Intelligent policing: a GIS approach to spatialising crime

Part I

Introduction

The link between geography and crime was noted by sociologists and criminologists in the 1980s, and followed by police pin-maps depicting crime distribution (Kumar & Chandrasekar, 2011). Crimes have been theorised as non-randomly dispersed, being based on offenders and their targets co-existing in space (Akpinar & Usul, 2004).

This spatial understanding of crime has encouraged spatial solutions, for analysing and then reducing crime (Chainey, et al., 2008; Cozens, et al., 2005). Geographic Information Systems (GIS) tools are increasingly used to highlight crime's spatial patterns and inform policies as a versatile, portable, and powerful method of analysis as a digital repository (Wieczorek & Hanson, 1997). This paper seeks to contribute towards both aims of (i) analysing the spatial pattern of crime and (ii) producing a reproducible piece of research as a tool for subsequent studies to inform policy recommendations regarding crime.

Additionally, the current context has seen significant cuts to the UK police budget. Consequently, Dalton (2018) notes that entire cities have been left without police stations, raising questions about safety. This makes it extremely pertinent to accurately analyse crime data, to allow limited police spending to be best informed for maximum benefits. Per the context, this research will be city-level in the UK. In line with the second aim above, it seeks to provide an easily replicable guide for future crime distribution studies at the convenient (in terms of data accessibility and analysis manageability) level of the city.

Manchester city was chosen as the study site for high crime rate (Figure 1).

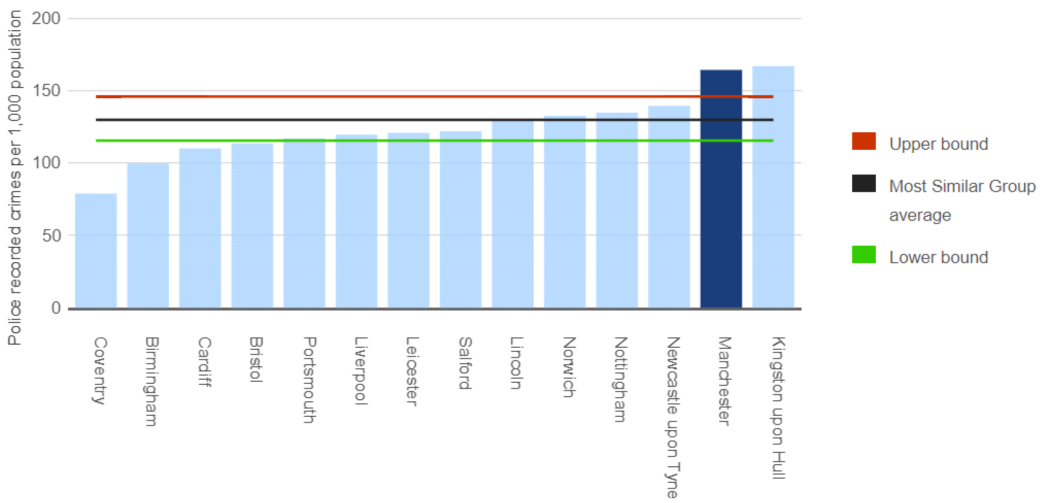

Figure 1: UK Crime statistics for year ending June 2019. Manchester in second highest place. (ONS, 2019)

Literature Review

GIS has been discussed in criminology literature to have three notable uses: visualising crime distribution, revealing crime predictors and thereafter contributing to crime control and prevention policies (Tengbeh, 2006).

Firstly, GIS has enormous potential to visualise crime distribution by detailing and thereafter analysing different spatial patterns (such as crime density hotspots) using software (Lab, 2000; Ractiffe & McCullagh, 1999). Ahmadi (2003) has used GIS to study the locational aspects of crime by identifying zones of abnormally high or low crime. Such visualisations have been done internationally in Turkey, Iran and Nigeria (Akpinar & Usul, 2004; Nezami & Ehsan, 2016; Aov, et al., 2017). A commonly used technique is kernel density estimation (KDE), which was found to consistently outperform others (Chainey, et al., 2008).

GIS has also been used to examine predictors of crime. Nezami and Ehsan (2016) used a Geographically Weighted Regression (GWR) to model crime distribution by a range of variables including population density, distance from city and police stations, and illiteracy. Likewise, Sohn (2016) used GIS to study the effect of various factors such as street density, population density, and distance from police station on crime. Both agreed that crime rates are proportional to distance from a police station, echoing others (Murray, et al., 2001; Sherman & Weisburd, 1995; Akpinar & Usul, 2004). Additionally, Nezami and Ehsan (2016) found that there was neither a meaningful relation between population density nor illiteracy rates and crime occurrences. Akpinar and Usul (2004) found otherwise, noting that a higher crime rate was associated with higher population densities, higher unemployment rates, and lower education levels.

Through its visualisation and predictor-analysis abilities, GIS can be used to inform crime control and prevention policies. Weisburd et al. (2014) argue that with GIS' spatial analysis, the unit of analysis for the crime problem can be more focussed, centred around areas vulnerable to crime. One such strategy is crime prevention through environmental design (CPTED), involving altering physical design, risk assessments, and socio-economic/demographic profiling in GIS-identified crime hot-spot areas (Cozens, et al., 2005). Additionally, the study of effectiveness of police station locations in discouraging crime in hotspots has helped better site future ones (Malaika, et al., 2014; Millie, 2012). Crime visualisation and analysis thus informs effective police activities and policies (Eck, et al., 2007).

The increasing acceptance of GIS in criminology academia must however be tempered by several reservations.

Zhang et al. (2014) argue that GIS' effectiveness in policing has been insufficiently and independently researched. Similar findings surfaced by Bowers and Johnson (2014): only 29% of officers felt that GIS mapping informed operational decisions. This marks a disconnect between the academic interest in GIS and its operational impact. Further research should thus have clearly interpretable/operationalisable findings.

GIS analyses are also heavily dependent on the quality of data used and presented. Tompson et al. (2015) note that public UK crime data is processed using geomasking techniques for victims' privacy. Hence, though the spatial accuracy of this data is good till LSOA level, it becomes significantly erroneous at the postcode level, making micro-level GIS research untenable. Chainey and Tompson (2012) further critiqued poor cartographic practice in the form of misleadingly presented GIS data on the national mapping website. As such, clearer maps must be produced from the crime datasets.

Research Questions and Hypotheses

Research Question 1 (RQ1): Are crimes randomly dispersed in Manchester?

Research Question 2 (RQ2): What is the relationship between crime distribution patterns and police station locations, if any?

Hypothesis 1: Crime clusters non-randomly in Manchester city.

Hypothesis 2: Crime is dispersed away from police stations, controlling for population density and deprivation.

Methodology

Data and Software

This paper uses Manchester city to analyse the spatial pattern of crime, and to produce a reproducible R-tool easily replicable for other cities in future: https://tsin95.github.io/CASA0005GISProj/.

A shapefile of Greater Manchester by wards was taken from UK 2011 census data (UK Data Service, 2020) and then cropped to Manchester city. ONS attribute data for Manchester wards (population density and deprivation) was used (ONS, 2013; ONS, 2013). These variables were selected as controls given existing literature above suggesting possible links with crime occurrences (Nezami & Ehsan, 2016; Sohn, 2016). Deprivation was measured based on households being deprived on 0-4 dimensions of employment, education, health and disability, and household overcrowding. The average number of dimensions of deprivation per household in each ward was used, proxying income and standard of living.

A GeoJSON file of police station locations in greater Manchester was derived from OpenStreetMap using the overpass-turbo API (overpass turbo, 2020). It was clipped to the 4 police stations in Manchester city.

Crime data for June 2019 of Greater Manchester was taken from the police website (DATA.POLICE.UK, 2020), and clipped for Manchester. Spatial repeats were retained as more than one crime occurrence could have happened at the same spot.

All data was mapped using packages in R (see website). R was chosen as an open-source software, which would allow the research to be replicable from the code posted online.

Techniques

Descriptive statistics and visualisations were performed for each of the variables (population density, deprivation, and crime occurrences).

The analysis was then split into three main components.

First, a Kernel Density Estimation (KDE) was done for crime data in Manchester city. This was to visualise of crime distribution, in helping to answer RQ1. However, to perform statistical for Complete Spatial Randomness (CSR) across Manchester was unfeasible given limited computational power. As such, Bradford ward was selected as a proxy for the city, given its relatively high crime rate and the presence of two police stations which would help in answering RQ2.

