CEGE0097 Spatial Analysis And Geocomputation

Title

Investigating the Spatial Statistical Relationship between Crime and Stop & Search occurrences by Ethnicity when accounting for Police Perceptions in London

Group

B6

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1. INTRODUCTION

London has the highest crime count in the UK (CrimeRate, 2021). After the June 2016 Brexit referendum, hate crime in the city has increased by around 15-25% (Clifton-Sprigg, James and Vujic, 2020). While Carl (2018) documented various reasons given to vote ‘leave’, the most prevalent was to ‘regain control over EU immigration’; a topic which, as highlighted by Hutchings and Sullivan (2019), is intrinsically related to racism.

The project will conduct a series of spatial analyses to investigate the relationship between London crime and stop & search (SS) rates in 2016, while accounting for ethnicity and police perceptions (PP). It is hypothesised, that while crime trends will inherently be related to population density, noticeable differences in race will be observed when stratifying models by ethnicity.

Given this broad scope, the topic has been divided into 3 tasks: First, a non-spatial Exploratory Data Analysis (EDA) to extract pertinent variables followed by three Spatial Autocorrelation (SA) analyses (one for each dataset) which were then used to fit a spatial regression model. Group responsibilities are delineated in Table 1.1.

Table 1.1: *Breakdown of Group Responsibilities*

	Data Tasks	**Research/Report Writing**
Danni	Pre-processing, EDA/SA analysis and Spatial Autocorrelation for Stop & Search dataset(s)	Introduction, Methodology (global autocorrelation), Results (Autocorrelation for S&S)
Pratibha	Pre-processing, EDA/ SA analysis and Spatial Autocorrelation for Crime dataset(s)	EDA, Methodology (local autocorrelation), Results (Autocorrelation for Crime)
Tommy	Pre-processing, EDA/ SA analysis and Spatial Autocorrelation for Police Perception datasets.	EDA, Data Description, Methodology (local autocorrelation), Results (Autocorrelation for PP)
Claudia	Initial Pre-processing & Early EDA, Spatial Regression for all datasets	EDA, Methodology (Spatial Regression), Results (Spatial Regression), Discussion

2. DATA DESCRIPTION

The project required datasets that were freely available, within the appropriate spatial and temporal scale (London, June 2016) and at the highest obtainable spatial resolution, where the latter provides the greatest scope for spatial analysis at neighbourhood scales. Crime, SS, and boundaries data were collected for the same period, whilst Ethnicity was sourced from the latest published UK Census (2011). PP was amalgamated from 2016-21 to provide sufficient coverage and representation of each minority group in the sample. Data sources and requirements are summarized in Tables 2.1 and 2.2 respectively.

2.1 Data Sources

Table 2.1: *Data sources and descriptions*

Theme	Currency	Provider	Description
Crime	2016	police.uk	Details of crime occurrences including approximate point locations.
Stop & Search	2016	police.uk	Details of S&S occurrences including approximate point locations.
Police Perceptions	2016-21	MPS/ MOPAC	Subset of the Public Attitude Survey (PAS) used to measure confidence in the police. Responses are given to MTS Neighbourhood level.
Boundaries	2014	GLA	London boroughs and wards primarily concerned with the provision of government and electoral services
Police Stations	2013	GLA	Travel times for each LSOA in London to publicly accessible police counters. Includes front counter locations - derived from the postcode of each counter's address using the OS Open Code Point dataset.
Population	2013	GLA	Demography including population, ethnic diversity, and crime. Includes ward boundaries from May 2014.

2.2 Data Requirements

Table 2.2: *Data requirements and source rationales*

Data Acquisition	All datasets were acquired from open providers including policing and government authorities, where data is licensed for personal use. The team made a specific request to the Mayor's Office for Policing & Crime (MOPAC) for a bespoke flavour of the PP dataset, which included an ethnicity breakdown. This resulted in all input datasets sharing ethnicity as a common variable for analysis.
Data Formats, Representations	The project primarily required data formats to be readily exploitable in R for spatial analysis. Crime, S&S & PP data were stored in a csv format, where spatial 'descriptions' (e.g., names, codes, coordinates) were read as spatial objects in R. Moreover, the project required spatial data to be represented using an appropriate spatial data model. As all the input data were either discrete points (e.g., S&S events) or points aggregated into polygons (e.g., police perceptions). This project used a geographic vector data model for representing information in the form of points, lines, and polygons.
Sampling	The project required authoritative datasets, of sufficiently high sample size and gathered using robust sampling strategies. PP data was collected through the Public Attitudes Survey (PAS) – a stratified sample survey based on random respondents from pre-selected addresses, where each response was coded into a percentage score per indicator (e.g., fairness) (MOPAC, 2017). MTS affirms the sample size (~12,800 responses) was suitable for London-wide analysis; comprising a confidence interval of ±2% points at 95% confidence (MOPAC, 2017).
Resolution & Privacy	Analysis of open data in the crime domain is complicated by concerns over privacy. Crime datasets are often highly sensitive; micro-level, person-specific and spatiotemporal (Haberman et al., 2021). They subsequently provoke concerns around privacy, confidentiality, and protection of victims. MTS attempted to offset privacy concerns using a process of 'pseudonymisation', which intentionally deteriorates the quality of location data. This involves replacing exact coordinates with coordinates of a snapped map point or omitting coordinates when the difference exceeds 20km (MOPAC, 2017). Both scenarios allow transgression across boundaries and can affect the aggregation values. The project was conscious of precision error when framing the results.
Aggregation	The project required a common boundary dataset as a prerequisite for spatial analysis. As the project utilised a combination of non-aggregated (points) and aggregated (polygons) datasets, non-aggregated datasets were summarised into London borough and ward boundaries[1]. While local processes relating to crime do not lend themselves to arbitrary, Tobler's Law contends that they are likely to exhibit spatial interaction, with the caveat of some boundary effects.

[1] The project intended to use the MPS 'policing neighbourhoods', which are a bespoke groupings of electoral wards based on their similarity according to London Datastore Ward Atlas and UK 2011 Census variables (GLA, 2014). As this grouping mechanism was underpinned by the theory of spatial dependency, it would ensure similar communities were grouped according to their unique characteristics. However, these boundaries were not made available publicly, to the detriment of this project.

