Feedback Form

School of Geography FACULTY OF ENVIRONMENT **UNIVERSITY OF LEEDS** *Students to complete all of the following (or work will not be accepted)*	Name (optional): Richard Thomas
Student ID: **200818341**	Assessment Name (e.g. Essay 2, Group Project etc): Assignment #2: Burglary analysis
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Content, research and reading

Structure and argument

Writing, presentation and referencing

Areas for improvement to prioritise

Marker's signature:	Date:	Provisional mark:

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How can spatial analytical techniques be used to highlight the geography of burglary in Leeds?

INTRODUCTION

Although socio-demographic classification of areas is also important to the analysis of burglaries, this report focuses on analysis of their spatial clustering. After a literature review highlighting the expected nature of spatial clustering of burglaries, several relevant spatial analysis techniques are discussed in turn, followed by a short discussion including the limitations of these techniques.

PREVIOUS FINDINGS ON CLUSTERING OF BURGLARIES

Although many have analysed characteristics of an area that make it more liable to above average rates of burglary, a study of Leeds (2000 – 2002) by Hirschfield et al (2013) details the strong influence of adjacent areas on burglary rates. This can be either a negative influence (a source of potential offenders) or a positive one (an area acting as a buffer zone reducing the likelihood of through journeys by offenders). He also discusses the idea of ‘permeability’ of streets – the ease with which an offender could access (or escape from) another area and also whether streets are likely to generally encourage more passers-by.

Even within a high-crime area, crime levels can vary strongly, even on adjacent streets or street sections (Felson, 2010). ***Optimal Forager Theory*** lends credence to such clustering within areas, with an offender seeking to repeat previous successes by going to the same type of properties (Johnson, 2010), which by their nature are usually clustered together - Tobler’s first law of geography. Johnson recommended that if forager theory is considered valid, such transitory behaviour could be predicted by applying techniques such as Kernel Density Estimation (KDE) to analyse crimes over just the previous few weeks. In a study of a police burglary reduction initiative in Leeds, Addis (2012) found strong indications of such optimal forager behaviour in crime figures analysed. Repeat victimisation in burglary is a further step in clustering. Johnson (2010) stated that although figures as high as 29% of burglaries have been reported for this, such repeats are usually under-reported due to growing loss of faith in the authorities by victims.

In a study of crime “generators and attractors”, Brantingham (1995) highlight ‘edges’ of areas (whether a transition is real or perceived) as often being high crime locations, partly due to outsiders feeling less conspicuous there rather than in the centre of a close-knit community.

The popular ***Routine Activity Theory*** requires that for a crime to occur there needs to be a "likely offender", a "suitable target" and no "capable guardian" (Felson, 2010, p276). Most of the rest of this report focuses on the second of these (the burglary location), although the “capable guardian” could be location-specific such as in the form of an overlooking neighbour. In a rigorous statistical analysis of means and likelihood of entry for burglary, Coupe and Blake (2006) highlights that an entry points visibility from the street is less important than the visibility (and presence of) neighbouring properties.

OVERVIEW: CHLOROPLETH MAPPING

Figure 1 gives an indication of distribution (and therefore clustering) of burglaries in Leeds. In order to map where burglary is above average it is important to normalise the counts by the ‘population’ at risk, typically number of households (Turton and Turner, 2011). However, this still isn’t entirely accurate as repeat burglaries can occur at a household.