Next, a KDE of crime in Bradford was performed, followed by testing for clustering or CSR using Ripley's K, the Kolomogorov-Smirnoff test, and the G and F function tests. Density-based spatial clustering of applications with noise (DBSCAN) was then performed to locate the clusters. This would shed light on both RQ1 and RQ2, the latter as police station locations could then be compared to the cluster locations.

Finally, crime occurrences across Manchester city by ward were tested for spatial autocorrelation using Moran's I and Geary's C, answering RQ1, and a range of spatial regressions were run to determine if police station location was related to crime distribution, for RQ2. Beginning with the Ordinary Least Squares (OLS) regression as a base, these included the Spatial Lag Model (SLM), the Spatial Error Model (SEM), and Geographically Weighted Regression (GWR).

Limitations

Limitations exist with this methodology, such as with data. As noted by Tompson et al. (2015), the jitter introduced by the police into the crime data would increase errors, especially at postcode level. This was managed by ensuring that the smallest unit of analysis adopted was ward level, above the minimum recommended LSOA level by Tompson et al. (2015). Furthermore, the dataset was for reported crime, omitting the important component of unreported crime, though this remains a systemic weakness of criminological analyses (Willis, 1983).

Secondly and more broadly, this paper could not conduct detailed statistical analyses for the entire Manchester city with regards RQ1 owing to insufficient computational capacity. Instead, a subset (Bradford ward) was chosen. This paper thus recommends an extension of replicating the research across the rest of Manchester (by wards).

Part II

Results and Discussion

Descriptive Statistics and Visualisation

The dependent variable, crime occurrences, was positively skewed (Figure 2). A log transformation was adopted for regressions for a more normal distribution (Figure 3). Blue lines represent median and red mean. The City Centre ward was an hi-Tukey outlier, but was retained due to its centrality increasing crime likelihood.

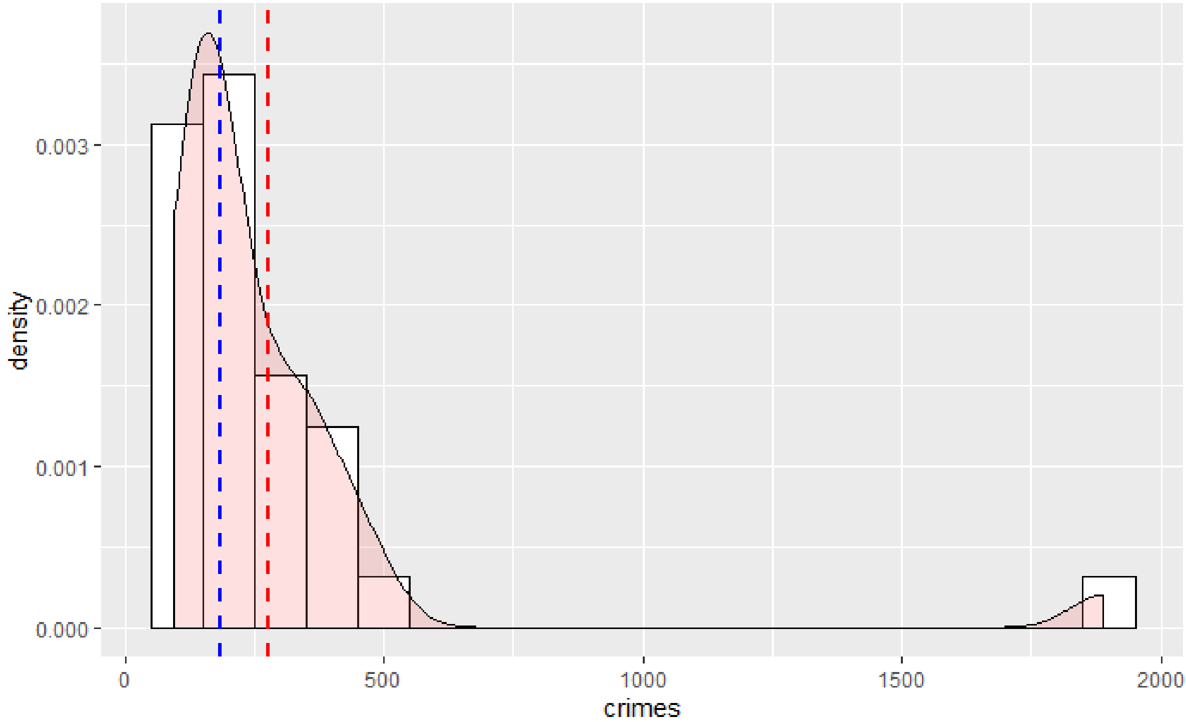

Figure 2

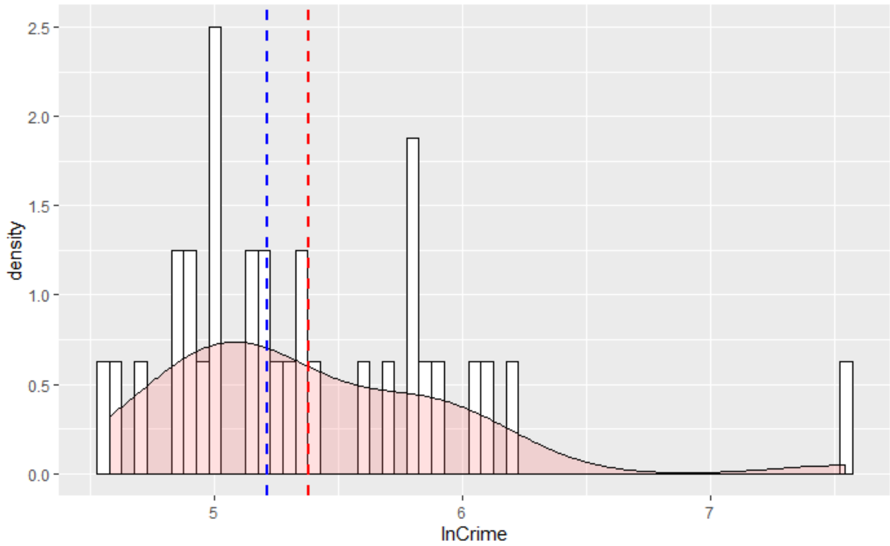

Figure 3: Histogram of log-transformed crime occurrences

The data was joined by ward to the Manchester shapefile (Figure 4), along with locations of the 4 police stations (blue dots).

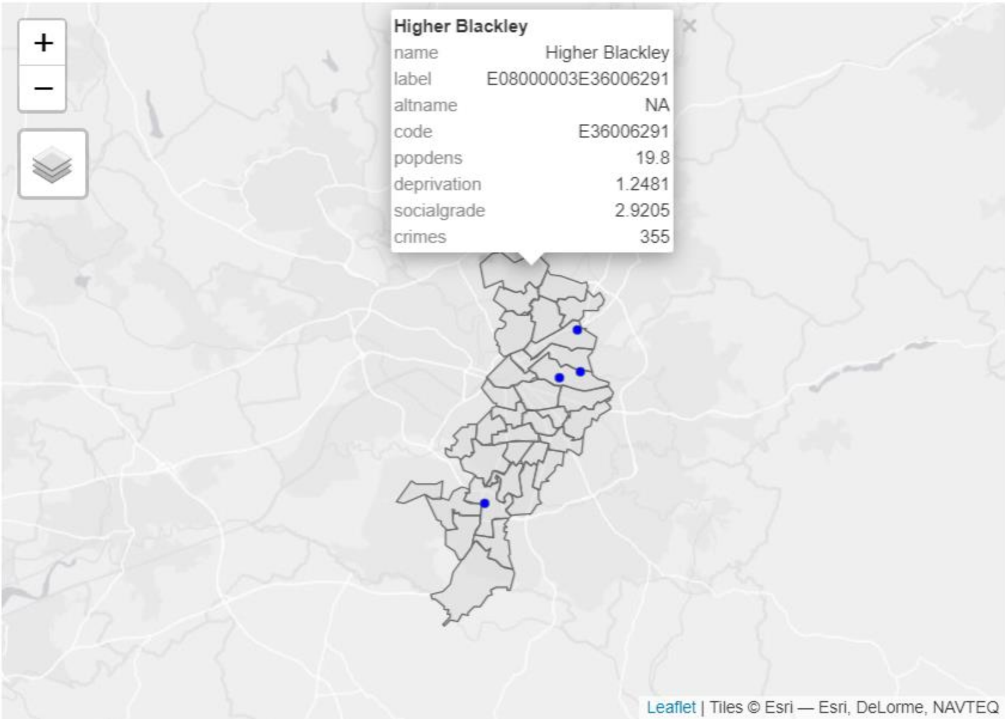

Figure 4: Screenshot of interactive map of Manchester city with joined data by ward, which can be found by scrolling up from https://tsin95.github.io/CASA0005GISProj/Journal.html#4_choropleth_maps_by_variables_across_manchester.