3. EXPLORATORY DATA ANALYSIS

The primary aim of an EDA is to examine the data for distribution, outliers, and anomalies to direct further analysis (Natrella, 2010). Since ethnicity is central to the project scope, only ethnicity variables were considered for the EDA. While there are many categories of ethnicity, this analysis only fits models for combined White, Black and Asian ethnicities.

3.1 Data Cleaning

Missing values and irrelevant variables were omitted from all datasets. As a prerequisite for multivariate spatial analysis, all datasets must conform to a common CRS and distance unit. Data was received as geographic coordinates referencing WGS1984 (4326) and transformed into projected coordinated referencing BNG. Given the spatial extent of our AOI, there was minimal distortion.

Point datasets were aggregated to the ward polygon shapefiles using a point-in-polygon test and shapefiles merged onto the original dataframe. This was also done for the population dataset, but a point-in-polygon test was not needed, and ward codes were used. Since the original shapefiles for the PP data were not available, data was aggregated up to the borough level for SA analyses. Boroughs were omitted where more than 25% of its neighbourhoods were NA to avoid the ecological fallacy of few neighbourhoods falsely representing a whole borough.

3.2 Descriptive Statistics

<u>3.2.1. Crime:</u> The crime data was primarily examined in terms of crime occurrences, in which the data ranged between 1 (minimum) and 1246 (maximum), with a mean of 134.2 overall. The most commonly occurring crime is anti-social behaviour(~26%), followed by violence and sexual offences (~21%), together accounting for almost half of the crime in London (Fig 3.1).

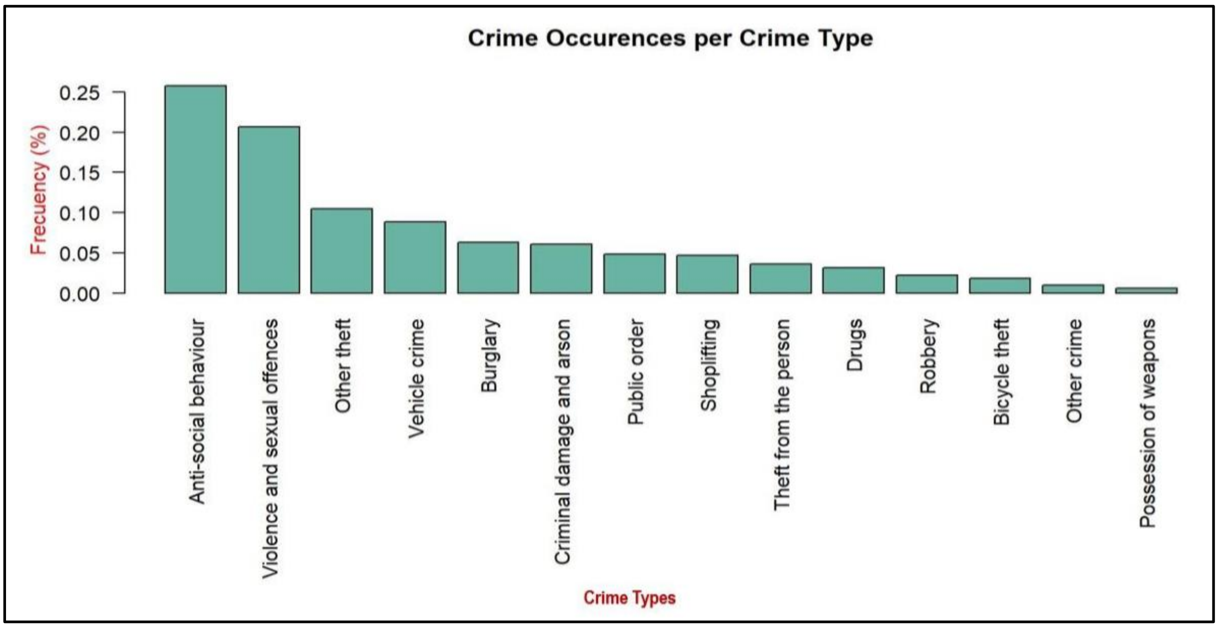


Fig 3.1: *Frequency distribution of crime types.*

<u>3.2.2. Stop & search:</u> SS occurrences ranged from 1 (minimum) to 179 (maximum), with a mean of 16.15 overall. Looking specifically at self-defined ethnicity, most SS victims were white(~38%), followed by Black/Black British (~33%), accounting for more than 70% of SS in that month (Fig 3.2).

