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Isolated Entities or Integrated Neighbourhoods? An Alternative View of the Measurement of Deprivation

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Abstract

The use of area-based deprivation indices is now a firmly established means of assessing which areas ought to be the focus of government policy, with separate indices of deprivation established for each constituent part of the UK. In England, the Index of Multiple Deprivation 2004 has been widely used to support decision-making for key urban policies and in more local assessments of deprivation. Implicit in the development and use of these indicators is the notion that area matters and that it can be an important influence on a whole range of different activities. However, there is also a sense in which contemporary measures of deprivation are spatially short-sighted since they are not able to account formally for the spatial context of individual locations. This paper therefore offers an alternative approach to the measurement of local conditions by combining spatial statistical approaches with a much-used deprivation index.

Introduction

Across the United Kingdom, area-based deprivation indices are used in the decision-making process when determining which areas are in need of policy intervention. This situation has emerged from an historical trajectory of area classification and has now coalesced with the more recent vogue for 'evidence-based policy'. Simultaneously, academic work on 'area' or 'neighbourhood' effects has sought to understand, in an increasingly sophisticated way, the extent to which local context matters (for example, Johnston *et al.*, 2004; Bolster *et al.*, 2007). Despite a lack of consensus regarding the importance of area effects, there is sufficient evidence to support their existence (see Dorling, 2001; Dietz, 2002; Lupton, 2003; Blasius *et al.*, 2007; Galster *et al.*, 2007). Therefore, it is somewhat disappointing that metrics used as arbiters of social need do not currently incorporate

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a locally sensitive spatial dimension. This paper presents an alternative methodological approach to the one currently employed and in so doing offers a new way of interpreting area deprivation at the local level.

The distribution of funding for spatial policy interventions and the identification of local need in England are closely tied to an area-based deprivation index that has become the *de facto* measure of deprivation: the Index of Multiple Deprivation 2004 (IMD).[1] Not without its critics (for example, Deas *et al.*, 2003; Schuurman *et al.*, 2007), the IMD is, nonetheless, a very effective small-area evaluation tool which produces a relative measure of deprivation for each area in England.[2] However, it has a very important geographical limitation: there is no in-built mechanism for assessing the extent to which individual areas might be related to their wider spatial context. In effect, the IMD overlooks Tobler's 'first law of geography' in a formal sense since it cannot account for the way in which "everything is related to everything else" (Tobler, 1970, p. 236).[3] Such geographical limitations might not be important were it not for the potentially serious issues related to area effects which, it has been argued, can compound local disadvantage and exacerbate social exclusion in areas of concentrated deprivation (Atkinson and Kintrea, 2001; Lupton, 2003; Dietz, 2002; Atkinson, 2006).

This paper therefore seeks to make an original contribution to the literature by presenting an approach to the measurement of area deprivation which is cognisant of local spatial context and which could subsequently be used to support more spatially sensitive area targeting. It acknowledges the importance of the area effects debate and exploits recent advances in spatial statistical software in order to arrive at a better understanding of the spatial context of individual areas in England. If it can be quantifiably demonstrated that certain localities have a particularly unfavourable spatial context because they sit within larger geographical concentrations of deprivation, then this ought to be taken formally into account by area-based policies which seek to target places rather than people (for example, New Deal for Communities, Working Neighbourhoods Fund).

The remainder of the paper is divided into two sections, followed by some concluding comments. First, we discuss some technicalities in relation to spatial units of analysis and spatial context, with reference to the literature on area effects. In this discussion, it is argued that areas which are spatially embedded and integrated need to be understood within their broader context rather than as isolated neighbourhoods. Secondly, we attempt to formalise the concept of spatial context in terms of a 'nearest neighbour IMD' which offers new insight into the geographical characteristics of deprivation at a local level in England. This section comprises the bulk of the paper. In addition, and in order more rigorously to validate the procedure, some formal measures of spatial association are presented. These capture the degree to which local areas are similar or different in terms of attributes *and* location. The contribution here is not intended to solve the area effects debate, but rather to provide a firm footing for further investigation into the impact of spatial context in relation to indices of deprivation and the allocation of funding for area-based initiatives.

Area Effects, Spatial Units and Spatial Context

The literature on area effects is both voluminous and illuminating, spanning the breadth of the social sciences. In his survey of the topic, Dietz (2002) comments critically on this diversity and in doing so updates a previous influential review by Jencks and Meyer (1990). He also notes the tendency for different academic disciplines to use the techniques most familiar to them. Similarly, Lupton (2003) views work on area effects as being one of co-existence between disciplines rather than effective complementarity. Lately, however, there has been a tendency towards more interdisciplinary working and collaboration, as evidenced by a recent issue of *Housing Studies* (Volume 22, Issue 5, 2007) which explores the 'frontiers of quantifying neighbourhood effects' across a range of topics including individual incomes, tenure, fertility, education, deviance, gender, ethnicity and race (see Blasius *et al.*, 2007). A common thread running through the research on area effects, and one which resonates here, is the doubt over their existence and/or strength. The motivation for this paper, however, is not so much to prove they exist, but rather to provide empirical evidence, in the English context, of their likely impact in individual locations. The contention is that if "neighbourhoods have a strong and independent effect upon the well-being and life chances of individuals" (Blasius *et al.*, 2007, p. 627), then formal policy intervention mechanisms ought to have some way of recognising which areas might be at greater risk.

At this juncture, it is necessary to consider what we mean by area effects and what type we are discussing. Whilst Manski (1993, 2000) identified three different types (endogenous, correlated and exogenous), Atkinson and Kintrea (2001) identify six (concentration, location, milieu, socialisation, physical and service) and Buck (2001) highlights many more, they are primarily conceptualised as *within*-area effects. This research, on the other hand, considers *between*-area effects as a means to determining the importance of spatial context in local outcomes. Dietz (2002, p. 541) commented on the heavy weighting towards the former and the dearth of evidence regarding the latter, whilst Buck (2001, p. 2252) was more direct, asking: "Does it make my life chances worse if my neighbour is poor rather than rich"? The pertinence of this question is reinforced when one considers sociological research into the neighbourhood context of well-being which has shown that, although internal processes and population composition are important, they are "constrained by the spatial context of adjacent neighbourhoods" (Sampson, 2003, p. S60). This expansion of the area effects paradigm has also been explored by Morenoff where he considers "not only the local neighbourhood but also the wider spatial context" (2003, p. 977; see also Baller *et al.*, 2001; Smith *et al.*, 2000). Before proceeding to some empirical analysis, then, further conceptual and theoretical clarification is necessary.