Choropleth maps of the city for each variable were plotted (Figures 5, 6 and 7). There was a higher crime concentration in the north-west and higher deprivation in the north-east nearby. Population density was higher around central Manchester.

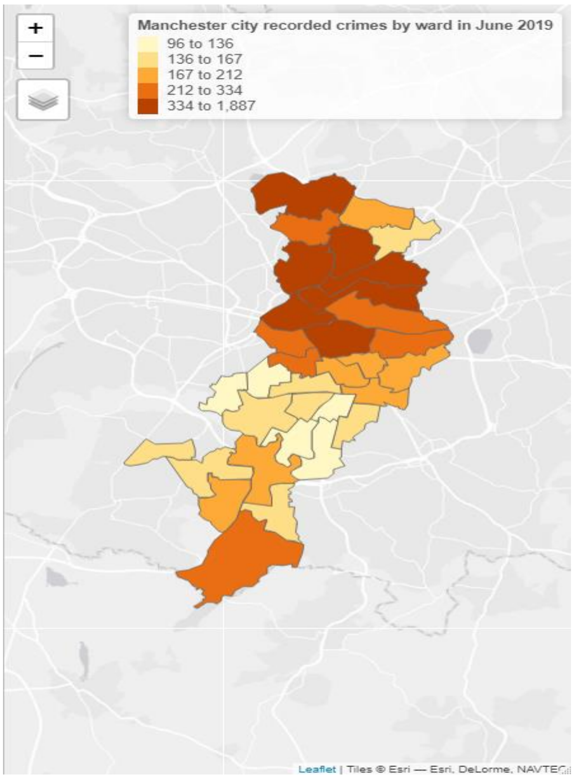

Figure 5: Darker areas represent higher crime rates

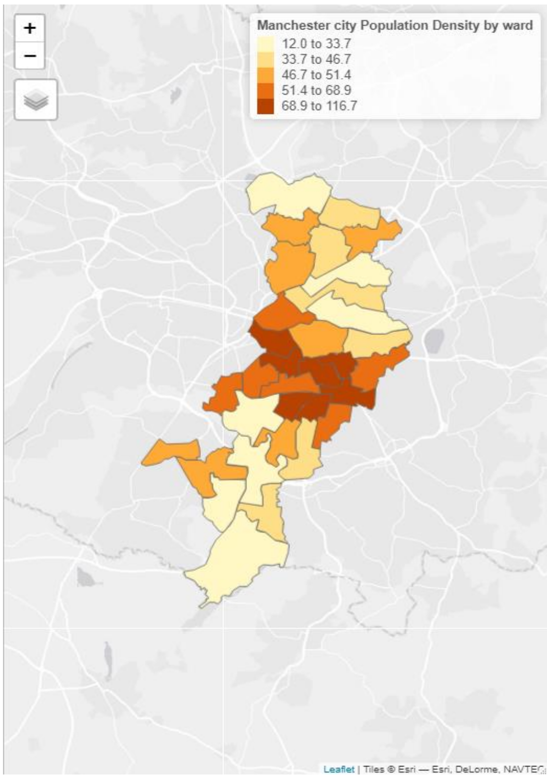

Figure 6: Darker areas represent higher population density

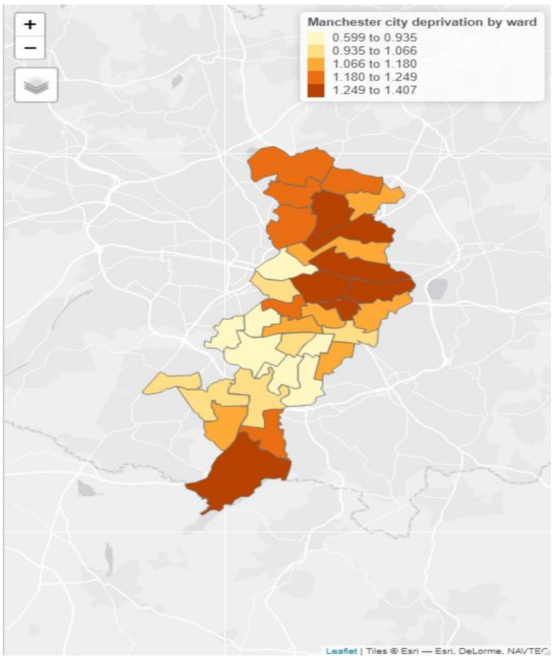

Figure 7: Darker areas represent greater deprivation

KDE for crime occurrences in Manchester

A KDE analysis on crime occurrences in Manchester city was then performed (Figure 8). A concentration of crime at a north-western spot in Manchester was seen, consistent with Figure 7.

Computational limitations hindered detailed geo-statistical analysis of the significance of city-level clusters. As such, the same analysis was subsequently carried out on Bradford ward, with the intention of future replicability across other wards.

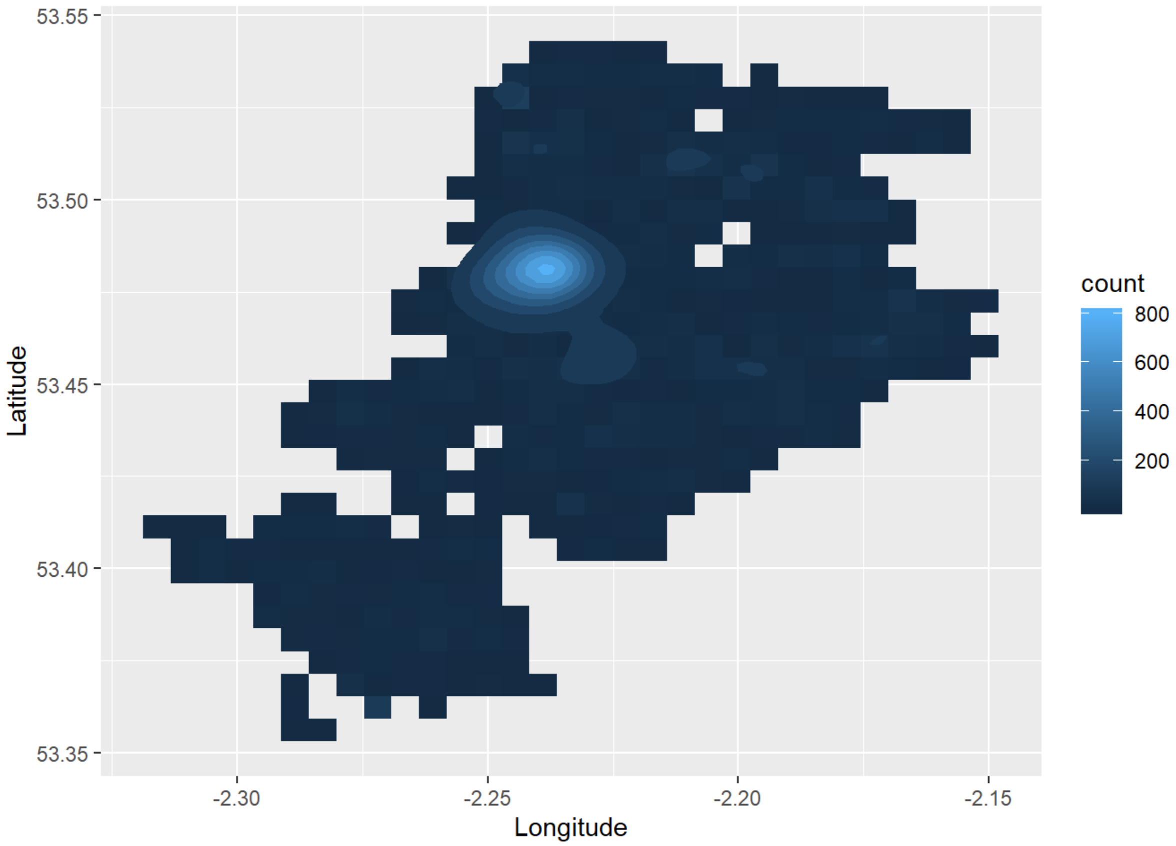

Figure 8

RQ1: Bradford analysis

The locations of crime occurrences were plotted, alongside the 2 police stations, overlaying the Bradford ward (shaded, Figure 9).

