rate of the neighbouring areas), and low-low (low rate in an area surrounded by low values of the weighted average rate of the neighbouring areas). There are also two forms of negative spatial associations (i.e. association between dissimilar values); high-low (high rate in an area surrounded by low values of the weighted average rate

of the neighbouring areas), and low-high (low rate in an area surrounded by high values of the weighted average rate of the neighbouring areas).

Visually comparing the maps for each individual time point (Fig. 5 a, b, c) displays some distinctive geographical patterning that remains largely consistent over the decades; Birmingham, Liverpool, Manchester, Leeds, Sheffield, Nottinghamshire, Newcastle and the north east have high-high clustering at all three time points. Geographical patterning of low-low clusters is also broadly consistent over time, with this type of spatial cluster predominantly found in inland southern England and these have clearly become more spatially continuous over time. A distinctive band of low-low clustering is also located on the west coast of Scotland that appears to have contracted over time.

Several marked changes over time are also apparent. There is pronounced change over time in London with high mobility of LLTI clusters observed. In 1991, high-high clustering was observed in central London, but this cluster type is not present in 2001 where the most common cluster-type is non-significant. By 2011 some low-low health clusters had emerged. The extreme shift in health status observed in London is an especially interesting finding given that the geography of inequality is recognised to generally not change particularly quickly over time. The west of Scotland has gained high-high clusters over the two decade period with very few visible in 1991. These high-high clusters are concentrated predominantly around the coast. Clustering of poor health in Lincolnshire and along its coastline also appears to have expanded over the twenty year period, and expansion of poor health [high-high] clustering is distinctive in south Wales. Glasgow has had poor health clustering across all three time points but appears less tightly clustered over time. The north east of England has also seen a reduction in the geographical spread of high-high clusters over time.

The use of consistent geographical areas demonstrates that 16.77% of areas have been persistently spatially autocorrelated at all three time points (7.81% with persistent poor health [high-high clusters] and 8.85% with persistent good health [low-low clusters]). Persistently clustered small areas as seen in Fig. 5d have a very clear geographic patterning which reveals some important characteristics. It appears that persistent high-high clustering of poor health is mainly located in two specific area types. One area comprises of traditional industrial and mining areas such as south Wales, north east England, Liverpool, south Lancashire and the Yorkshire-Derbyshire-Nottinghamshire coalfield. The other consists of coastal districts which are popular with retirement migrants (ONS, 2014b) and those seeking affordable private rental accommodation (Depledge et al., 2017) including south and east coastal resorts, north Wales and the Lancashire coast. Table 4 demonstrates how areas which were found to be persistently spatially autocorrelated across all three time points were distributed by area classification type.

Of all area types Mining Heritage and Manufacturing areas had the highest rate of persistently clustered small areas over time (28.59%), closely followed by areas classified as Prosperous England where 26.19% of small areas were persistently clustered across all three time points, suggesting that it is cells within these area types that see the least change in clustering over time. Comparatively, London Cosmopolitan areas experienced the highest rates of mobility, with 99.18% of small areas within this classification reported as not persistently clustered over time. The results identify polarity of cluster types in some area classification types. For example, Mining Heritage and Manufacturing areas have the highest percentage of persistent high-high clusters (27.06%) but have experienced very low proportions of persistent low-low clusters over time. In comparison, 25.86% of cells classified as Prosperous England are persistently low-low clustered, with less than 1% of areas within this area classification type reporting high-high clustering over time. Business and Education Centres experience notably high rates of persistent high-high clustering over time (14.24%) but a comparatively large persistent low-low cluster rate (6.10%) is also present, along with the highest rate of any area classification for persistence in the negative spatial association cluster types.

Table 4
Crosstabulation of persistent clustering type by area classification.

		Cluster Type						Total (=100%)
		Not Significant	HH	LL	LH	HL	Neighbourless	
Area Classification	Business & Education Centres	79.31	14.24	6.10	0.32	0.03	0.00	3461
	Coast & Heritage	80.58	16.05	3.33	0.04	0.00	0.00	7338
	English & Welsh Countryside	89.15	6.70	4.13	0.02	0.01	0.00	60411
	London Cosmopolitan	99.18	0.00	0.82	0.00	0.00	0.00	609
	Mining Heritage & Manufacturing	71.41	27.06	1.32	0.21	0.01	0.00	13860
	Prosperous England	73.81	0.21	25.86	0.00	0.13	0.00	20278
	Scottish Countryside	84.92	4.23	10.72	0.04	0.05	0.04	26458
	Suburban Traits	87.63	2.55	9.76	0.03	0.03	0.00	3760
Total		113747	10722	11583	66	46	11	136175

Authors calculations using PopChange data derived from ONS and NRS data.