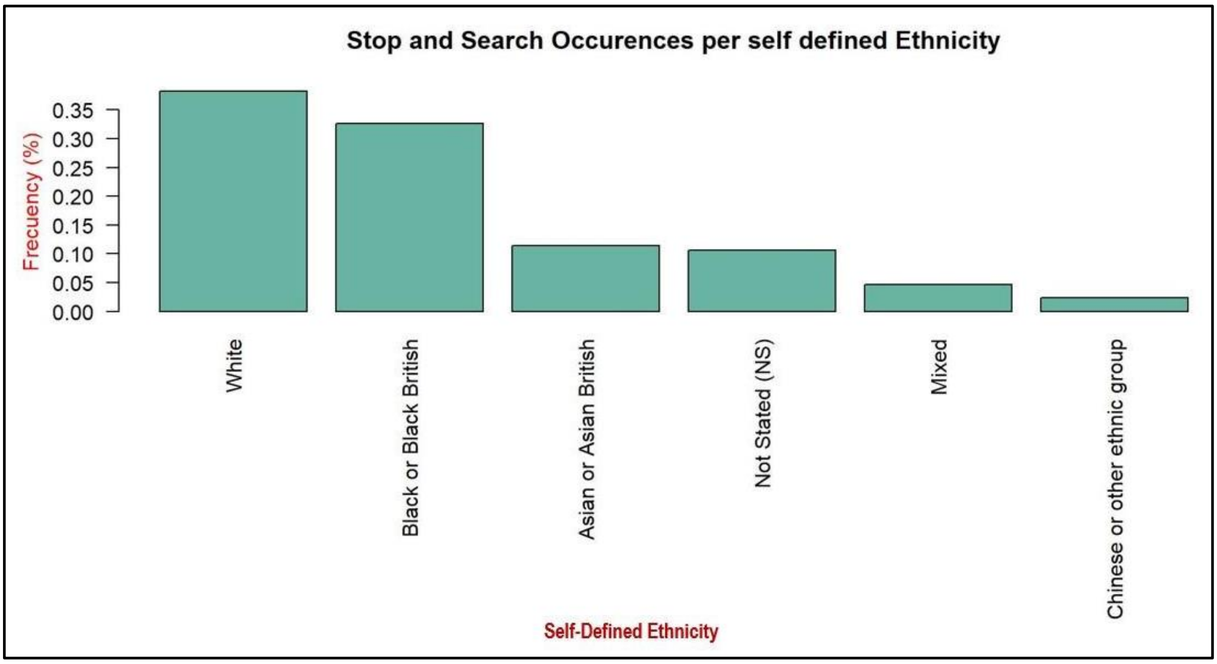


Fig 3.2: *SS occurrences per self-defined ethnicity*

<u>3.2.3. Police Perception</u>

The 'Fair S&S' indicator explicitly relates to S&S practises directly, whilst other related indicators provide wider context and comparison (see Appendix 1 for methods). The 'Fair S&S' indicator was the most polarising indicator by ethnicity (Fig 3.3 & 3.4) and points to disproportionate impacts of S&S practises on the black community at the global level.

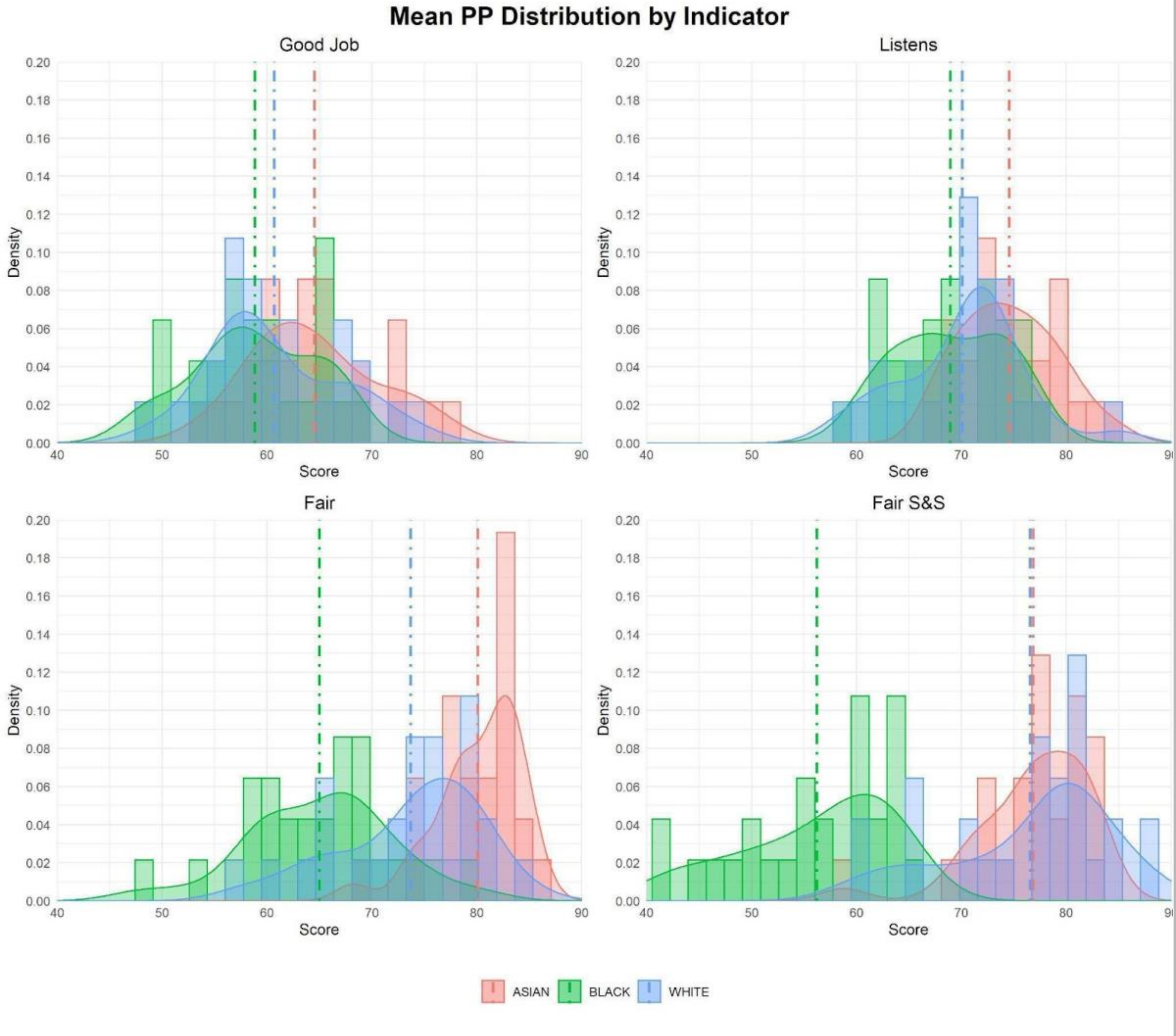


Fig 3.3: *Exploring Distribution: Mean PP Distribution by Ethnicity*
A grouped histogram series enabled direct comparison between the distribution of ethnicity subsets by indicator. The results show that each subset is normally distributed but distinguished by their density arrangement (colour fill) and mean value (dotted line). 'Good Job' and 'Listens' share similar concentrations while 'Fair' and 'Fair S&S' show clear divergence (bottom-right).