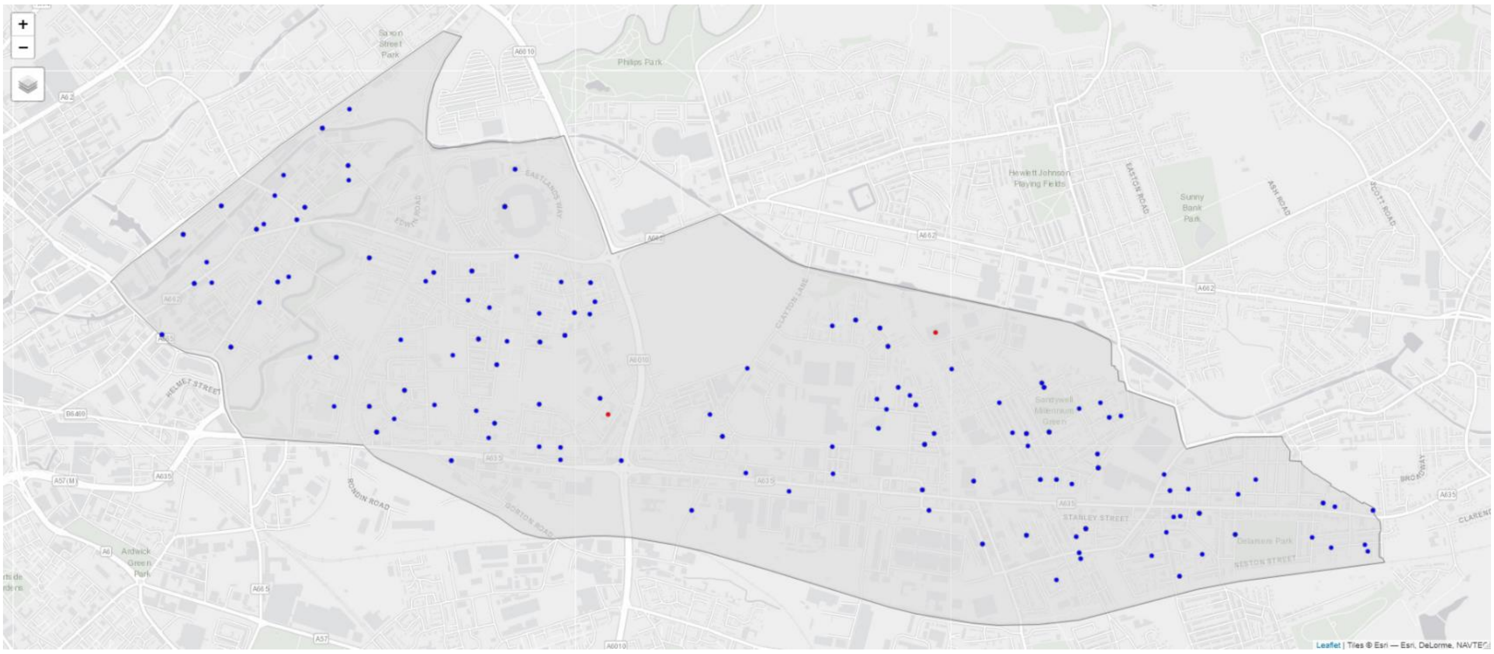

Figure 9: Blue points denote crime occurrences, red points police stations

A KDE was first performed on crime occurrences in Bradford suggesting two clusters visually – one in the east and the other in the west, illustrated by Figure 10's contoured density map.

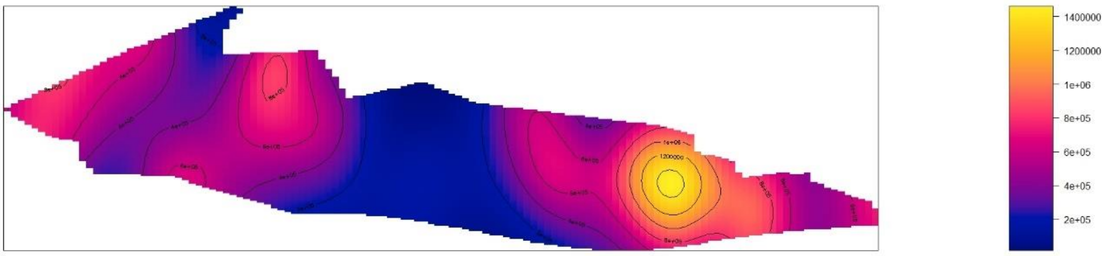

Figure 10: Hotter colours indicate higher crime density

Ripley's K confirmed that there was clustering across the ward (Figure 11), with the unbroken line falling above the dotted line at all distance windows.

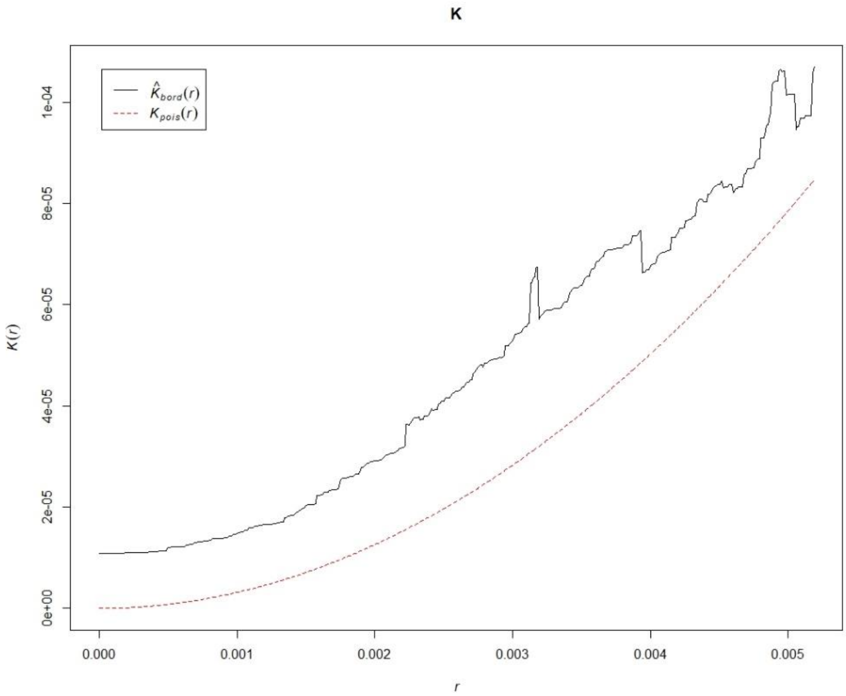

Figure 11: The dotted line represents the theoretical value for K under a Poisson assumption of CSR for each degree increase in longitude at 53.5degrees latitude (Manchester) – each increase of 0.001 is approximately 110m. The unbroken line refers to the estimated values of K accounting for effects on the Bradford border.

Next, the spatial Kolmogorov-Smirnoff test of CSR was performed (Figure 12). It used a real function defined at all crime occurrence locations, comparing the evaluated result at each with the predicted distribution under CSR assumptions (Burchfield, 2019). The observed and predicted T distributions are significantly different, from the low p-value, suggesting that crime occurrences in Bradford are not randomly distributed.

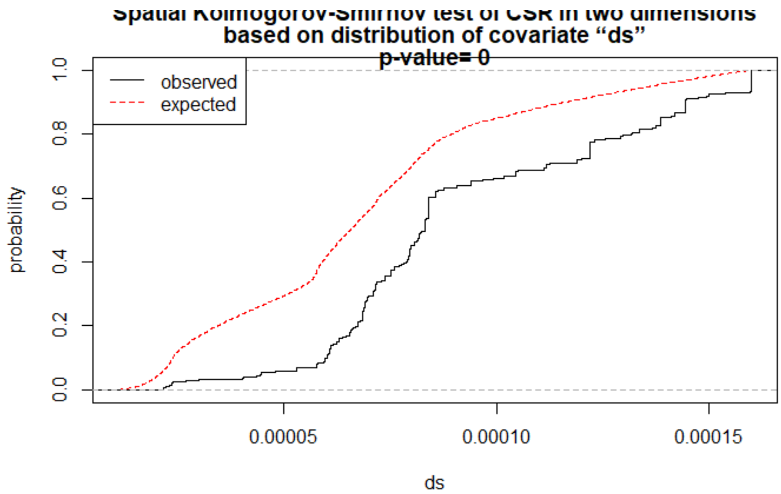

Figure 12

The G and F functions (Figures 13 and 14 respectively) were also used. The former measures nearest neighbour distances from any crime occurrence; the latter the average space left between events. For the former, if the empirical function is greater than the theoretical one, nearest neighbour distances are smaller than in a CSR scenario, suggesting clustering. For the latter, clustering is indicated by the empirical function being smaller. Both tests indicated non-random clustering.