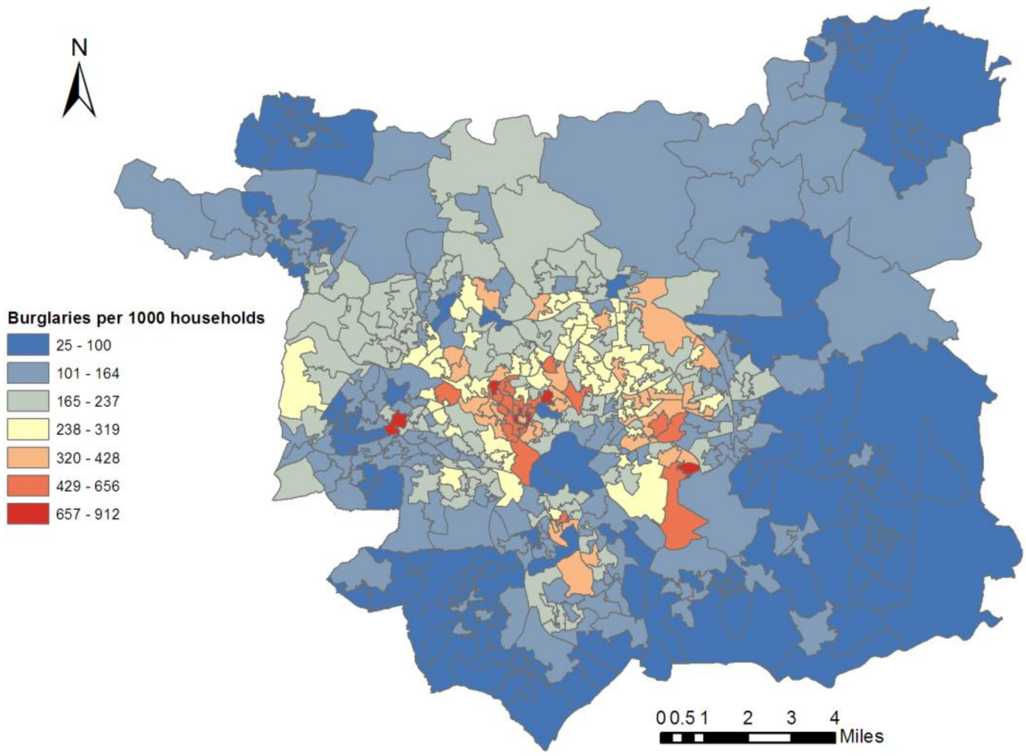

Figure 1: Burglaries by each census 'LSOA' in the Leeds Metropolitan District for the period 2000 - 2003

'HOT SPOT' STATISTICAL ANALYSIS

The Getis-Ord Gi* 'hot spot' analysis is a local method (acting on geographically nearby data) that performs a mathematically rigorous test of statistical significance for clustering that many other methods such as KDE lack (Chainey and Ratcliffe 2005).

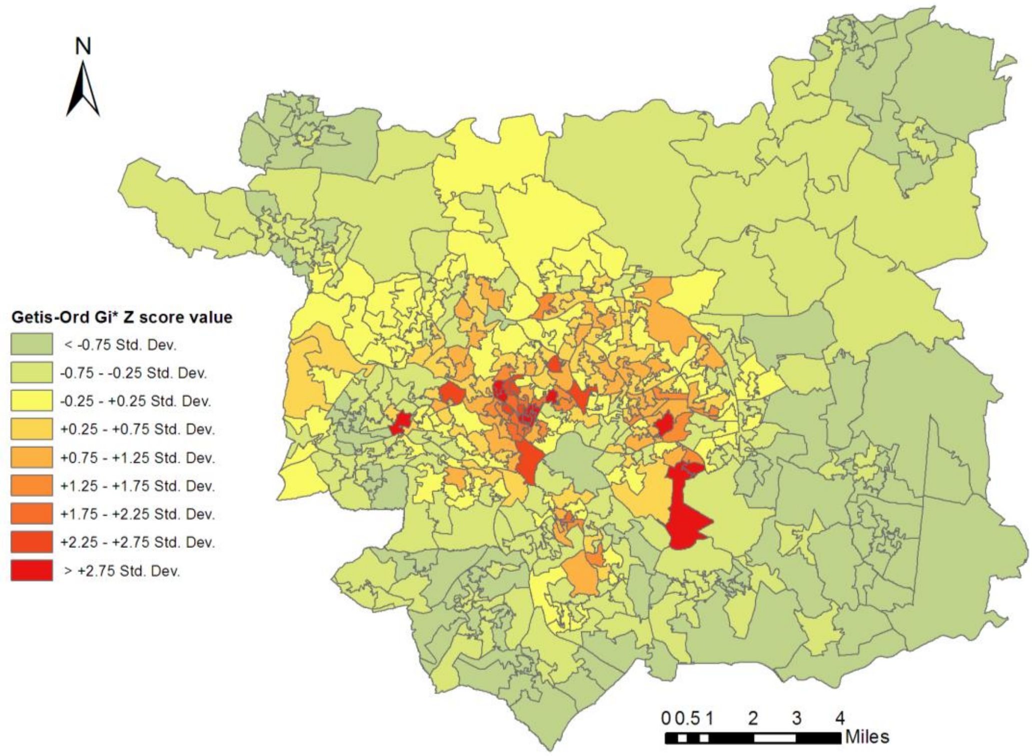

Figure 2: Getis-Ord Gi* Z score value (Burglaries) by LSOA for the period 2000 - 2003

Although scaled in quite a different way, the hot spots highlighted in this map are remarkably similar to those of the previous map. However, their presentation may be somewhat misleading: assuming that the hot spots are spread relatively evenly throughout the whole area of each LSOA would be to commit the "ecological fallacy". In theory, the Gi* statistic could be directly calculated using the individual burglary locations. However, the nature of the calculation requires the search window to be big enough to ensure that each burglary has at least one neighbour within the search window. For the supplied data, this would require a 3km search window which in many cases would include over a thousand "neighbours" in the window, overwhelming the calculation. (The ArcGIS manual states that this can be overcoming by generating a "spatial weights matrix" to dynamically vary the window size, but even having done this the software repeatedly fails when trying to analyse the whole area).