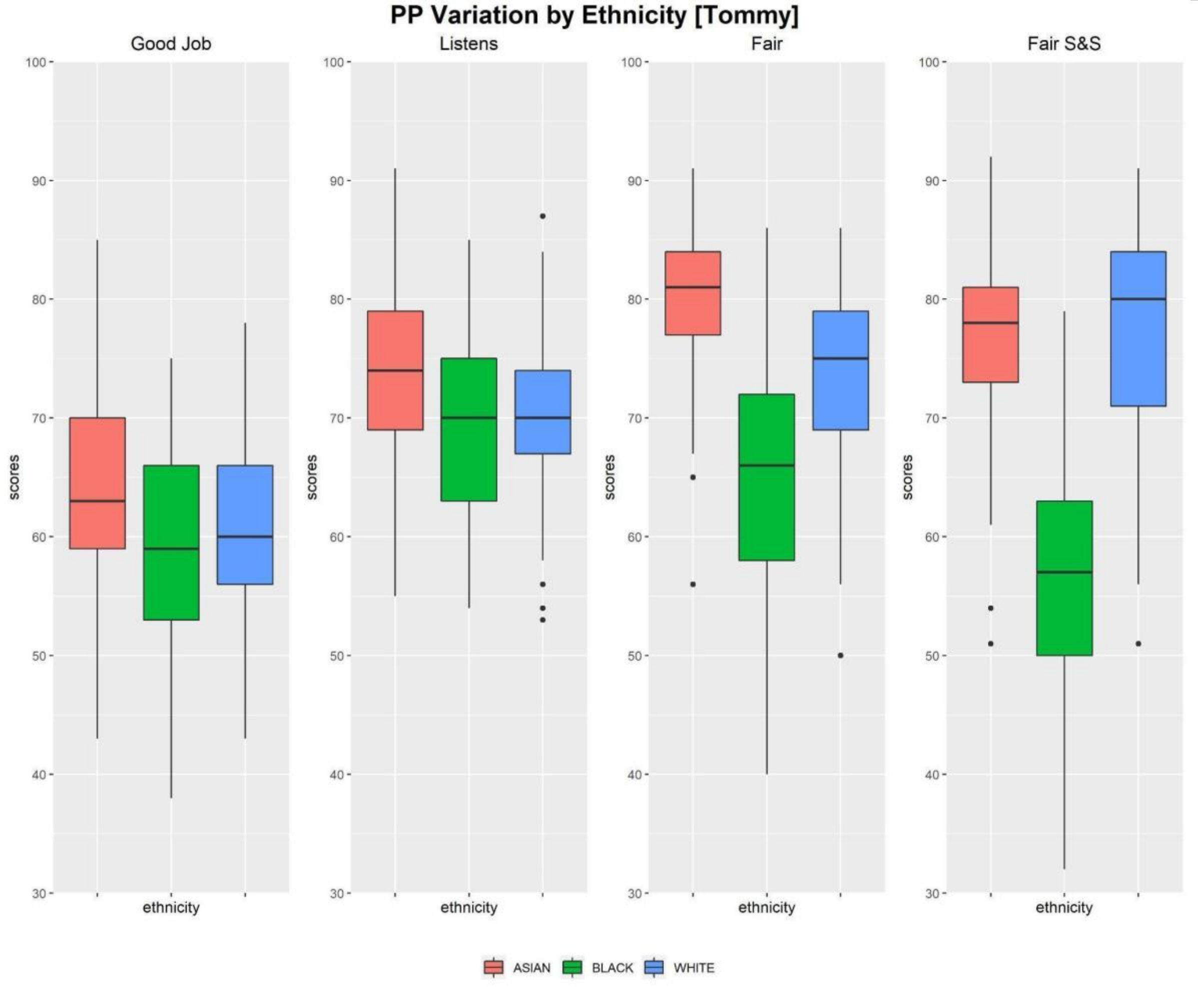


Fig 3.4: *Exploring Variation: Mean PP Variation by Borough*
A grouped boxplot series amalgamates variation by ethnicity and reaffirms divergence in the 'Fair' and 'Fair S&S' indicators.

3.3 Geographic Variations

An initial look at the spatial distributions for each dataset show that there is obvious autocorrelation between the wards for both crime (Fig 3.5) and SS (Fig 3.6). Both datasets indicate that crime and SS are more prevalent in central London. Dot density visualisation revealed enclaves of ethnic groups (Fig 3.7). As most datasets share ethnicity as a common variable, such geographies baseline further findings into crime, S&S and PP. The 'Fair S&S' indicator was revealed to be the most polarising indicator by ethnicity (Fig 3.8) across all boroughs and points to the disproportionate impacts of S&S practises on the black community at the local level, justifying local autocorrelation analysis. Given these spatial patterns, a spatial analysis plan was devised.