Spatial Units of Analysis

In an illuminating study of neighbourhood effects and income dynamics, Bolster *et al.* (2007) provide an exploratory analysis of the subject matter in a wider spatial context (similar in approach to previous work by Buck, 2001; Johnston *et al.*, 2000; and Johnston *et al.*, 2004). They focus on 'micro-neighbourhoods' and use the British Household Panel Survey dataset in order to track income trajectories over time. Their conceptualisation of spatial scale is a population-based measure which considers different levels between 500 and 10 000 people in the enumeration districts (EDs) surrounding individual panelists. Adjacency was determined by means of distance from population-weighted ED centroids until each of the population thresholds was met. The specification of place in this paper is conceptually different since it does not rely on the individual as the starting-point for defining a neighbourhood, but rather uses pre-defined areal units which have at least some internal logic, even if they are not a wholly suitable proxy for neighbourhood. The assertion here is that the specification of areas in research into spatial context needs to have some functional basis in order for it to be properly effective.

Therefore, more work is needed in this strand of analysis in order that quantitative studies can make a greater contribution to our knowledge of area effects and their relationship to the spatial context of deprivation.

In order for subsequent empirical analysis to have real explanatory power, it is essential that the spatial units of analysis have some geographical logic and are of a suitably small population size. Recent improvements in census geography in England have made this possible, with the availability of data for super output areas (SOAs), of which there are three levels (lower, middle and upper).[4] Lower SOAs (LSOAs) have an average population of just over 1500 and were formed by merging smaller output areas, taking into account population size, mutual proximity and social homogeneity (ONS, 2007). They are far from being a perfect definition of 'neighbourhood', but they do allow researchers to perform more meaningful fine-grained area analysis at the local level, in contrast to more heterogeneous census tracts, blocks or wards. The use of LSOAs in this study goes some way, therefore, to avoiding the spatial aggregation constraints associated with previous studies (for example, Burgess *et al.*, 2001; McCulloch and Joshi, 2000) and makes more longitudinal work on the subject a realistic possibility, since one of the aims of implementing the new LSOA geography is to allow comparability through time. In summary, the adoption of a new census geography in this research remains something of a compromise, but one which represents a significant advance on previous approaches which were unable to specify a suitably small neighbourhood for analysis.

Spatial Context

The adoption of a standard spatial unit here, albeit an imperfect one, allows us to consider the issue of spatial context in more depth. This approach therefore tackles one of the issues identified by Dietz

> In studies of within neighbourhood effects, no interaction occurs among the neighbourhoods; that is, the neighbourhood possesses no spillover characteristics. Thus, neighbourhoods with identical characteristics but dissimilar neighbouring neighbourhoods are considered equivalent (Dietz, 2002, p. 541).

In relation to the identification of local need for area-based interventions in England, such an observation is both prescient and challenging since it recognises the limitations of viewing the nation as the spatial context and requires us to think carefully about how we can more meaningfully locate deprived areas in place.

Many commentators have noted the lack of success achieved by area-based regeneration programmes in England and the necessity of tackling deep-seated concentrations of poverty (for example, Gripaios, 2002; Lawless, 2004; Rhodes *et al.*, 2005). However, government policy in England is typically concentrated on the 'most deprived' 10 per cent or 20 per cent of areas nationally without taking local spatial context into account or the potential area effects they may engender. This situation is somewhat ironic given the desire to understand and deal with concentrated poverty and the fact that, by virtue of the existence of area-based policy, there would appear to be an explicit acceptance of the importance of neighbourhood context in local outcomes (SEU, 2001; DTLR, 2002; ODPM, 2004a). Indeed, a recent summary of research in Scotland recommends that, although the Scottish IMD should remain the principal measure of local deprivation, there was also a need for Community Planning Partnerships

> to adopt a range of other methods to enhance understanding of geographically concentrated deprivation at a local level (Communities Scotland, 2007, p. 2).

By exploring the matter of spatial context, the intention here is to shed light on an issue that has previously been explored within a qualitative framework (see Lupton, 2003), in order more fully to 'localise' and 'contextualise' an evaluation tool that is used as the arbiter of social need in England's most deprived locations.

Towards the Measurement of Spatial Context

The analysis is comprised of three parts. First, we describe the different ways in which spatial context has been formally conceptualised and implemented during the compilation of spatial weights matrices. This part refers to more technical aspects of the study conducted using Anselin's *GeoDa* software (Anselin, 2003). Secondly, we construct a more spatially sensitive version of the IMD based on nearest neighbour analyses. In this section, detailed results are given in order to illustrate the extent to which a nearest neighbour IMD can provide a more geographically cohesive view of local area deprivation in England. Finally, we present an LSOA classification based on some further spatial statistical analysis. It is clear from this approach that current understandings of the importance of spatial context, in policy circles and the academic literature, can be usefully supplemented by incorporating more spatially sensitive empirical approaches.

Deriving Spatial Weights

In geographical information science, the influence of the study area boundary is a key concern and one that must be given proper consideration prior to any analysis taking place (Bivand, 1998; Lee and Wong, 2001; Getis and Aldstadt, 2004; Mitchell, 2005). Since we are considering area effects and the potential impact of spatial context, it is necessary to use some conceptualisation of neighbourhood in order that spatial weights matrices can be derived and used as the basis for further analysis. However, determining the best method here is difficult since we could use adjacency, distance or a *k-nearest* neighbours approach,[5] each of which has its advantages in different situations (Anselin, 2003). Each of these three approaches was tested based on different specifications. For the adjacency-based method, first-, second- and third-order contiguity neighbourhoods were used in constructing spatial weights. With first-order contiguity, only immediately adjacent LSOAs are presumed to have an influence on the target feature, whereas with lower orders the influence extends outwards at different levels of adjacency, as shown in Figure 1.

For the distance method, spatial weights were determined using population-weighted centroids and fixed radii of 403, 805 and 1609 metres (quarter, half and one mile respectively) in order to specify a more tightly bounded local neighbourhood. Using population-weighted centroids offers clear advantages (Figure 2), but there are often issues relating to the nature of relationships over distance, especially where motorways, rivers or other barriers reduce physical and social interaction. Furthermore, the use of population-weighted centroids might also lead to some proximate LSOA neighbours being excluded from the analysis if the centroid falls outside the distance band but a proportion of the LSOA population falls within the specified area. In LSOAs with many neighbours, this is likely to become a bigger issue as more people are excluded.