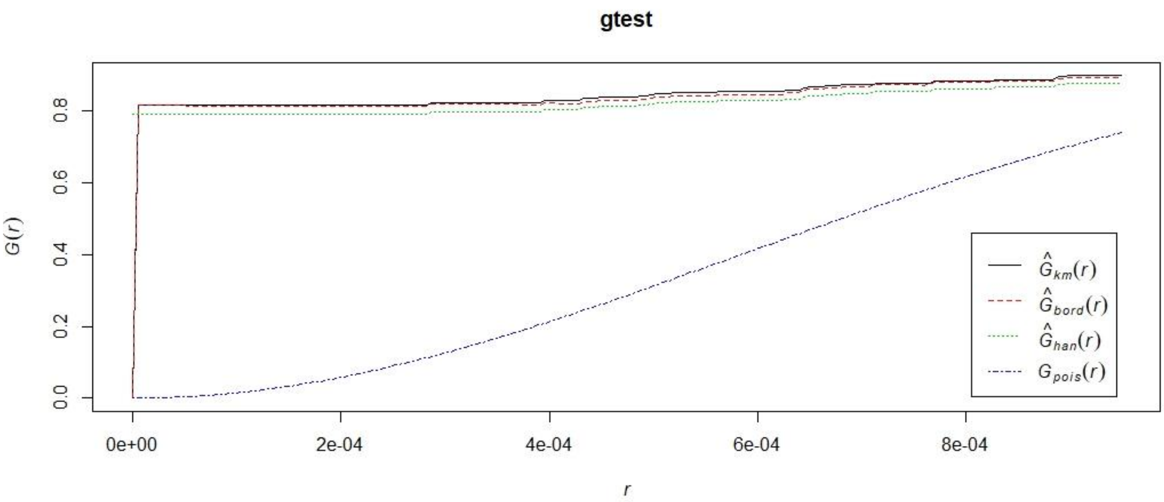

Figure 13: theoretical function denoted by blue dotted line below.

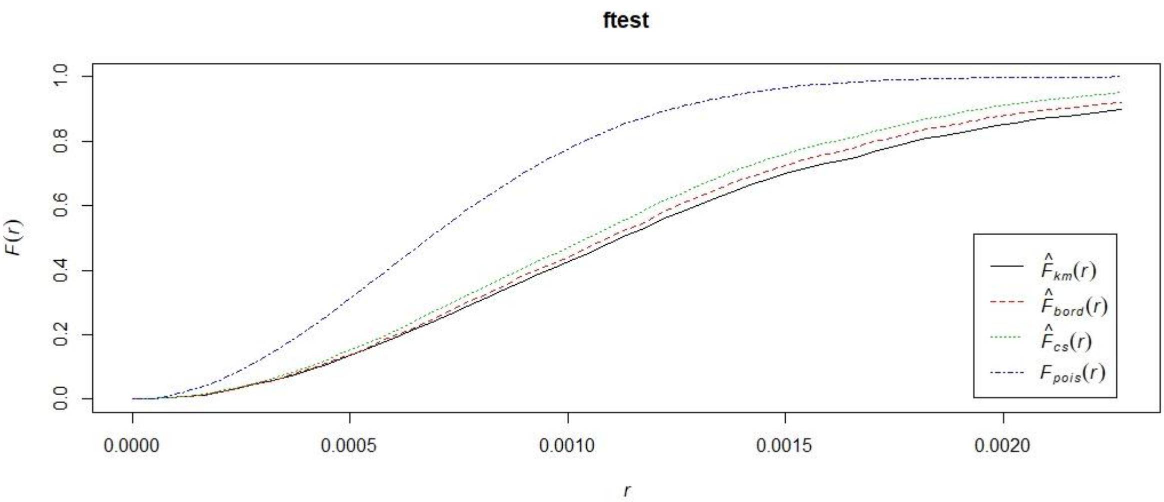

Figure 14: theoretical function denoted by blue dotted line above

After statistically confirming their presence, this paper sought to determine the locations of the clusters using DBSCAN.

The kNNdistplot() function determined that a suitable epsilon value was 300m (Figure 15), or 0.003 longitude degrees, with cluster sizes as 30. The two previously visually observed clusters were confirmed (Figure 16). Additionally, the crime clusters did not seem far from the police stations, prompting further analysis in the next section.

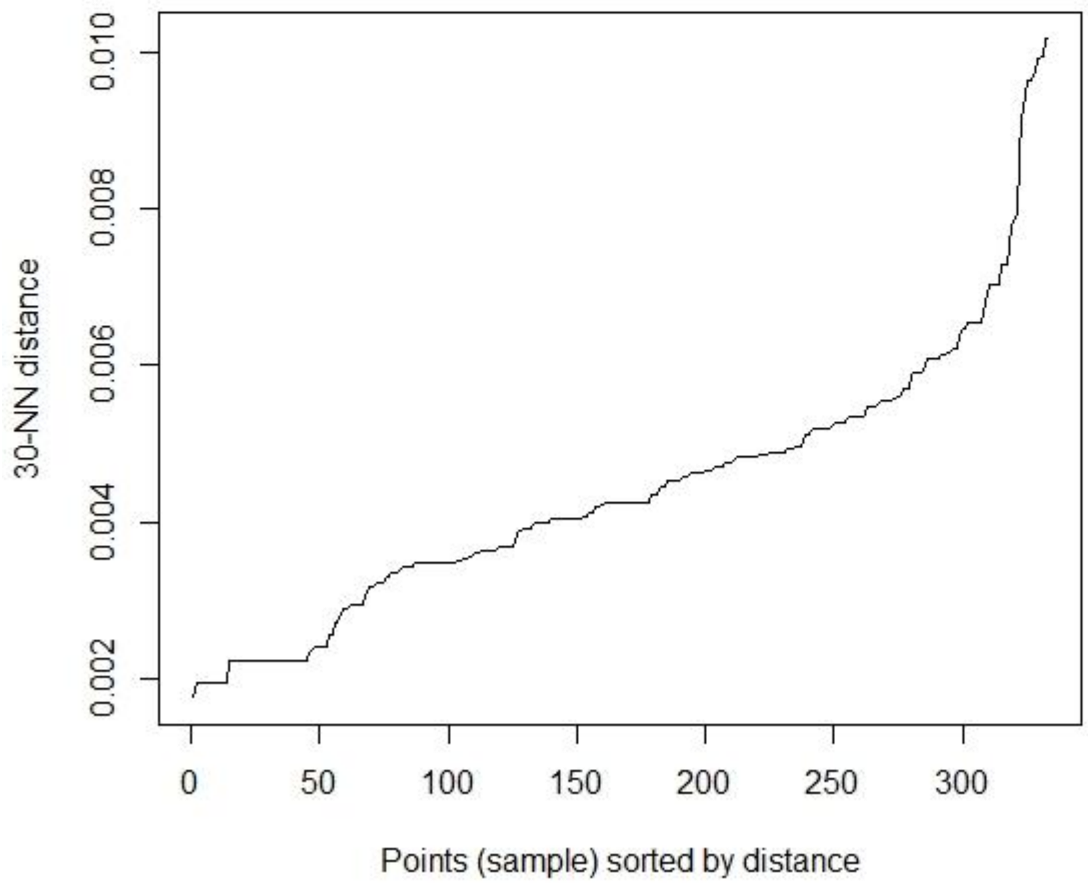

Figure 15: knee at 300m

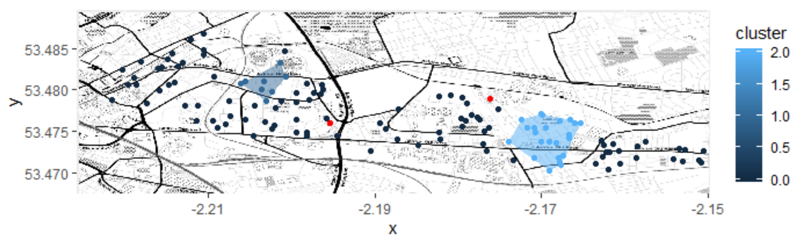

Figure 16: Bradford crime clusters marked in blue, police stations locations in red

RQ2: Manchester city analysis

To examine the relationship between crime distribution and police stations, a city-wide analysis was conducted.