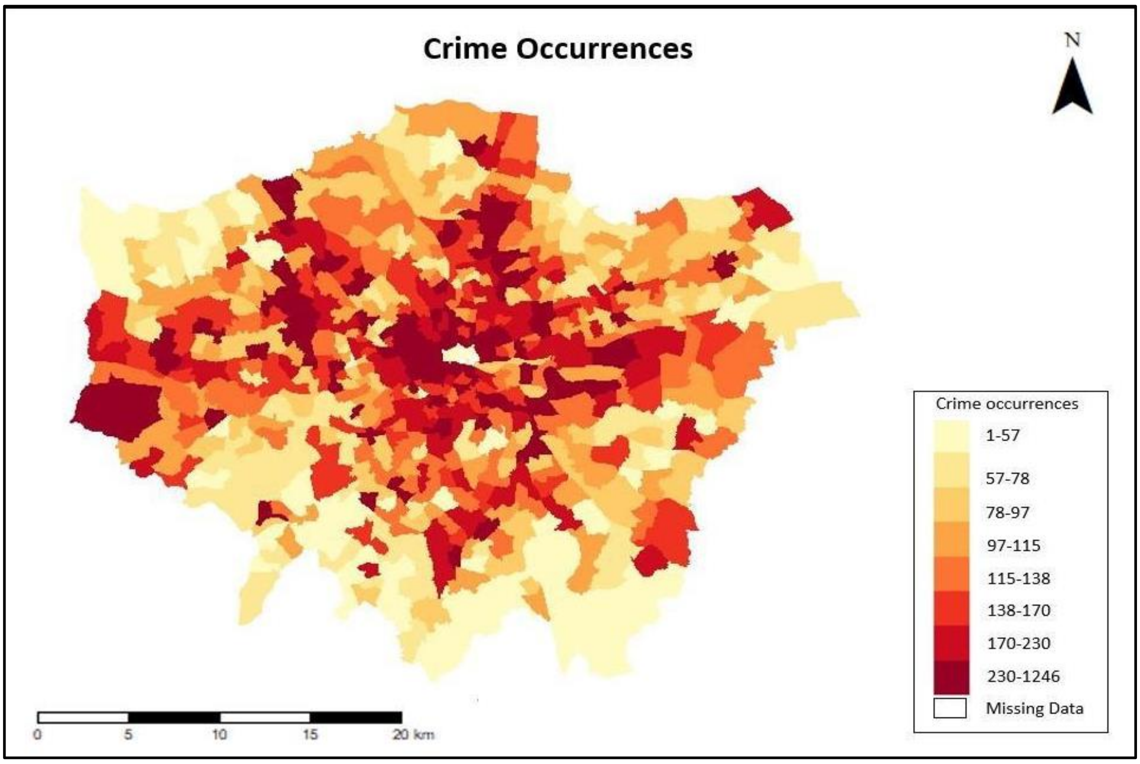


Fig 3.5*: crime occurrences per ward*

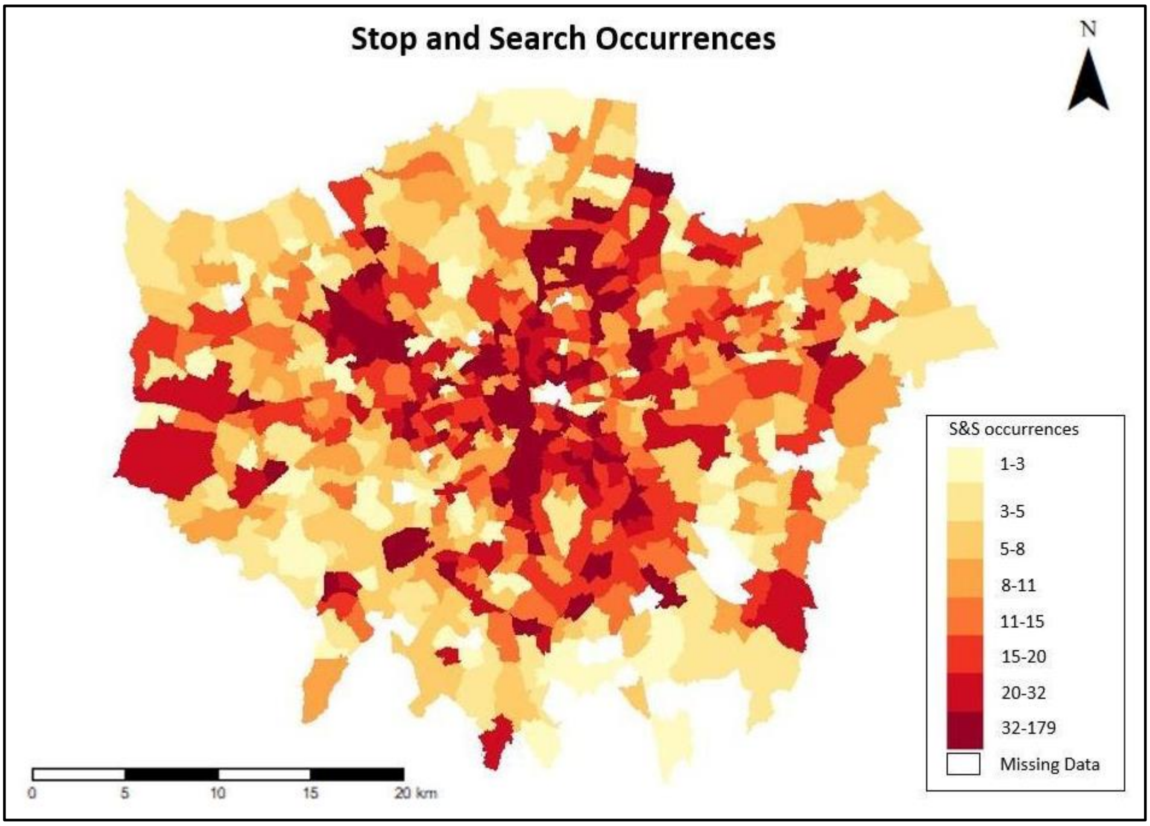


Fig 3.6*: Stop and Search occurrences per ward*

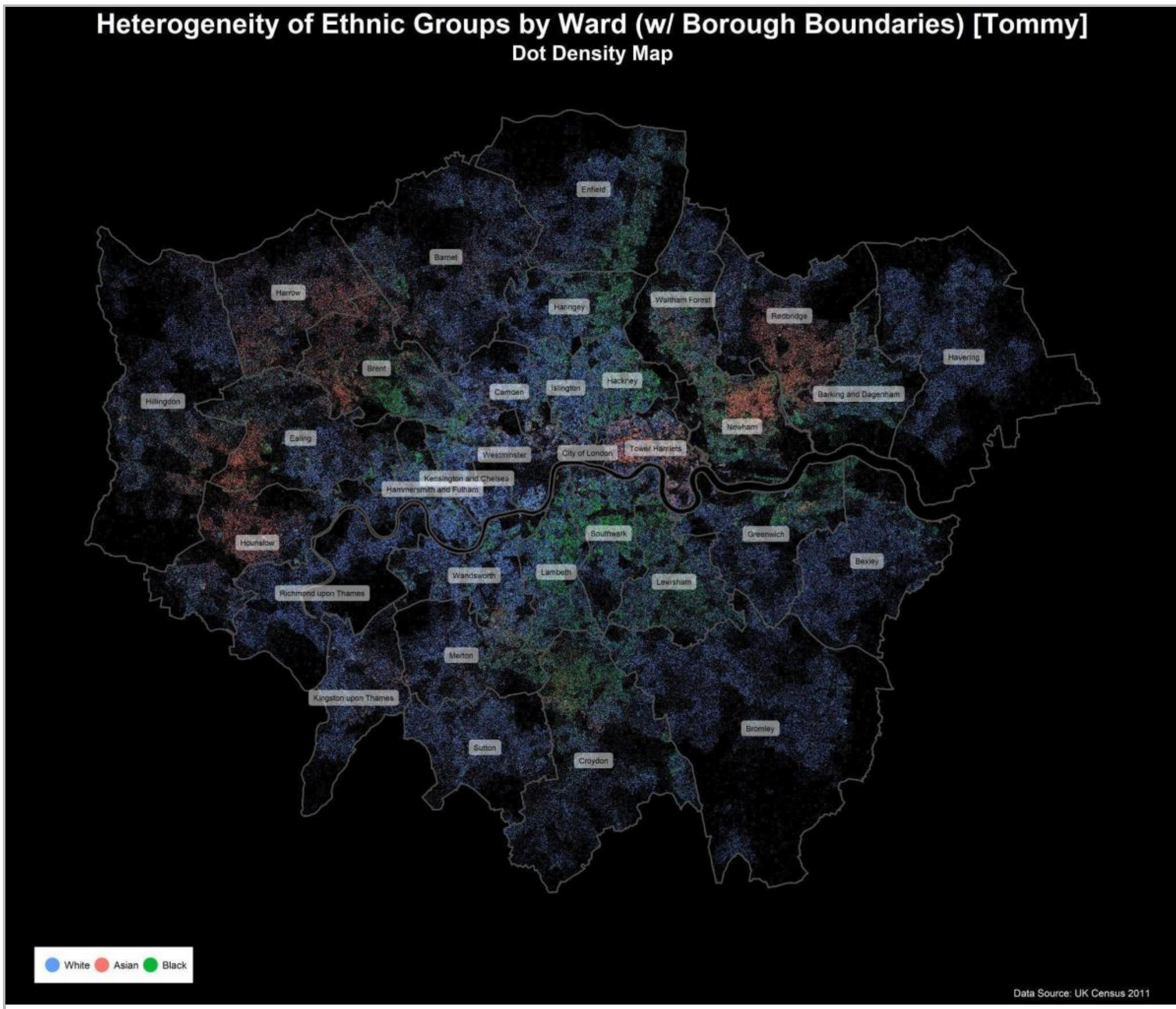


Fig 3.7: *Exploring Distribution: Ethnicity by Ward*
Dot Density was the most effective mechanism for portraying heterogeneous (pseudo)distribution of multiple attributes in R; mimicking the natural distribution of fine-grained point data, where 1 dot represents 10 people, spaced according to density. The map notably shows concentrated