The *k-nearest* neighbours approach was also tested with the nearest 4, 8 and 16 neighbours being included in neighbourhood specification for the spatial weights matrices.[6] However, this approach is the least satisfactory since there is no way of ensuring that a geographically consistent weights matrix will be specified owing to the fact that the *k-nearest* neighbours may not actually enclose the target feature (Figure 3). This is also a possibility

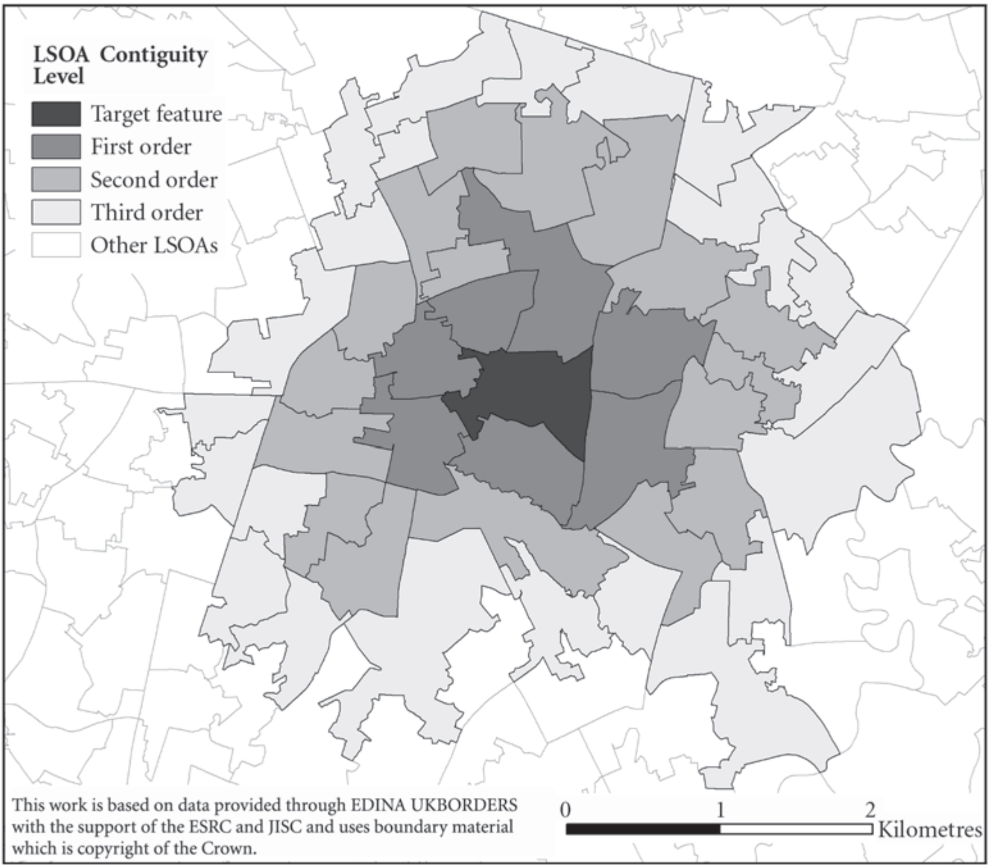

Figure 1. Adjacency-based neighbourhoods: Different levels of contiguity

with the distance approach to determining neighbourhood but to a lesser extent.

The outcome of testing these different methods for determining the best approach to specifying an area of influence and deriving spatial weights was that the adjacency criteria were preferred over the distance or *k-nearest* neighbours measure. It is clear that in specifying spatial weights and determining an area of influence there is no perfect solution (Johnston *et al.*, 2004; Mitchell, 2005), but adjacency offers three advantages over other approaches: it guarantees that only physically connected areas have an influence on each other; it ensures that the area of interest (i.e. the 'target feature') is the central location in a clearly defined and enclosed neighbourhood; and it results in a method that is more sensitive to spatial structure in urban and rural areas where the influence of distance might vary considerably depending upon different functions.

A Nearest Neighbour Index of Multiple Deprivation

Using the adjacency-based spatial weights matrix at three different levels of adjacency, a new nearest neighbour IMD (NNIMD) score was derived for each of the 32 482 LSOAs in England. This score represents the mean value of IMD scores for all adjacent LSOAs at the three different levels. When comparing these new values with that of the original IMD score for each LSOA there are obvious differences, both conceptually and empirically. In relation to the former, we