Table 5
Crosstabulation Spatial Autocorrelation cluster types 1991 and 2011.

		2011						Total
		Not Significant	H-H	L-L	L-H	H-L	Neighbourless	
1991	Not Significant	41.18	7.44	11.52	0.39	0.49	0.00	83098
	H-H	6.76	9.21	0.52	0.33	0.02	0.00	22923
	L-L	8.80	1.00	10.65	0.05	0.23	0.00	28228
	L-H	0.38	0.26	0.02	0.09	0.00	0.00	1033
	H-L	0.32	0.03	0.24	0.00	0.06	0.00	882
	Neighbourless	0.00	0.00	0.00	0.00	0.00	0.01	11
Total		78211	24428	31263	1169	1093	11	136175 (=100%)

Authors calculations using PopChange data derived from ONS and NRS data.

This indicates that these are locations of high diversity, with key implications for addressing self-reported spatial health inequalities. Uncovering the trajectory of change in health structure is a unique contribution of this analysis. Table 5 demonstrates the mobility of small areas through changing cluster type over the period 1991 to 2011.

In Britain, health has become more distinctively spatially clustered over time with a reduction in variation and greater spatial continuity in clusters evident so that larger sets of neighbouring areas have similar health profiles. Identifying these changes over time is a novel and unique aspect of this work afforded by the spatially consistent PopChange data used.

Between 1991 and 2011 the low-low cluster category experienced growth (+3035) over the 20 year study period and was the most common cluster type in 2011 (31263 cells). This growth largely resulted from the movement of not significant clusters becoming low-low clusters, which was the most common type of mobility. Fig. 4 demonstrates that many of the cells which changed cluster type in this way are located in central southern England and the South East region where low-low clustering has become visibly more spatially continuous over time. High-high clusters also experienced growth (+1505) largely due to not significant clusters becoming high-high (7.44%) over the study period. Again, visualisation of spatial autocorrelation at the three time points (Fig. 4) indicates that the locations of cells where such movement took place were those in close proximity to established high-high clusters predominantly in areas with industrial heritage in Wales and northern regions of England, such that areas of high-high clustering became more widespread and continuous over time. Research suggests that local spatial health inequalities are especially influential in individual health (Zhang et al., 2011), therefore, exploring local inequalities is vital. Analysis reveals that 710 cells (0.52%) which were high-high clustered in 1991 became low-low clusters in 2011 and 1359 cells experienced worsening health over time, reflected by their change from low-low cluster classification to high-high.

3. Discussion

An assessment of the changing degree of residential health segregation and clustering by LLTI is important in understanding the spatial structure of health inequalities. Concentrations of disadvantage can have disproportionate effects upon the lives and opportunities of people exposed to them. Therefore, developing methods for understanding the complex spatial structuring of health is important, providing tools for addressing spatial inequalities in health and for assessing the most appropriate scale at which to introduce interventions to improve health and well-being and create a more equal society. In evidencing the geographies of health inequalities over time, this paper makes unique contributions to understanding the spatial structure and trajectory of change of health, raising many questions about the formation and impact of inequalities and their wider geographies. The results presented have successfully quantified the nature of the spatial structure of health in Britain. Overall decreasing unevenness values, coupled with increased positive spatial association, suggests that neighbouring areas are becoming more similar – the distinction between areas characterised by poor health or by good health is decreasing. This investigation used consistent spatial units to examine how the population of Britain in 1991, 2001 and 2011 was spatially structured by self-reported health, including exploring the trajectories of change, demonstrating quantitatively a complex, yet distinctive, patterning of health inequalities. A framework that explains how resources, accessed by individuals through various domains at different spatial scales, are transformed into distinctive geographic health inequalities remains beyond the scope of this paper but this is the subject of ongoing work.

Spatial inequalities in health are a complex mix of demographic, economic, social, environmental and political processes. Associations between the chances of developing a limiting, long-term illness and age (Marmot, 2010), gender (Wright et al., 2014), social class and employment status (Chandola and Marmot, 2010; Cooper et al., 2015) are also clear and there is an extensive literature on various aspects of

spatial segregation and health inequalities in Britain (Norman et al., 2005; Lymperopoulou and Finney, 2016). However, the way in which these demographic, socioeconomic and geographic factors interact over time to create the distinctive geography of health inequalities observed is less clearly understood. As health is multifaceted with many determinants, attempting to explain the causal mechanisms underpinning the spatial trajectory of health in Britain is complex. Within a framework of existing literature, the quantitative evidence base reported in this work provides a crucial tool for explaining the patterns of persistent poor health clusters and in assessing how health status in an area in the most recent time period is related to health status in previous periods. In addition, it allows for novel analyses of associations between the persistence of poor health and area change more generally.