A spatial weights matrix using queen's contiguity was calculated in preparation for spatial autocorrelation testing via Moran's I and Geary's C.

The former (Figure 17) returned a p-value of 0.007, suggesting sufficient evidence to reject the null hypothesis of no spatial autocorrelation. However, the Moran I statistic was small at 0.09, suggesting weak clustering. The latter (Figure 18) suggested disagreed, suggesting insufficient evidence (p-value=0.4, Geary C statistic = 0.959). Further analysis was thus required.

```
        Moran I test under randomisation

data:  manchester_final@data$crimedensity
weights: Mward.queens_weight

Moran I statistic standard deviate = 2.4325, p-value = 0.007498
alternative hypothesis: greater
sample estimates:
Moran I statistic       Expectation          Variance
      0.089142919      -0.031250000       0.002449644
```

Figure 17

```
        Geary C test under randomisation

data:  manchester_final@data$crimedensity
weights: Mward.queens_weight

Geary C statistic standard deviate = 0.24572, p-value = 0.4029
alternative hypothesis: Expectation greater than statistic
sample estimates:
Geary C statistic       Expectation          Variance
       0.95945997        1.00000000        0.02721973
```

Figure 18

An OLS regression was done of log crimes against population density, deprivation, and number of police stations. This model was inadequate, with a low adjusted R^2 value of 0.0551 and no statistically significant variables, even for the controls (Figure 19), despite a linear relationship between dependent and independent variables, normally distributed residuals and no multicollinearity. Since Global Moran's I test for residuals indicated that there might be spatial autocorrelation with p-values<0.05 for both queen's and nearest neighbour contiguity (Figures 20 and 21 respectively), Lagrange multiplier tests were used to confirm if spatial regressions would return better results.

```
Call:
lm(formula = log1p(crimes) ~ popdens + deprivation + polstns,
    data = manchester_df)

Residuals:
    Min      1Q  Median      3Q     Max
-0.4695 -0.3300 -0.1003  0.1369  2.5334

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  4.552933   0.623038   7.308 4.76e-08 ***
popdens     -0.003269   0.004834  -0.676   0.5043
deprivation  0.911520   0.494899   1.842   0.0757 .
polstns      0.042547   0.263064   0.162   0.8726
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.5787 on 29 degrees of freedom
Multiple R-squared:  0.1437,    Adjusted R-squared:  0.05512
F-statistic: 1.622 on 3 and 29 DF,  p-value: 0.2057
```

Figure 19

```
        Global Moran I for regression residuals

data:
model: lm(formula = log1p(crimes) ~ popdens + deprivation + polstns, data = manchester_df)
weights: Mward.queens_weight

Moran I statistic standard deviate = 3.7725, p-value = 8.08e-05
alternative hypothesis: greater
sample estimates:
Observed Moran I      Expectation         Variance
      0.36845178      -0.05835548       0.01279961
```

Figure 20

```
        Global Moran I for regression residuals

data:
model: lm(formula = log1p(crimes) ~ popdens + deprivation + polstns, data = manchester_df)
weights: Mward.nn_weight

Moran I statistic standard deviate = 3.4091, p-value = 0.0003259
alternative hypothesis: greater
sample estimates:
Observed Moran I      Expectation         Variance
     0.269773641     -0.062950514      0.009525663
```

Figure 21

The first two Lagrange Multiplier Tests (Figure 22) indicated that a spatial error model (SEM) and a spatial lag model (SLM) might improve on the OLS model (p-values of 0.0199 and 0.00395 respectively).

However, when run, both SEM and SLM for both queens and nearest neighbours contiguity returned no statistically significant variables. Figure 23 shows how the p-values for all 3 SEM variables are well above 0.05, and likewise for the SLM in Figures 24 and 25. This implied potential non-stationarity – the global SEM and SLM not best capturing locally-varying relationships between variables.

```
        Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = log1p(crimes) ~ popdens + deprivation + polstns, data = manchester_df)
weights: Mward.nn_weight

LMerr = 5.4191, df = 1, p-value = 0.01992


        Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = log1p(crimes) ~ popdens + deprivation + polstns, data = manchester_df)
weights: Mward.nn_weight

LMlag = 8.307, df = 1, p-value = 0.003949


        Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = log1p(crimes) ~ popdens + deprivation + polstns, data = manchester_df)
weights: Mward.nn_weight

RLMerr = 2.1493, df = 1, p-value = 0.1426


        Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = log1p(crimes) ~ popdens + deprivation + polstns, data = manchester_df)
weights: Mward.nn_weight

RLMlag = 5.0371, df = 1, p-value = 0.02481


        Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = log1p(crimes) ~ popdens + deprivation + polstns, data = manchester_df)
weights: Mward.nn_weight

SARMA = 10.456, df = 2, p-value = 0.005364
```

Figure 22

```
Call:errorsarlm(formula = m, data = manchester_df, listw = Mward.queens_weight)

Residuals:
      Min        1Q    Median        3Q       Max
-0.538925 -0.245918 -0.052433  0.128232  2.009450

Type: error
Coefficients: (asymptotic standard errors)
              Estimate Std. Error z value Pr(>|z|)
(Intercept)  5.3364619  0.6052271  8.8173   <2e-16
popdens     -0.0045779  0.0042227 -1.0841   0.2783
deprivation  0.2379737  0.4909464  0.4847   0.6279
polstns     -0.1408868  0.1842669 -0.7646   0.4445

Lambda: 0.61019, LR test value: 9.9545, p-value: 0.0016046
Asymptotic standard error: 0.14506
    z-value: 4.2064, p-value: 2.5947e-05
Wald statistic: 17.694, p-value: 2.5947e-05

Log likelihood: -21.66624 for error model
ML residual variance (sigma squared): 0.19362, (sigma: 0.44002)
Number of observations: 33
Number of parameters estimated: 6
AIC: 55.332, (AIC for lm: 63.287)
```

Figure 23

```
Call:lagsarlm(formula = m, data = manchester_df, listw = Mward.nn_weight)

Residuals:
      Min        1Q    Median        3Q       Max
-0.662125 -0.215728 -0.097012  0.121927  2.129947

Type: lag
Coefficients: (asymptotic standard errors)
              Estimate Std. Error z value Pr(>|z|)
(Intercept)  1.8755373  0.9061059  2.0699  0.03846
popdens     -0.0027521  0.0038313 -0.7183  0.47256
deprivation  0.3381174  0.3945617  0.8569  0.39148
polstns      0.0265561  0.2069473  0.1283  0.89789

Rho: 0.6108, LR test value: 8.4388, p-value: 0.0036729
Asymptotic standard error: 0.14954
    z-value: 4.0844, p-value: 4.4195e-05
Wald statistic: 16.682, p-value: 4.4195e-05
```

Figure 24

```
Simulated p-values:
            Direct  Indirect Total
popdens     0.58202 0.93192  0.90972
deprivation 0.54634 0.93618  0.91582
polstns     0.88922 0.94559  0.92836
```

Figure 25

A GWR was then conducted. Figures 26, 27 and 28 show the results for the coefficients by wards of population density, deprivation, and police stations respectively. Wards in Figures 29, 30, and 31 (for population density, deprivation and police stations respectively) with value greater than 0 have statistically significant coefficient estimates of the variable.

Unexpectedly, Figures 29-31 indicate that the coefficients in Figures 26-28 are statistically insignificant at the 5% level of significance. Despite statistical tests above suggesting spatial autocorrelation, a GWR with these variables does not explain crime distribution well. Implications are discussed subsequently.