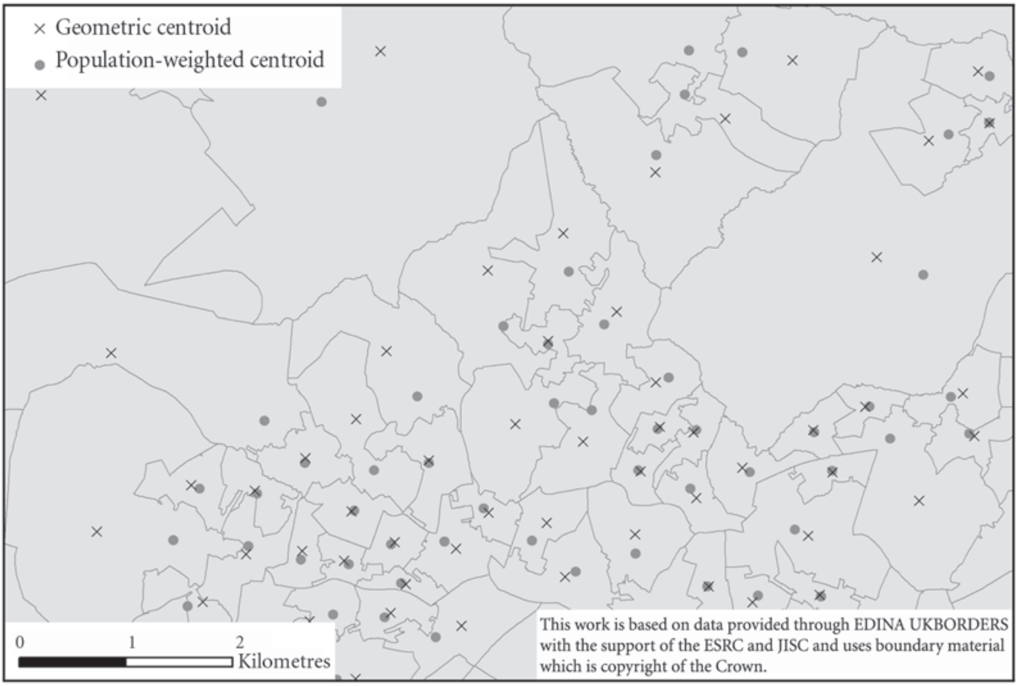

Figure 2. Geometric vs population-weighted centroids

Figure 3. *K-nearest* neighbours

observe a pattern whereby the spatial context for each area is defined by the deprivation scores of adjacent LSOAs only. In visual terms, this produces a successively smoother surface as the order of contiguity increases (Figure 4) but, in statistical terms, there is an averaging-out of spatial context when we use the lower orders so that the validity of using the adjacency-based approach is diluted since it takes into consideration areas which we would not expect to have any influence on one another, owing to distance. However, the lower orders are a useful tool for assessing the extent to which some areas are spatially embedded in deprived areas, particularly in inner urban locations where each LSOA is relatively small. These areas might justifiably be classified as being multiply deprived in terms of attributes *and* spatially deprived in terms of being at the heart of deep-seated geographical concentrations of deprivation. For the purposes of using the NNIMD at a national level, then, it is more logical to consider first-order contiguity as the appropriate conceptualisation for determining spatial context.

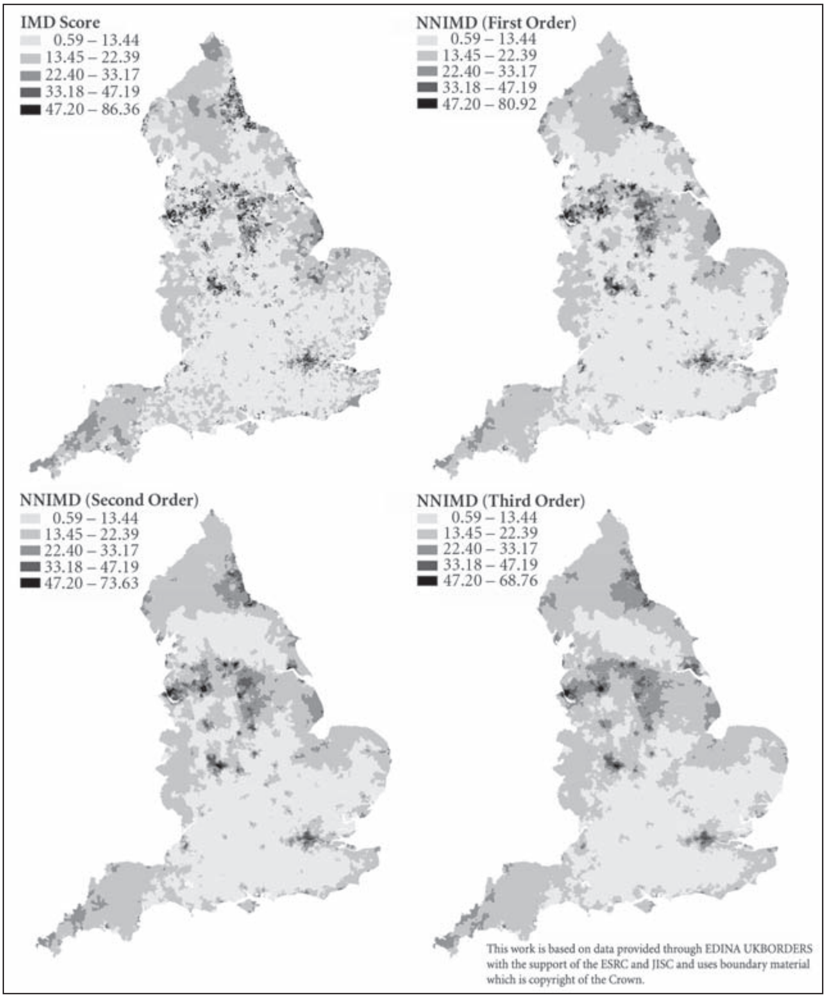

Figure 4. The IMD and NNIMD (first, second and third orders)

The impact of taking different approaches is given in Table 1 where the 20 most deprived LSOAs in England are shown in relation to their original IMD score and the three NNIMD levels. Since this research is concerned with the validity of the IMD as a tool for highlighting areas of local deprivation and area-based policy targeting, it is interesting to note that each of the 20 areas defined by the IMD as being most deprived fall well within the 20 per cent most deprived[7] in England on the NNIMD based on the first-order criteria. At the second-order level, all but one area (shown in bold) fall within the 20 per cent most deprived and it is interesting to note that this is the only LSOA outside the north of England. At the third-order level, all but two LSOAs (shown in bold) are within the 20 per cent most deprived. Whilst this level of spatial extent is too wide a band to use at a national level, it is a potentially useful evaluation tool in identifying areas that are isolated in terms of housing and labour market interactions with their wider regions. In short, it seems most appropriate to use a first-order NNIMD to assess local spatial context at a nation-wide level and to use lower orders to shed further light on the nature of spatial entrenchment in relation to larger geographical clusters, particularly in regions

Table 1. England's 20 most deprived LSOAs: First-, second- and third-order NNIMD

	Individual LSOA		*First-order contiguity*		*Second-order contiguity*		*Third-order contiguity*	
LSOA	*IMD score*	*Rank*	*NNIMD1 score*	*NNIMD1 rank*	*NNIMD2 score*	*NNIMD2 rank*	*NNIMD3 score*	*NNIMD3 rank*
Liverpool 018C	86.36	1	77.72	7	66.47	34	60.70	65
Manchester 009C	85.76	2	79.85	3	65.76	42	57.22	126
Liverpool 059C	85.59	3	69.72	64	45.39	1193	37.44	2712
Manchester 013D	84.92	4	70.85	53	62.11	99	67.74	4
Manchester 009B	84.78	5	68.34	85	59.59	160	60.11	76
Manchester 020A	83.08	6	64.90	163	71.46	6	57.05	134
Knowsley 008C	82.30	7	78.54	5	61.40	109	52.04	271
Liverpool 044D	82.04	8	73.26	28	60.77	123	58.47	97
Manchester 009A	81.89	9	71.16	47	64.14	59	58.27	103
Liverpool 018D	81.39	10	73.28	27	67.50	24	60.82	62
Manchester 015D	81.26	11	72.21	35	72.03	4	60.64	66
Manchester 017A	80.65	12	59.36	376	58.28	195	56.44	146
Liverpool 014E	80.62	13	70.74	55	57.55	219	55.60	168
Knowsley 008D	80.49	14	65.67	138	57.82	209	43.89	979
Knowsley 003C	80.31	15	65.37	147	48.70	776	35.88	3351
Rochdale 010E	80.29	16	53.22	827	41.44	2090	32.70	4793
Middlesbrough 001C	80.20	17	58.53	427	44.95	1278	37.74	2582
Rochdale 010C	79.99	18	52.77	867	38.47	3005	28.72	**7057**
Bristol 031C	79.98	19	54.21	754	29.31	**7340**	25.79	**9162**
Manchester 024A	79.97	20	59.37	375	52.79	451	42.17	1272

Note: Areas with a rank of 6496 or lower are among England's 20 per cent most deprived areas in each classification.

which have a disproportionate share of England's most deprived, such as Liverpool, Manchester and inner London.