pockets of the Asian (e.g., Newham) and Black (e.g., Southwick) communities, amongst a more dispersed white population.

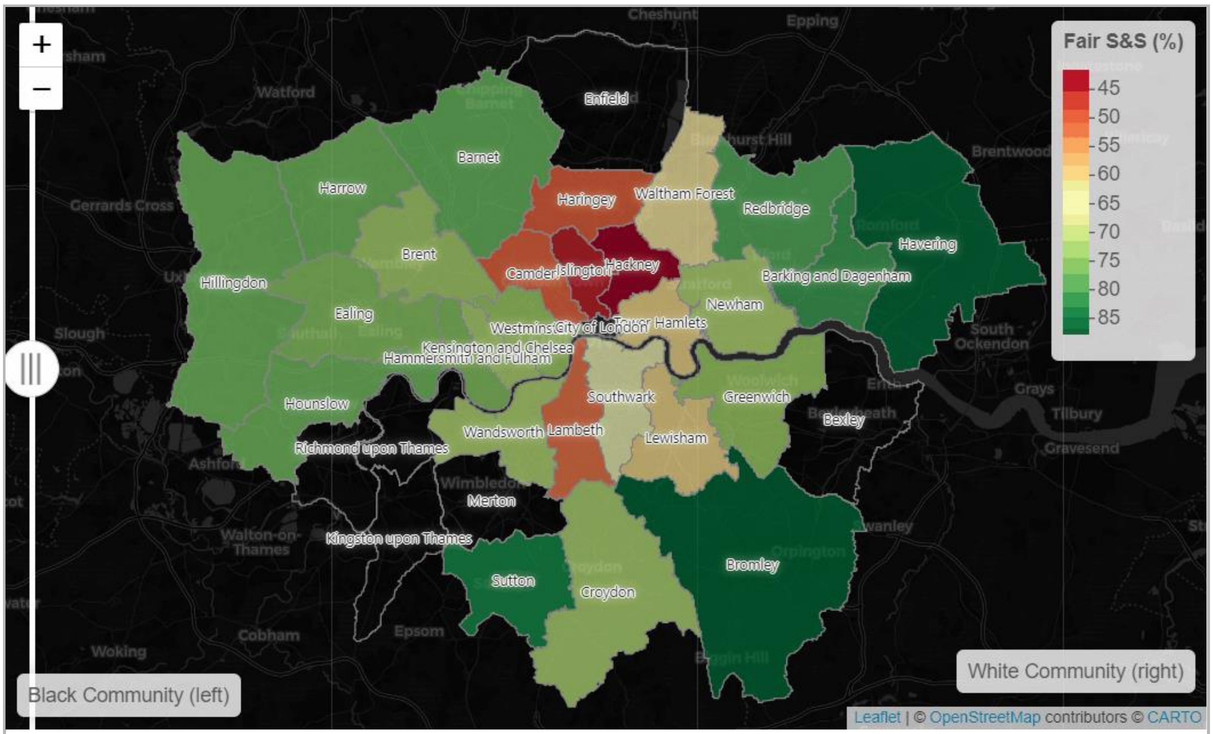


Fig 3.8: *Distribution of Ethnic Groups by Ward*
After narrowing the scope towards the 'Fair S&S' indicator, an animated choropleth (.gif) with slider function was created to show responses by borough between black and white ethnicities. The animation revealed a selection of inner-city boroughs that consistently exhibit poor perceptions relating to poor application of S&S practises.