GEOGRAPHICAL ANALYSIS MACHINE (GAM)

The GAM/K algorithm was "designed to detect localised spatial clustering without knowing either where to look or at what scales to look for patterns." (Openshaw et al, 2000, p94). As such it seemed ideally suited to running before KDE which requires prior knowledge of expected cluster size. However, with the supplied data it seemed remarkably sensitive to it parameter settings; only on reducing the 'max circle size' below a certain threshold would it suddenly able to detect a large central cluster. However once tuned (circle range: 250m to 2km), figure 3 shows statistically significant cluster detection in line with the Gi* calculation. Unfortunately, with this incarnation of the software, the spatial resolution of the output is fixed at quite a low resolution.

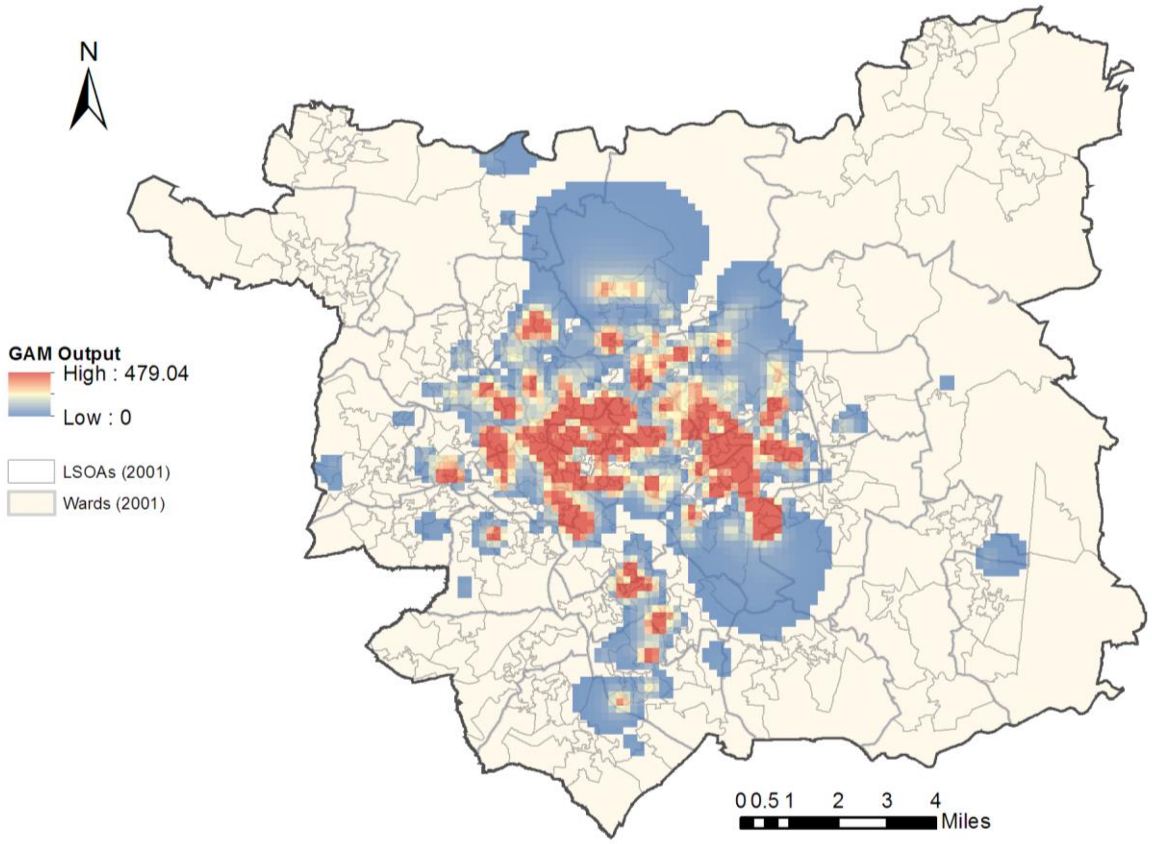

Figure 3: Geographical Analysis Machine (GAM) cluster detection output for the period 2000 - 2003

KERNEL DENSITY ESTIMATION (KDE): CLARIFY PROBLEM AREAS + EVOLUTION

Due to its simplicity of operation, KDE output is relatively simple to visually interpret and can have its bandwidth (circle radius) tuned to detect large clusters or to explore smaller scale clustering within those larger clusters (Johnson 2010). However, the flip-side of that flexibility is that for meaningful results, suitable bandwidths must be determined. A popular method (Chainey and Ratcliffe, 2005) taking into account the actual dispersion of crimes is to set it to the mean distance of the Kth nearest neighbour, though K is then chosen somewhat arbitrarily. For the analyses in this report, for Leeds-wide cluster detection, a radius of 500m was settled upon as giving similar results to the GAM output and seeming of the right order for a typical housing neighbourhood. The actual calculations performed were of 'double density' KDE type (dividing by a 'population' figure representing a 'local' household count); this should give a burglary risk factor normalised for the density of housing in an area.