The analysis thus far has considered the spatial context of individual LSOAs only in relation to their immediate area. This can help us to understand more about the setting of each LSOA in relation to its wider neighbourhood, and the potential for any negative or positive between-area effects, but it does not take into account the level of deprivation in the individual LSOA itself (i.e. the 'target feature' in nearest neighbour analysis). This is an inherent limitation of the spatial statistical approach used here, although it is entirely feasible to employ the NNIMD as a supplement to the IMD in order to determine which areas ought to receive most attention or as a stand-alone tool to evaluate spatial context. What makes more sense, however, is to derive a combined IMD/NNIMD, giving some weight to the former and some to the latter. In-built into this formulation is the assertion that 'geography matters' and that the IMD, in its current form, does not give this due consideration, despite attempts at the district level to take spatial context into account.[8] Given the level of debate about the extent, intensity and even the existence of area effects (Atkinson and Kintrea, 2001; Dietz, 2002; Lupton, 2003; Durlauf, 2004; Bolster *et al.*, 2007), there is a need to incorporate this into the construction of the NNIMD. Therefore, NNIMD scores were calculated based on a 25 per cent, 50 per cent and 75 per cent weighting being assigned to the neighbourhood surrounding each LSOA (Table 2).

As we can see in Table 2, the weightings themselves do not radically alter the ranking of LSOAs within England, even when using a 25 per cent or 75 per cent weight. This is to be expected given the degree of spatial concentration of deprivation across the country, but it is also an important consideration for identifying areas in need of policy targeting because it provides hard evidence relating to the extent of spatially embedded deprivation based on a metric used by government to assess areas of local need.

Since this paper is concerned with the pragmatic use of the IMD, it is important to understand what impact a NNIMD approach might have in policy application, in terms of which areas fall within the 20 per cent most deprived and might therefore be subject to greater levels of targeting. This was explored for both the first-order method (NNIMD1) and the 50 per cent neighbourhood weighting method (NNIMD50) and compared with the original IMD score for each area. In total, 4586 LSOAs are amongst the 20 per cent most deprived on both the original IMD and the new NNIMD1 measure. This figure accounts for 70.6 per cent of the areas ranked within the worst 20 per cent on the original IMD. By comparison, 5678 LSOAs are amongst the 20 per cent most deprived on both the original IMD and the new NNIMD50 measure. This figure accounts for 87.4 per cent of the areas ranked within the worst 20 per cent on the original IMD. When we focus on the 6496 most deprived LSOAs on the NNIMD1 measure, the rank of areas which are not among the 20 per cent most deprived on the original IMD extends from 6498 to 27 504, whereas on the combined NNIMD50 measure the rank of areas not among the 20 per cent most deprived on the original IMD extends from 6498 to 19 473. What we begin to see with these more spatially sensitive measures, then, is some differentiation between local areas in terms of their spatial context *and* their individual attributes. The intention here is not to suggest areas which are not worthy of attention and funding, but rather to highlight those areas which are deprived both in terms of internal characteristics and embedded in terms of spatial setting within larger concentrations of disadvantage. The next section considers this issue in more detail by means of developing a statistically more

Table 2. England's 20 most deprived LSOAs: NNIMD weightings

	Individual LSOA		*Neighbourhood 25 per cent weight*		*Neighbourhood 50 per cent weight*		*Neighbourhood 75 per cent weight*	
LSOA	*IMD score*	*Rank*	*NNIMD25 score*	*NNIMD25 rank*	*NNIMD50 score*	*NNIMD50 rank*	*NNIMD75 score*	*NNIMD75 rank*
Liverpool 018C	86.36	1	84.20	2	82.04	2	79.88	3
Manchester 009C	85.76	2	84.28	1	82.81	1	81.33	1
Liverpool 059C	85.59	3	81.62	3	77.65	8	73.68	24
Manchester 013D	84.92	4	81.40	4	77.89	7	74.37	16
Manchester 009B	84.78	5	80.67	6	76.56	15	72.45	38
Manchester 020A	83.08	6	78.54	12	73.99	38	69.45	77
Knowsley 008C	82.30	7	81.36	5	80.42	3	79.48	4
Liverpool 044D	82.04	8	79.84	7	77.65	9	75.45	10
Manchester 009A	81.89	9	79.21	10	76.53	16	73.84	23
Liverpool 018D	81.39	10	79.36	9	77.34	12	75.31	12
Manchester 015D	81.26	11	79.00	11	76.73	14	74.47	15
Manchester 017A	80.65	12	75.33	43	70.00	96	64.68	192
Liverpool 014E	80.62	13	78.15	16	75.68	19	73.21	31
Knowsley 008D	80.49	14	76.78	24	73.08	48	69.37	78
Knowsley 003C	80.31	15	76.58	28	72.84	52	69.11	83
Rochdale 010E	80.29	16	73.52	78	66.76	189	59.99	389
Middlesbrough 001C	80.20	17	74.78	56	69.36	108	63.95	216
Rochdale 010C	79.99	18	73.19	90	66.38	205	59.58	413
Bristol 031C	79.98	19	73.54	77	67.09	173	60.65	364
Manchester 024A	79.97	20	74.82	55	69.67	102	64.52	197

Note: Areas with a rank of 6496 or lower are among England's 20 per cent most deprived areas in each classification.

rigorous assessment of which areas might be most disadvantaged by their spatial context *and* individual characteristics.