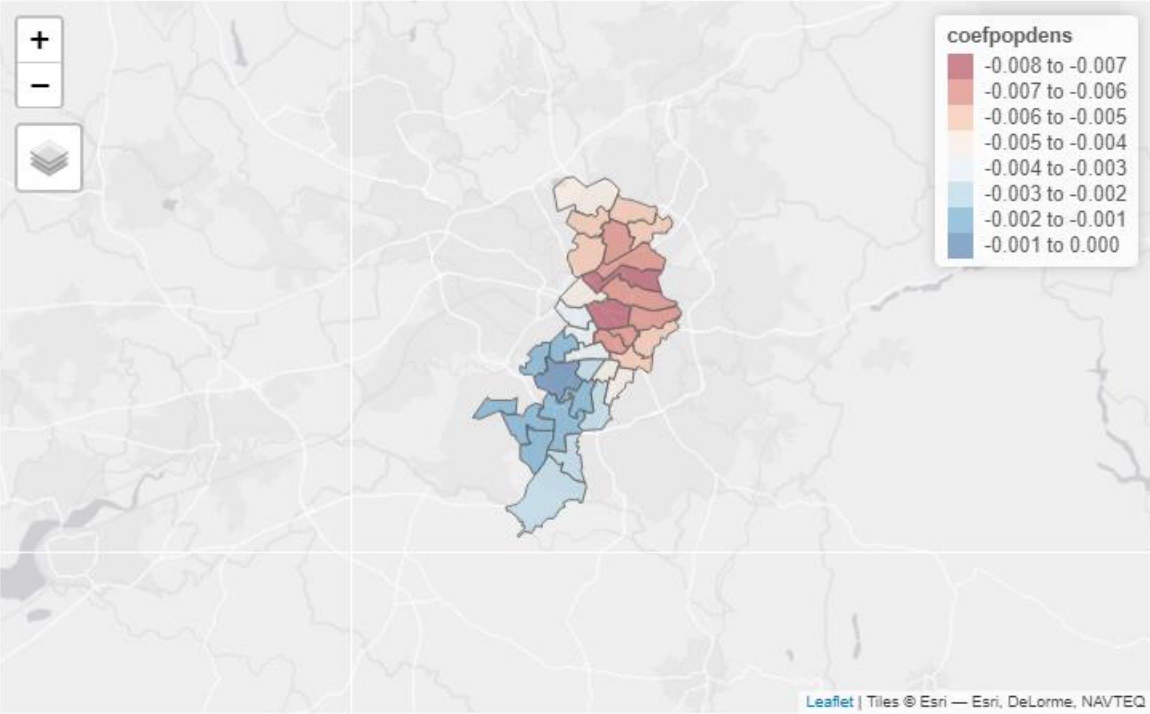

Figure 26

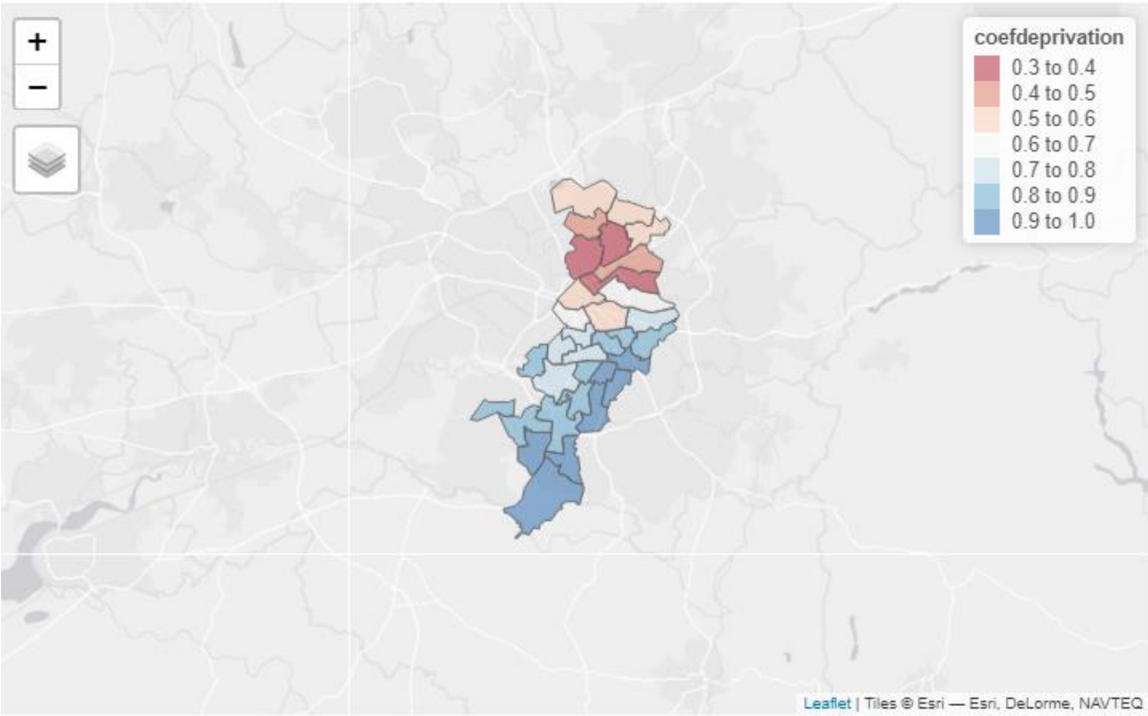

Figure 27

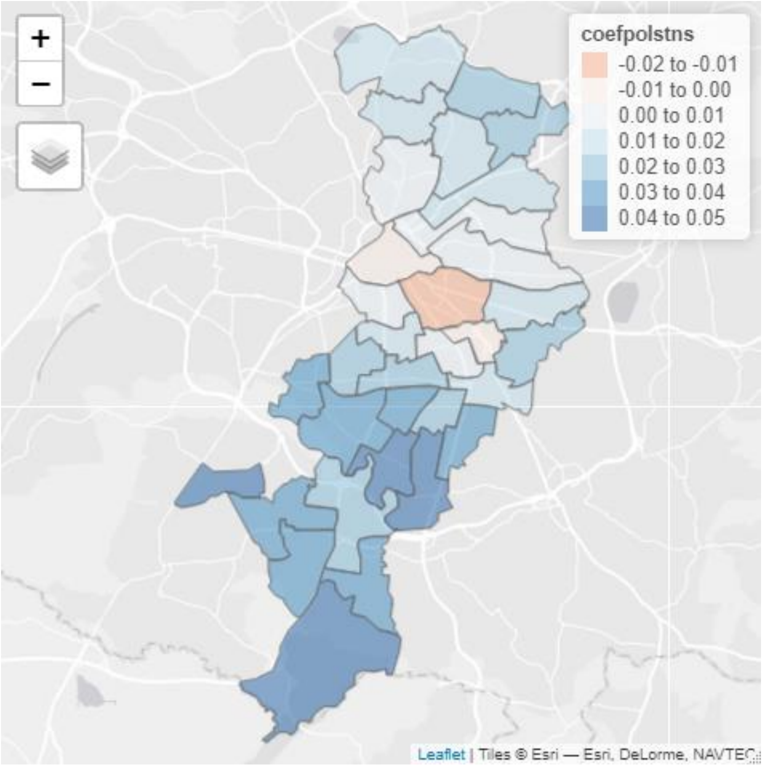

Figure 28

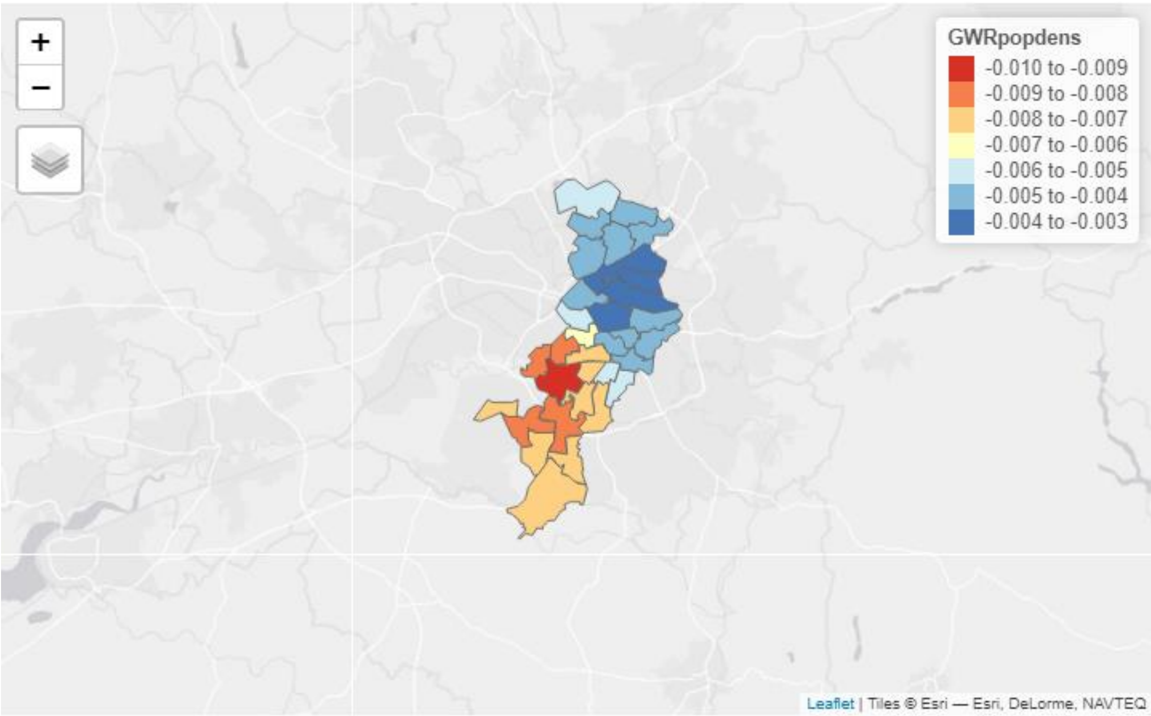

Figure 29

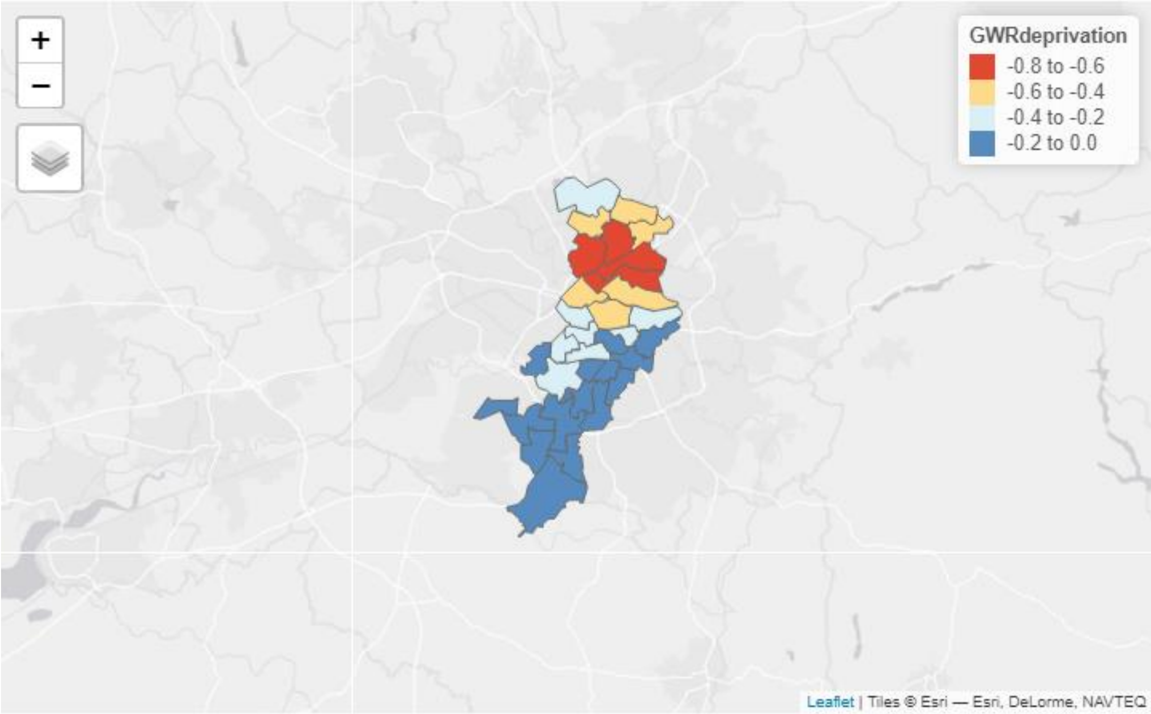

Figure 30

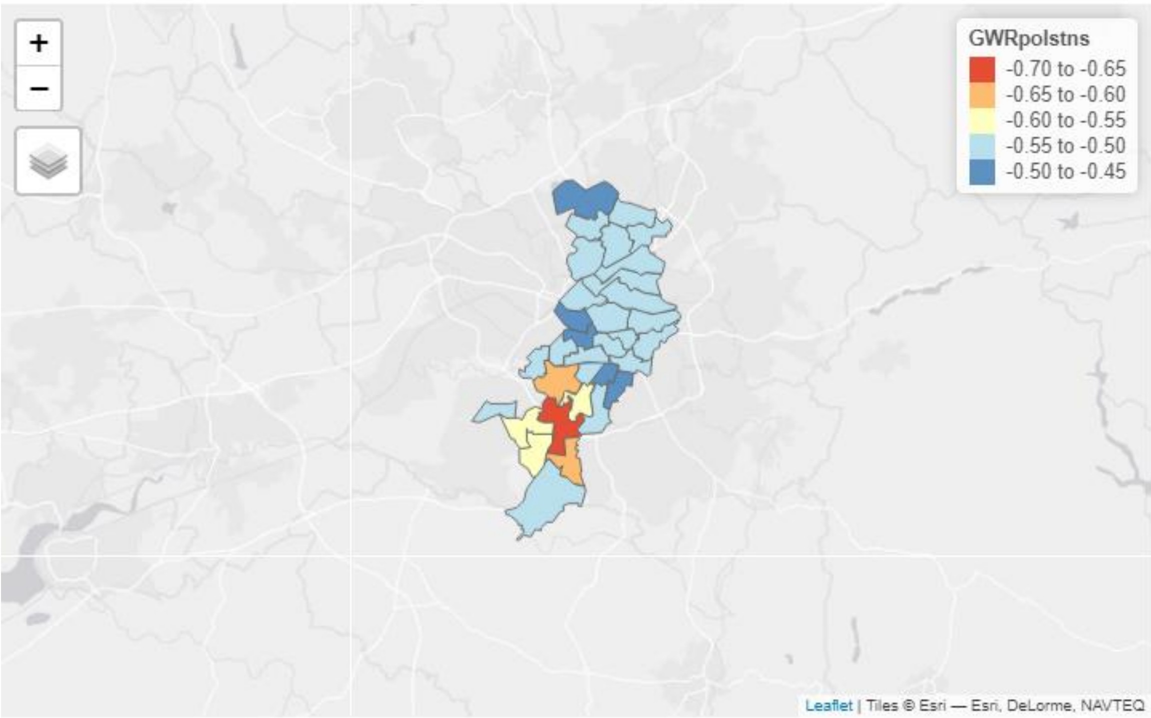

Figure 31

Conclusion and Recommendations

Preliminarily, KDE visually displayed a northwest cluster of Manchester's crime occurrences close to high deprivation in the northeast. Further detailed analysis was conducted on Bradford ward, to statistically confirm (a) the presence of clusters (b) their location. A KDE visually identified a cluster each in the east and west. Four tests – Ripley's K, the Kolmogorov-Smirnoff test, and the G and F functions – confirmed (a).

Thus, it can be concluded on a city-level (visually), and ward-level (statistically), that crime distribution is clustered, in response to RQ1, confirming Hypothesis 1.

Cluster locations in Bradford were then determined using DBSCAN, visually ascertained to be not far from the police stations.

Spatial regressions on the city-level were then used to investigate the relationship between station locations and crime distribution. While spatial autocorrelation of crime occurrences was indicated by Moran's I test on OLS residuals and the Lagrange multiplier tests, neither SEM nor SLM returned any statistically significant predictor variables.

A GWR was then conducted across Manchester, for log crime against the predictor variables population density, deprivation and police stations per ward. However, all three variables' coefficients were found to be non-statistically significantly different from zero.