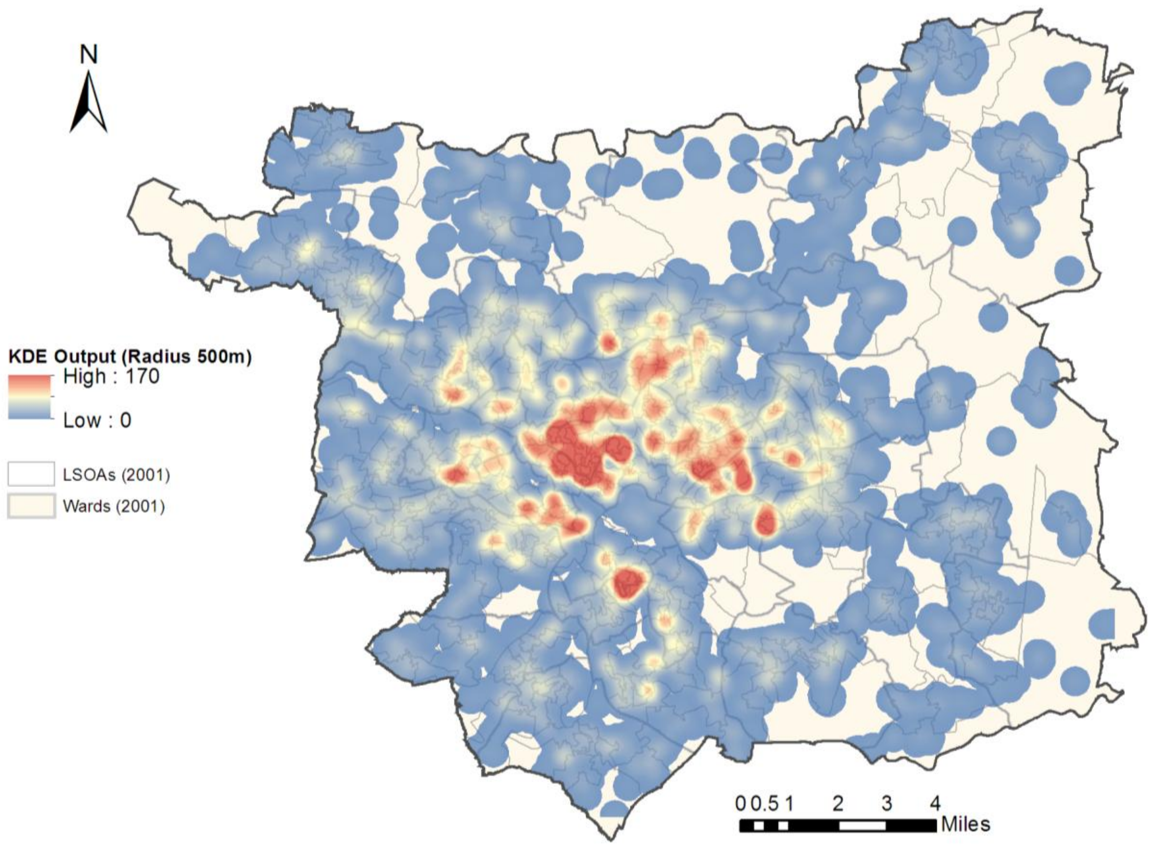

Figure 4: Kernel Density Estimation (KDE) cluster detection output for the period 2000 - 2003

From this Leeds-wide view, we can zoom in to the area of hot spots and add a basemap to better identify some of the burglary cluster neighbourhoods (figure 5) which include: Halton Moor, Beeston Hill, Burley/Hyde Oark/Headingley/Meanwood, New Wortley/Armley.