Classifying According to Location and Attribute

The assertion here is that the current method of determining which areas are in need of intervention is not geographical enough. Fundamentally, the IMD, and deprivation measures in use elsewhere in the UK, are attribute-centric in that they focus very much on the 'what' but have no way of incorporating the 'where' component in a broader sense (ODPM, 2004b, p. 31). This situation is rather disappointing, but it is also opportune since it allows us to construct a new measure of deprivation, presupposed upon the notion that geography does matter and that it can, potentially, be a factor in local outcomes. In some ways, this follows on from the innovative semi-parametric approach of Bolster *et al.* (2007) and their original contribution to the literature. More accurately, however, the approach adopted here attempts to marry existing techniques to a subject matter that for too long has remained geostatistically dormant. The progeny of such a union ought to be a new way of looking at deprived areas which sees them as integrated neighbourhoods rather than isolated entities. To those familiar with the analysis of geographical patterns and clusters, these arguments will sound familiar, but it is often the case that more sophisticated measures of spatial location are not incorporated into mainstream analysis and are subsequently overlooked. Therefore, this final section on the development of a measure of spatial context for the IMD will take a closer look at global and local measures of spatial association, with brief reference to the former and more in-depth analysis of the latter.

In his review of spatial statistical techniques for location studies, Bivand (1998) traces the origins of geostatistical approaches in the social sciences and charts the sometimes diverging research traditions associated with them. He comments on both global and local indicators of spatial association and, in common with Mitchell (2005) notes the preference of users for the Moran's *I* measure over Geary's *C*. This preference is continued here, although the validity of alternative methods is not disputed (Lee and Wong, 2001). Put simply, Moran's *I* is a spatial autocorrelation statistic which tells us the degree to which features are similar in attribute *and* location. It can be computed as a single statistic for an entire dataset (global Moran's *I*) or for each feature in a dataset (local Moran's *I*). Where areas with similar attributes are clustered together, Moran's *I* tends towards its maximum value of 1.0 and, where nearby areas have different attributes, Moran's *I* tends towards its minimum value of –1.0. The computation of this statistic is subject to some technical discrepancies relating to 'boundary effects' where features on the edge of the study area will have fewer neighbours than other more central areas but, in general, it has proved to be a useful, and robust, measure (Bivand, 1998; Longley *et al.*, 2001; Mitchell, 2005; Dorling *et al.*, 2007). The spatial weights matrix used in the specification of both global and local Moran's *I* is the first-order contiguity option described earlier.

The calculation of a global Moran's *I* for the IMD across England's 32 482 LSOAs yields a score of 0.6853 and is graphically portrayed in Figure 5 with spatial weights plotted against IMD scores. This value represents strong positive clustering of deprived areas within England and essentially provides a quantifiable measure relating to the spatial patterns depicted in Figure 4. It also reinforces Tobler's 'first law of geography', whereby "everything is related to everything else, but near things are more related than distant things" (Tobler, 1970, p. 236). If we were to repeat this process using the same index and spatial units over time, it would show the extent to which

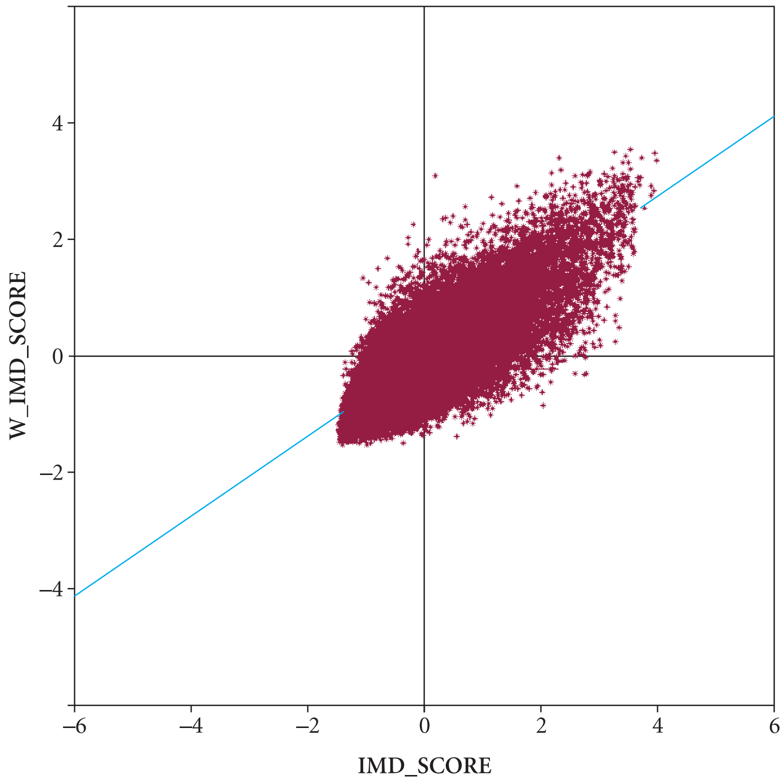

Figure 5. Global Moran's *I* graph for the English IMD 2004 (Moran's *I*: 0.6853)
Note: The Moran scatter plot displays standardised variables, rather than the raw data.

deprivation was becoming increasingly clustered across England as a whole and, in effect, whether the government's policy of spatial targeting was actually working to reduce geographical disparity.[9] At present, however, this is not the intention so it is more useful to consider the extent to which individual areas contribute to the strong positive national figure. This is where the local Moran's *I* statistic is useful since it can help us to differentiate between deprived areas in a statistically more rigorous manner than does the use of the NNIMD alone. For this purpose, the work of Getis and Ord (1992, 1996; see also Ord and Getis, 1995); and Anselin (1995) has been pioneering and the development of new spatial statistical software particularly helpful (Anselin, 2003). Therefore, using Anselin's *GeoDa* package, a range of local indicators of spatial association (LISA) statistics were computed using English IMD data and the first-order contiguity spatial weights matrix.

For each LSOA in England, the local Moran's *I* value was calculated, in addition to the significance values for each statistic and the spatial autocorrelation category for each LSOA. The added value of the LISA approach, above and beyond the NNIMD measure, is that it gives us a score for each individual area relating to the spatial embeddedness of deprivation. It also allows us to determine the significance of each statistic locally and to classify all areas according to this value. A value of 1 represents high-high clusters (enclosed deprivation, in terms of the IMD), 2 represents low-low clusters (enclosed affluence), 3 represents low-high clusters (isolated affluence) and 4 represents high-low clusters (isolated deprivation). A value of 0 is returned where the spatial relationship is not statistically significant. LSOAs characterised as exhibiting 'enclosed deprivation' are highly deprived according to the original IMD and surrounded by other highly deprived areas in a statistically significant manner, according to the local Moran's *I* value. Areas identified as exhibiting 'enclosed affluence' represent the opposite situation, where non-deprived areas are surrounded by similar areas. LSOAs identified by the term 'isolated deprivation' are those which are highly deprived according to the original IMD but are surrounded by LSOAs which are not deprived, according to the local Moran's *I* significance test. Areas identified as exhibiting 'isolated affluence' represent the opposite situation, where non-deprived areas are surrounded by deprived areas in a statistically significant manner.