This finding agrees with Nezami's and Ehsan's (2016) results finding no spatial link between population density and illiteracy and crime occurrences. In contrast with Sohn (2016), Akpinar and Usul (2004), and Murray et al. (2001), this paper found that lower crime occurrences were not associated with police stations in the ward. It answers RQ2 in the negative, and rejects Hypothesis 2.

While crime occurrences were shown to be clustered, their relationship with none of the three variables was conclusive. Future studies could alter the control variables.

Operationally, these findings might advise patrol routes in covering crime clusters to provide a higher degree of surveillance. Policy-wise, the lack of a statistically significant association between police station locations and crime occurrences could be a justification for police stations' sale for budgeting (Dalton, 2018), since they seem to lack a crime deterrent effect.

This research can be reproduced for all Manchester wards to produce a comprehensive picture of clusters in each ward, and further replicated for other cities. After selecting additional control variables, it would provide both a clear visualisation and predictor analysis of crime patterns.

This research faced a few limitations, to which extensions are proposed here. Firstly, the GWR analysis required sub-ward level data to be carried out in Bradford ward – this could be done by the relevant authorities subsequently. Additionally, while the number of stations per ward was used as a variable in the GWR, a constructed variable of distance from nearest police station could be more accurate in future spatial regression/GWR studies. Finally, while statistical studies conclusively proved at ward-level crime clustering, computational limitations hindered their application to Manchester– these tests could be replicated across wards, or a stronger computer be used to run the Moran's I test across Manchester.

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