Between 1991 and 2011 small areas have become less different over time with distinctive spatial concentrations of good health and of poor health, that are closely linked with area typology, notable. As a result of the consistency of the PopChange data utilised, areas which have reported persistent clustering of LLTI over time are also documented. Persistent clustering of poor health is found to be very distinctly spatially organised with the type of spatial autocorrelation observed very closely associated with area classification type. Britain is characterised by its highly polarised skills structure (Whitehead, 2014). It is well established that traditional industrial areas have poorer health profiles (Whitehead, 2014), and this investigation has quantitatively confirmed the extent to which poor health is persistently concentrated in such areas. The decline of heavy manufacturing industries experienced in Wales and the North East, and the relative lack of alternative employment opportunities are possible reasons for this distinctive spatial patterning. The lasting effects of economic downturn on health appear to be exaggerated in coastal areas by two other distinct factors – post-retirement migration (Wilding et al., 2016; Depledge et al., 2017) and a disproportionate quantity of low quality HMO accommodation (Ward, 2015). Age is an important mechanism of residential location and, through propensity to move, spatial sorting. As might be expected, the likelihood of reporting an LLTI is closely associated with age (ONS, 2014). Interestingly, recent research from England and Wales reveals that spatial separation between older (65+) and younger (25–40) age groups has increased over the last 20 years (Sabater et al., 2017). The younger age structure of London's population partly contributes to this region's more favourable health status. Other likely contributing factors are a healthy worker effect resulting from the job-creating regeneration occurring in London during the first decade of the 21st Century (ONS, 2013). In addition, the attraction of migrants from other parts of the UK and from abroad to take up these employment opportunities in London is also likely to affect the socio-demographic structure towards a more trained and skilful workforce and a younger age profile. Research on migration and migration destinations using UK Census data suggests that health selective migration is an important factor driving the spatial clustering of morbidity in Britain (Norman et al., 2005; Wilding et al., 2016). Migrants are not a random subset of the population, and the social and demographic characteristics of migrants are likely to be quite different from those of non-movers (Norman et al., 2005) with population subgroups such as the young (Riva et al., 2011), highly qualified (Green et al., 2015) or affluent more likely to migrate (Champion, 2012).

4. Conclusion

Health status is not one-dimensional; the health and well-being of individuals is influenced by a range of factors, both within and outside of individual control (Brown et al., 2012), consequently, assessing health change over time is complex. The PopChange project has offered a new level of insight into changing population health and geographic inequalities which has not been available before. Unrivalled comparable census data together with the ONS Area Classification presents evidence of the changing spatialities of health across Britain. Before the

processes which contribute to spatial health inequalities can be explored comprehensively it was first important to gain a detailed understanding of how health inequalities have been spatially structured over time. This work captures the diverse nature of changing health inequalities at a geographically detailed scale and provides quantitative evidence that can be utilised in future work to explore the nature of this patterning. This paper has demonstrated that health varies spatially; locally, regionally and nationally, highlighting how health is inextricably linked to geography. More work is required to fully explore and explain why this spatial structuring is observed. There is a need to take a modelling approach and future work will build on the findings reported here to address this.

This analysis has successfully mapped the spatialities of LLTI change in Britain over time and is novel in demonstrating the persistence of clusters of poor health and the ways in which these clusters have changed. However, there are caveats which should be noted about the findings reported. Although areas used were consistent over time, the characteristics of the population within cells may have changed. In isolation the evidence presented does not allow an assessment of why the LLTI status of areas may have changed. Furthermore, as self-reported measures of health are subjective, integrate personal expectations, and result from a complex aggregation process of several elements and experiences, such measures may be affected by social, cultural, regional and temporal subjectivity more than physiological or mortality measures (Senior, 1998). Additionally, definitions of LLTI are not consistent across censuses and the change of the LLTI question wording possibly resulted in wider reporting of age-realted LLTI in 2001 that was not captured in 1991. Nevertheless, the study holds considerable advantages and provides the first geographically fine-grained exploration of spatial health structuring in Britain. This quantitative information can be used as a resource to comprehensively inform future health inequalities work.

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