In a conceptual sense, then, the NNIMD measures tell us how each area relates to its surroundings, while the LISA measures reveal more about the intensity and significance of these relationships. The local Moran's *I* value, LISA category and rank, and significance value for the 20 most deprived LSOAs in England are shown in Table 3. The majority of LSOAs here are among the highest-ranking 20 per cent according to the local Moran's *I* statistic and are classified as exhibiting enclosed deprivation. In the three LSOAs where the local Moran's *I* rank is much higher, this is not an indication of lack of deprivation but rather that these areas are set in more spatially mixed locations and do not have a statistically significant negative or positive spatial context.

These findings are particularly relevant in relation to issues of population turnover, or churning, whereby the socioeconomic composition of local areas can be significantly

Table 3. England's 20 most deprived LSOAs: LISA statistics

LSOA	*IMD score*	*Rank*	*Local Moran's I*	*Local Moran's I rank*	*LISA category*	*Significance value (p)*
Liverpool 018C	86.36	1	10.61125	7	1	0.002
Manchester 009C	85.76	2	6.78022	108	1	0.002
Liverpool 059C	85.59	3	12.22296	1	1	0.002
Manchester 013D	84.92	4	6.47106	132	1	0.002
Manchester 009B	84.78	5	5.98998	183	1	0.004
Manchester 020A	83.08	6	6.55409	126	1	0.002
Knowsley 008C	82.30	7	0.31811	14 426	0	0.410
Liverpool 044D	82.04	8	6.01872	180	1	0.002
Manchester 009A	81.89	9	9.52820	13	1	0.002
Liverpool 018D	81.39	10	10.39411	8	1	0.002
Manchester 015D	81.26	11	8.45011	32	1	0.002
Manchester 017A	80.65	12	11.91362	2	1	0.002
Liverpool 014E	80.62	13	7.53753	60	1	0.002
Knowsley 008D	80.49	14	4.48256	418	1	0.010
Knowsley 003C	80.31	15	8.59643	27	1	0.002
Rochdale 010E	80.29	16	3.53636	712	1	0.020
Middlesbrough 001C	80.20	17	0.17467	17 968	0	0.426
Rochdale 010C	79.99	18	1.46966	2 513	0	0.196
Bristol 031C	79.98	19	10.22856	9	1	0.002
Manchester 024A	79.97	20	7.77876	49	1	0.002

altered through processes of population mobility. In areas of enclosed deprivation, these processes are, in theory, less likely to have positive impacts than in areas of isolated deprivation given the deprived nature of surrounding areas in the former and the less deprived neighbouring areas in the latter. These themes have been explored in more depth elsewhere by Bailey and Livingston (2008) and particularly Robson *et al.* (2008) but are worthy of mention here since the new NNIMD measure helps to establish an empirical basis for estimating the potential for positive interaction through selective migration.

When we consider the high global Moran's *I* value for the IMD across England, it is not surprising that 17 out of the 20 most deprived LSOAs are classified as exhibiting enclosed deprivation. What is more useful here is to examine the distribution of the LISA typology across England, and for the most deprived LSOAs. What we find is a situation where 61.7 per cent of LSOAs nationally, and 50.2 per cent of the 20 per cent most deprived LSOAs, do not have a statistically significant spatial context. When we explore these data in Table 4, we see that the majority of the remainder of LSOAs for both England and the most deprived 20 per cent fall into the enclosed deprivation or enclosed affluence category. In addition, some of the most deprived LSOAs are classified as exhibiting isolated affluence. This might seem counter-intuitive given the focus on the most deprived small areas in England, but it makes sense when we consider that the LISA measures are spatially and statistically relative in as much that, if an area with a low IMD score and rank within the most deprived 20 per cent is located within a larger area of more highly deprived LSOAs, it will logically fall into this category. Following this reasoning, it is to be expected that no areas are classified as enclosed affluence. Given what we know about the level of global spatial association in England as a whole, the fact that only 54 LSOAs are classified as isolated deprivation is also to be expected. Overall, however, 48.8 per cent of the most deprived LSOAs exhibit spatial and attribute characteristics associated with enclosed deprivation.

The spatial pattern this produces is illustrated in Figure 6, where the LISA classification for south Manchester and nearby districts is presented. As with the original IMD, Manchester itself shows evidence of spatially embedded deprivation and most LSOAs within the district fall into the enclosed deprivation category, with some falling within isolated affluence and a much lower proportion of insignificant values than might be expected given the national pattern. By contrast, surrounding districts, with the exception of east Salford, show much more spatial variety. In addition to the NNIMD methods introduced earlier, then, there is added value in calculating local indicators of spatial association for three reasons. First, we are able to understand better the contribution local areas make to the pattern of geographically concentrated deprivation at a national level.

Table 4. Spatial context typology for the English IMD

LISA category	*IMD score relationship*	*Spatial context classification*	*All LSOAs (32 482)*	*Most deprived 20 per cent (6 496)*
1	High-high	Enclosed deprivation	4 403	3 172
2	Low-low	Enclosed affluence	6 657	0
3	Low-high	Isolated affluence	991	7
4	High-low	Isolated deprivation	401	54
0	Not significant	Variable	20 030	3 263