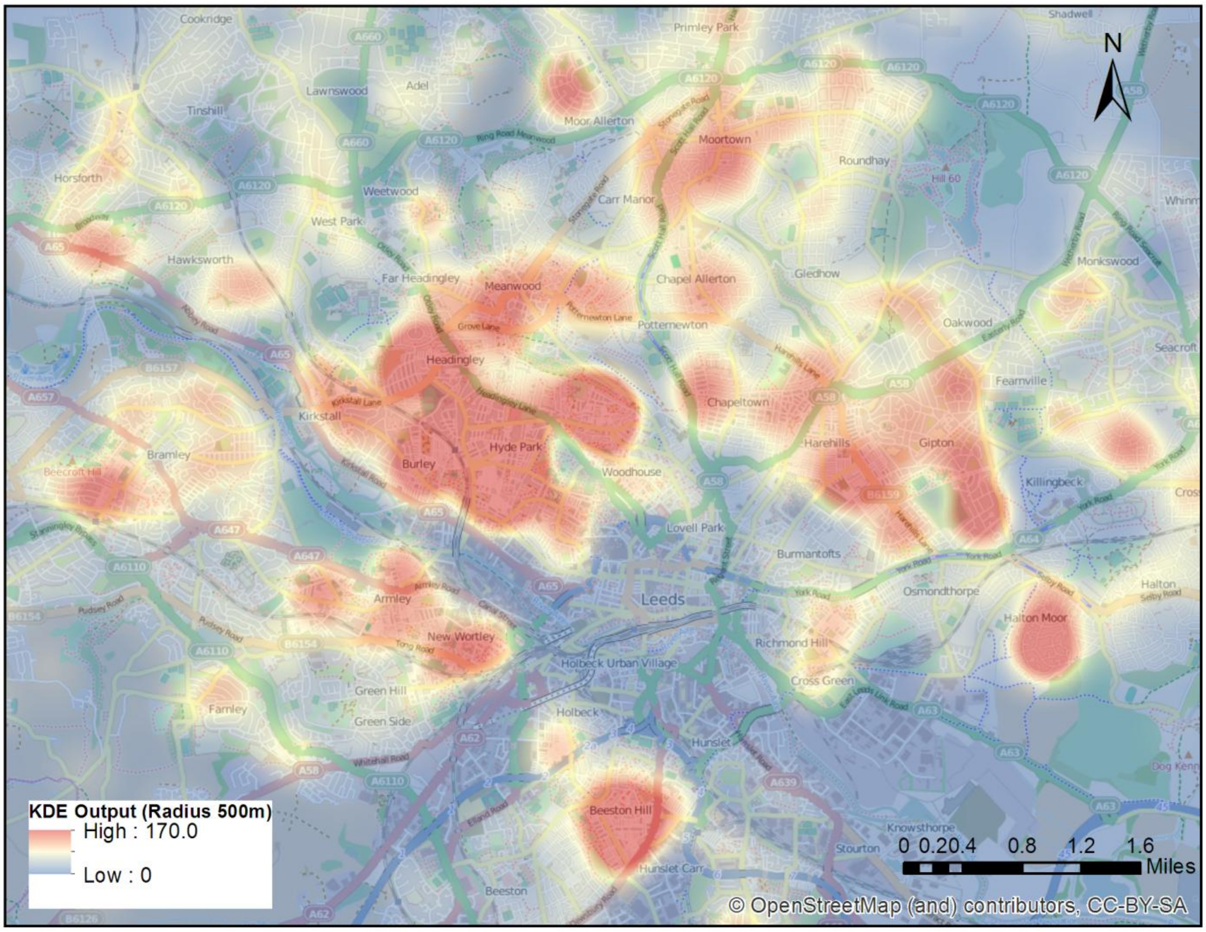

Figure 5: Kernel Density Estimation (KDE) cluster detection selection for the period 2000 - 2003

KDE: TEMPORAL ANALYSIS

It is important to consider how the hot spots evolve over time. By separating out the supplied data by year (figure 6), it is apparent how areas have changed (note how the New Wortley hot spot has appeared to extend to Armley in 2003). Over longer time frames this temporal analysis could be helpful in re-allocation of police resources to meet local needs. However, analysing up-to-date data in steps of just a few weeks could help predict localities targeted by ***Optimal Forager*** behaviour.