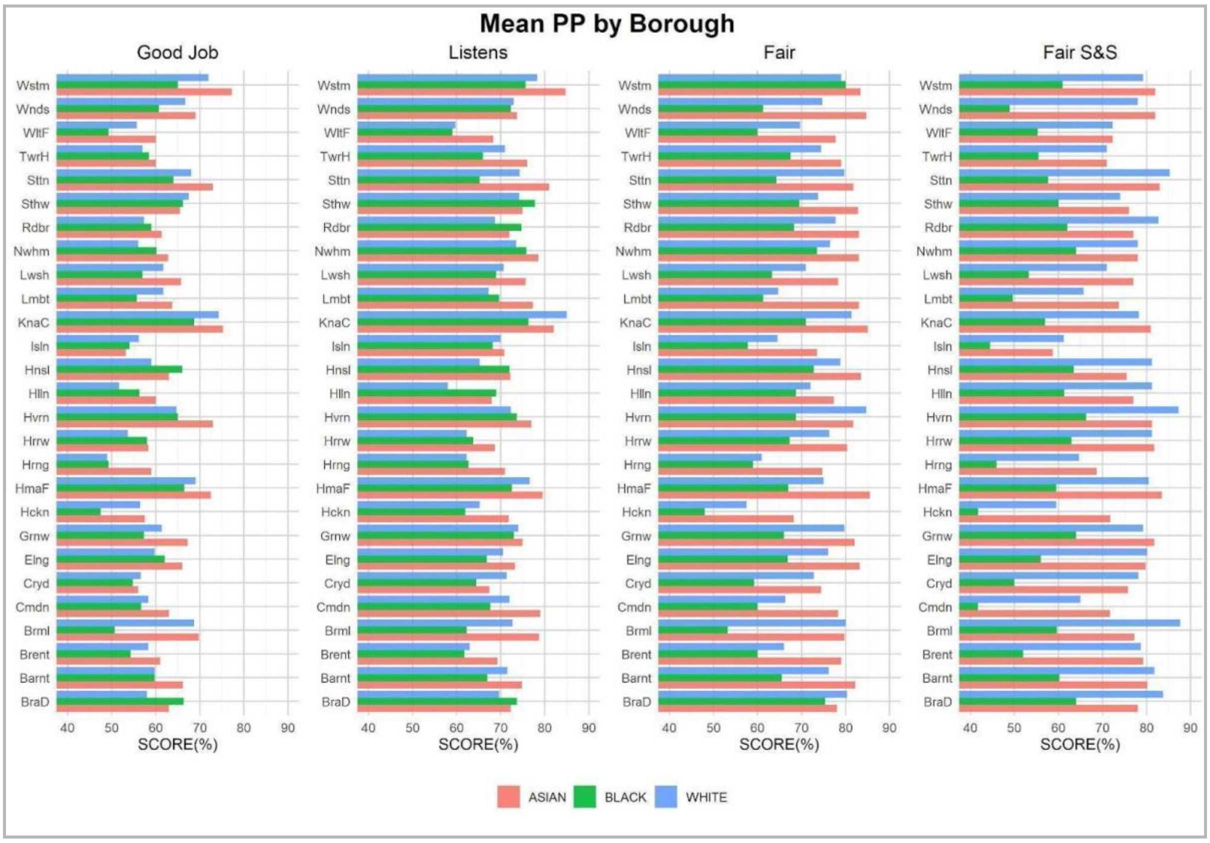


Fig 3.9: *Mean PP by Ward*
The bar chart displays the mean perception value for each indicator, where 0 indicates negative perceptions and 100 represents positive. The results show reasonable spatial homogeneity for the 'Good Job' and 'Listens' indicators, whilst the 'Fair' and 'Fair S&S' provokes polarising views, where Black respondents were significantly more negative than white & asian respondents. Most prevalent in Camden (Cmdn), Hackney (Hackn) and Islington (Isln).