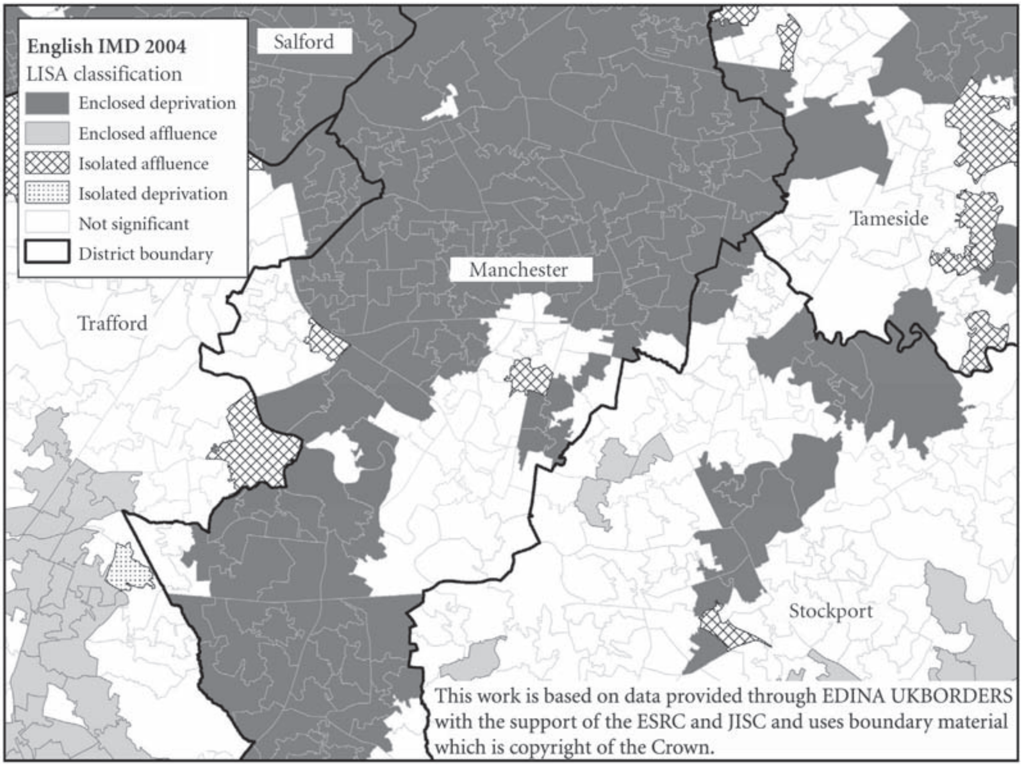

Figure 6. LISA classification in South Manchester and surrounding districts

This could become more relevant as each update of the IMD is released and could also be applied to each of its sub-domains individually. Secondly, the LISA statistics allow us to assess the degree to which the spatial context of individual areas is statistically significant in a formal manner. Conceptually, this is an advance on the NNIMD method alone since it provides further validation and helps to identify more severe cases of spatially entrenched deprivation. Finally, we are able to go beyond identifying statistically significant areas and assign them to a number of clearly identifiable types. These, in turn, can heighten our understanding of the ways in which local areas may or may not be subject to positive or negative area effects. Since the tools are available and the methods longstanding, future research into area effects and area-based policy targeting ought to make greater use of the available resources and give more weight to spatial location. At present, there is a lack of spatial awareness in the mechanism that most commonly identifies local need in England and this represents a potentially serious geographical shortcoming.

Conclusions

It is clear that there is a growing appreciation for, and use of, spatial statistical methods across a range of topics. Kalogirou and Hatzichristos (2007) implement similar techniques in order to develop a spatial modelling framework for income estimation in Athens; Patacchini and Rice (2007) explore the economic performance of Great Britain in the same way; and Orford *et al.* (2008) follow a similar logic in their investigation of differences in electoral turnout. More pertinently, Lorant *et al.* (2001) explore deprivation and mortality, as did Sridharan *et al.* (2007), whilst Dorling *et al.* (2007) examine poverty using spatial statistical techniques. The findings of the more recent work on deprivation and mortality are relevant here since they reaffirm the importance of spatial context, albeit in an exploratory manner and using a different measure of deprivation.

Notwithstanding some recent advances in academic research, then, the integration of spatial approaches into the policy mainstream is still some way off, despite the added value it can bring. What is needed now is further reinforcement and refinement of the ways in which such spatial thinking can act as an epistemological boon to the study of place and the identification of areas which ought to be the focus of policy. One aspect of this ought to follow in the footsteps of Openshaw (1984; also Openshaw and Taylor, 1979) by investigating the impact of using different geographical building-blocks and other fundamental spatial questions, such as the influence of 'boundary effects', influential interaction thresholds and developing more sophisticated controls for physical barriers to social interaction. Another aspect involves further empirical work examining the relationship between local spatial context as defined here and neighbourhood outcomes. Both aspects can be taken forward now that the methodological framework has been constructed.

Spatial context has been explicitly or implicitly identified as important by a range of different scholars without much in the way of consensus as to what it is or how to measure it (for example, Smith *et al.*, 2000; Baller *et al.*, 2001; Buck, 2001; Morenoff, 2003; Sampson, 2003; Bolster *et al.*, 2007). We offer an approach here as a means to demonstrating that it is possible to take a more geographical view of local deprivation and that this can be used as a spatial framework within which studies of area effects can be better informed. However, it will be most useful to those who use the IMD and other local area assessment tools in order to identify pockets of deprivation which are to be the subject of policy targeting. Raising awareness amongst policy-makers of issues relating to place and spatial interaction must be seen as an important aspect of improving the strategies for tackling urban and neighbourhood deprivation. The approach suggested in this paper should help to provide appropriate techniques to address such issues of spatial context.

Notes

1. The IMD 2004 was used to aid area-based targeting decisions for policies currently in operation. A new, comparable, version of the IMD was published in December 2007. The current IMD replaced the previous Index from 2000 and its antecedents the Index of Local Deprivation 1998 and Index of Local Conditions 1991.
2. For a quantifiable measure of deprivation over time, see Dorling *et al.*, (2007). The IMD is also summarised at local authority level and referred to at regional level; a situation which reflects the fact that deprivation is not always addressed at the neighbourhood scale (ODPM, 2004b).
3. In the spatial statistics literature, this 'first law' is most commonly cited with reference to formal measures of spatial autocorrelation (for example, Anselin, 2003; Mitchell, 2005).
4. The nature of upper super output areas has yet to be finalised, but they will have a minimum population of around 25 000.
5. There are many other possible options for choosing a weighting method. The ones presented here are the most logical in this situation (see Mitchell, 2005). The *k-nearest* neighbours approach considers a user-specified number of neighbours (k) in order to determine spatial weights and neighbourhood of influence.
6. The use of 4, 8 and 16 reflects the ideal situation where the spatial structure matches that of a chess board pattern. Whilst this does not exist in reality, it was found that using other multiples did not yield significantly different results.
7. The 20 per cent most deprived criterion is often used as a critical threshold in determining which

areas receive funding from central-government-sponsored area-based interventions.

8. The 2004 IMD has a district-level version in which 'local concentration' and the 'extent' of deprivation are taken into account. Whilst these shed some light on the context of deprived districts, they offer little in the way of spatially contextualising individual LSOAs (ODPM, 2004b, pp. 49–51).
9. The release of the 2007 IMD (in December 2007) at the same spatial level and using very similar methodology to the 2004 IMD does now make spatial and temporal comparison possible. This longitudinal aspect of research is now being taken forward and will be completed in due course.

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