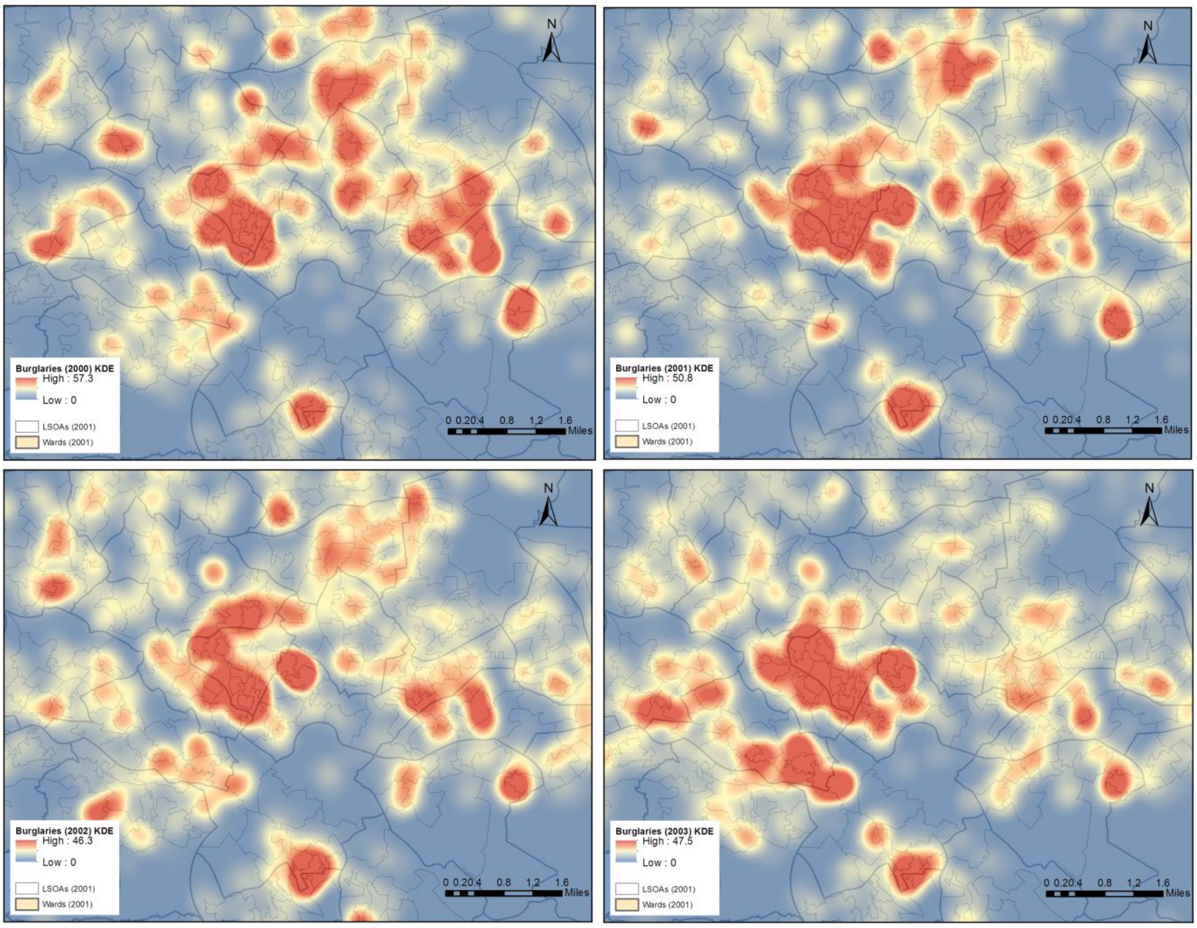

Figure 6: Kernel Density Estimation (KDE) sequence by year from 2000 - 2003

KDE: SMALL SCALE FOCUS ON PROBLEM AREAS

Re-running KDE with much smaller bandwidths (50m in figure 7) can help identify problem clusters of particular streets (or even street sections).

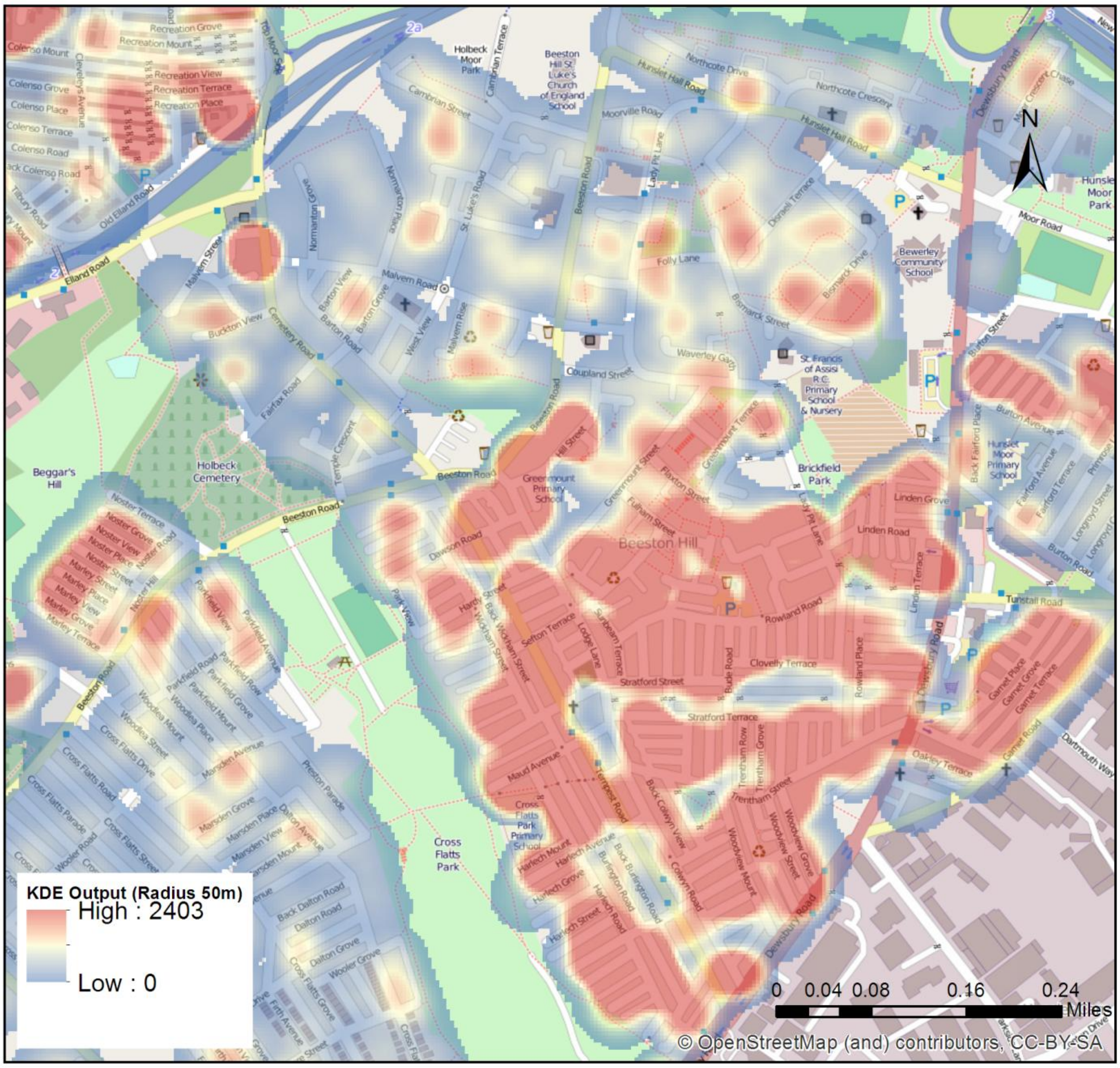

Figure 7: KDE Street level clustering within larger scale cluster (Beeston Hill)

REPEAT VICTIMISATION

Repeated burglaries of the same household can indicate systematic security or behaviour problems. In a study of burglary in Cambridge, Bennett (1995) found that 35% were repeat burglaries (corresponding with 19% of addresses). Figure 7 shows an alternative way to view the Beeston Hill area highlighting the incidence of repeat victimisation that cannot be seen with KDE or point mapping.

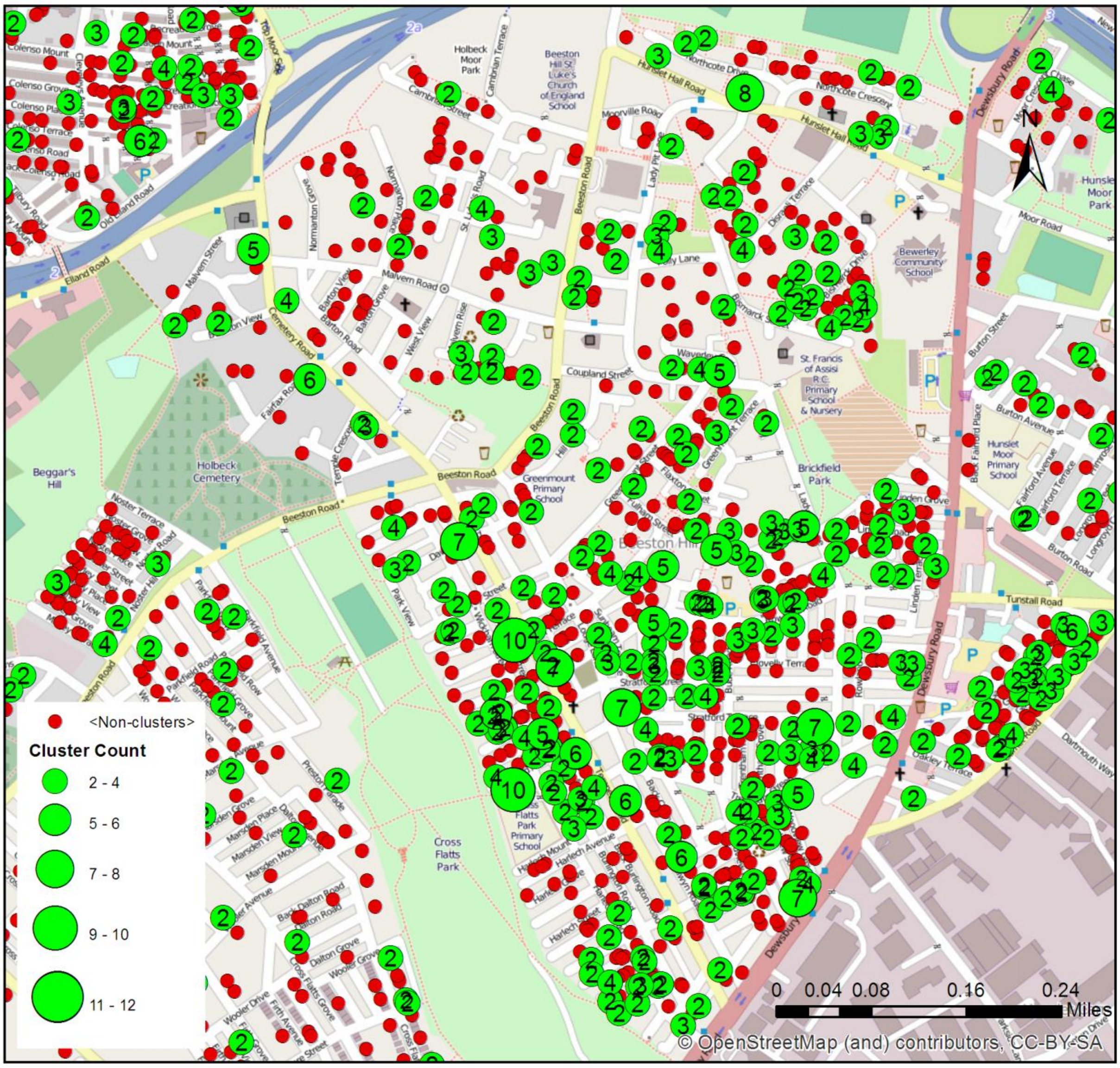

Figure 8: Repeat victimisation mapping within Beeston Hill cluster

SUMMARY AND CONCLUSION

This report has outlined several techniques to better analyse and visualize spatial clustering of burglaries, which should be used in conjunction with other techniques including socio-demographic classification-based attribute-clustering analysis. One of the limitations of these methods is the difficulty in considering temporal clustering and change, for which additional tools could be investigated (including ArcGIS CrimeAnalyst). The use of more dynamic tools such as Agent-Based Modelling of journeys to crime (Malleson et al, 2013) could help predict or suggest ways of deterring future burglaries.

REFERENCES

Addis, N. 2012. Exploring the impact and effectiveness of the ‘Project Optimal’Burglary Reduction Initiative in Leeds: A Spatio-Temporal Approach.

Atkinson, P. 2000. GIS and GeoComputation: Innovations in GIS 7.

Bennett, T. 1995. Identifying, explaining, and targeting burglary 'hot spots'. *European Journal on Criminal Policy and Research.* **3**(3), pp.113-123.

Brantingham, P. 1995. Criminality of place - Crime generators and crime attractors. *European Journal on Criminal Policy and Research.* **3**(3), pp.5-26.

Chainey, S. and Ratcliffe, J. 2005. GIS and crime mapping.

Coupe, T. and Blake, L. 2006. DAYLIGHT AND DARKNESS TARGETING STRATEGIES AND THE RISKS OF BEING SEEN AT RESIDENTIAL BURGLARIES*. *Criminology.* **44**(2), pp.431-464.

Felson, M. 2010. What every mathematician should know about modelling crime. *European Journal of Applied Mathematics.* **21**(4-5), pp.275-281.

Hirschfield, A.Birkin, M.Brunsdon, C.Malleson, N. and Newton, A. 2013. How places influence crime: The impact of surrounding areas on neighbourhood burglary rates in a British City. *Urban Studies.*

Johnson, S.D. 2010. A brief history of the analysis of crime concentration. *European Journal of Applied Mathematics.* **21**(4-5), pp.349-370.

Malleson, N.Heppenstall, A.See, L. and Evans, A. Optimising an Agent--Based Model to Explore the Behaviour of Simulated Burglars.

Openshaw, S.Turner, A.Turton, I.Macgill, J. and Brunsdon, C. 2000. Testing space-time and more complex hyperspace geographical analysis tools. *online at &lt.*

Rogerson, P. 2004. The application of new spatial statistical methods to the detection of geographical patterns of crime. *Applied GIS and Spatial Analysis.* pp.151-168.

Tate, N.J. 2000. Surfaces for GIScience. *Transactions in GIS.* **4**(4), pp.301-303.

Turton, I. and Turner, A. Putting the Geographical Analysis Machine on the Internet Revisited.