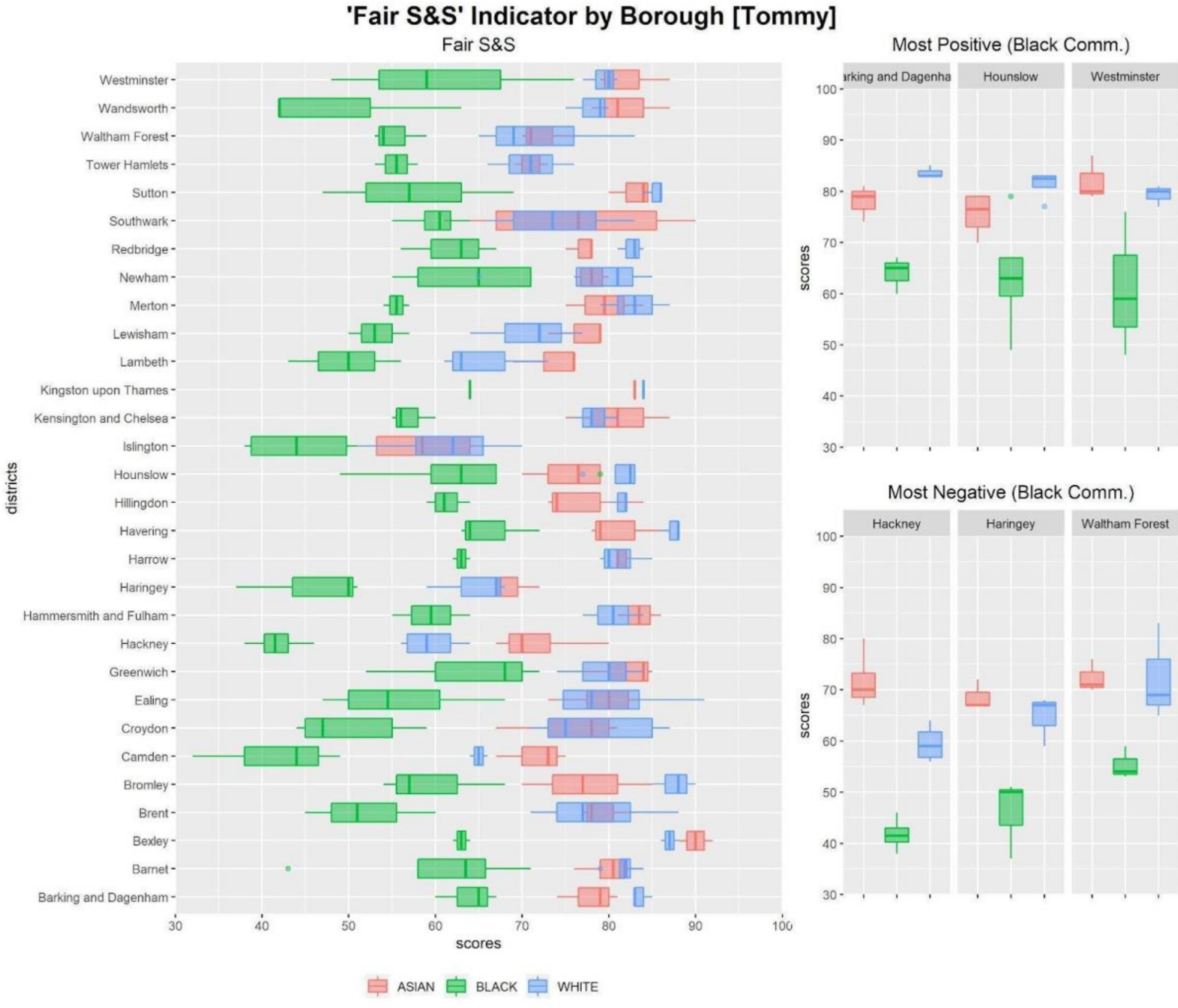


Fig 3.10: *Exploring Variability: 'Fair S&S' Indicator by Borough*
PP was interrogated at a neighbourhood level to show variability within Boroughs. The black community consistently exhibited the most variability. It can be inferred that boroughs like Hackney with low variability of negative perceptions are homogeneously impacted by unfair S&S practises. Whereas boroughs like Islington with high variability of negative perceptions contain specific enclaves most impacted.

4. METHODOLOGY

4.1 Plan of Analysis

Since the EDA indicated several avenues for analysis, the following section details the methodological approaches taken to detect spatial autocorrelation. These results will inform a stratified spatial regression analysis (tuned with a Linear regression model), which will ultimately address the research question. The following sections provide a detailed description of each of these analytical steps. Note that a p-value threshold of 95% will be used to determine every test significance (p<0.05).

4.2 Spatial Autocorrelation Analyses

Spatial autocorrelation is the term used to describe the presence of systematic spatial variation of a variable (Haining, 2001) and can be investigated using both global and local measures. Global measures create the illusion of homogenous populations, whilst local measures provide scope to unpick granular-level heterogeneity.

4.2.1 Moran's I

The Global Moran's I (GMI) tool measures spatial autocorrelation by reviewing feature locations and feature values simultaneously (ESRI, 2018). With a null hypothesis of Complete Spatial Randomness (CSR), the test statistic ranges from -1 (perfect dispersion) to 1 (perfect clustering) along with a z-score and p value (GIS Geography, 2021). The equation for GMI is shown below (Fig 4.1).

$$I = \frac{N\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\left(\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\right)\sum_{i=1}^{n}(x_i - \bar{x})^2}$$

- Where:

N is the number of observations (points or polygons)
$\bar{x}$ is the mean of the variable
X_i is the variable value at a particular location
X_j is the variable value at another location
W_{ij} is a weight indexing location of *i* relative to *j*

Fig 4.1: *Equation of Moran's I*

The GMI compares how much a given value at a given location differs from the data mean and further how it compares to its neighbours. If the location value *and* its neighbours are all above the mean, it could indicate positive spatial autocorrelation. Dispersion occurs when a point is above the mean but surrounded by points below the mean (Fig 4.2)

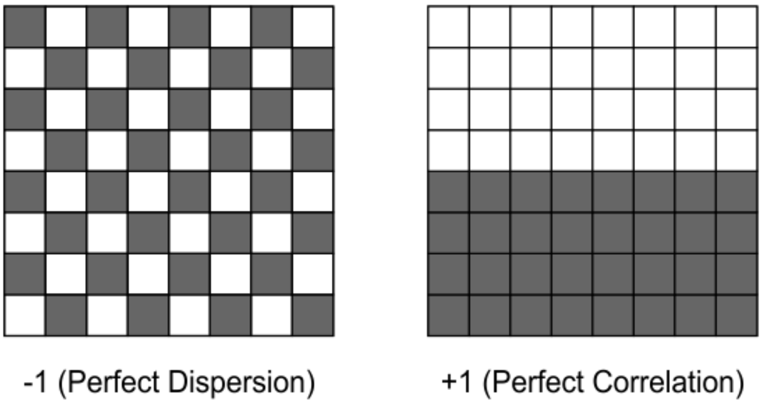


Fig 4.2: *Moran's I test statistic and associated spatial patterns (Geospatially, 2016).*

GMI was implemented in R using the moron.test and moran.mc functions (spdep library). The poly2nb function allows rook or queen adjacency to be used.

4.2.2 Getis Ord General G

The Getis Ord General G has a null hypothesis of CSR and returns a single value of spatial autocorrelation for the dataset. The General G adds to the results of the Moran I by also returning the direction of clustering (Fig 4.3). For example, assuming a significant p-value, positive z-scores indicate a hotspot, and negative z-scores indicate cold spots. The presence of strong cold *and* hot spots in the area will cancel each other out, leading to a misleading overall statistic. If this is the case, a local spatial autocorrelation method should be used instead.

$$G = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j}x_i x_j}{\sum_{i=1}^{n}\sum_{j=1}^{n} x_i x_j}, \ \forall j \neq i$$

where x_i and x_j are attribute values for features i and j, and $w_{i,j}$ is the spatial weight between feature i and j. n is the number of features in the dataset and $\forall j \neq i$ indicates that features i and j cannot be the same feature.

Fig 4.3: *Equation for Getis Ord General G statistic (ESRI, 2019).*

G uses Euclidean distance to polygon centroids rather than rook / queen adjacency to determine its neighbours. The method used to implement this analysis will determine how much control the researcher has. For example, in R, the globalG.test function returns the G statistic and p-value however ArcGIS Pro also allows the researcher to choose how they conceptualise spatial relationships.

4.2.3 Moran's I

Local Moran's I (LMI) endeavours to find local clusters and outliers from heterogeneous spatial objects to offer insight into how spatial processes proliferate at local levels. This is achieved by decomposing the GMI statistic into local statistics that reflect the contribution of each spatial object in the sample (Haworth, 2018). The results include an observed LMI statistic, for describing autocorrelation between each spatial object and its neighbours (0> is positive), an expected LMI statistic, for null hypotheses of no autocorrelation, and p-value, for assessing significance. All instances of Moran's reference a row standardised adjacency-based spatial weights matrix (SWM)[2] based on the Queen definition.

4.2.4 Moran Scatterplot

It is a tool to identify the clusters of high and low values in spatial data. Its horizontal axis is based on the values of the observations and is also known as the response axis. The vertical Y axis is based on the weighted average or spatial lag of the corresponding observation on the horizontal X axis. The plot is divided into four quadrants (Fig 4.4).

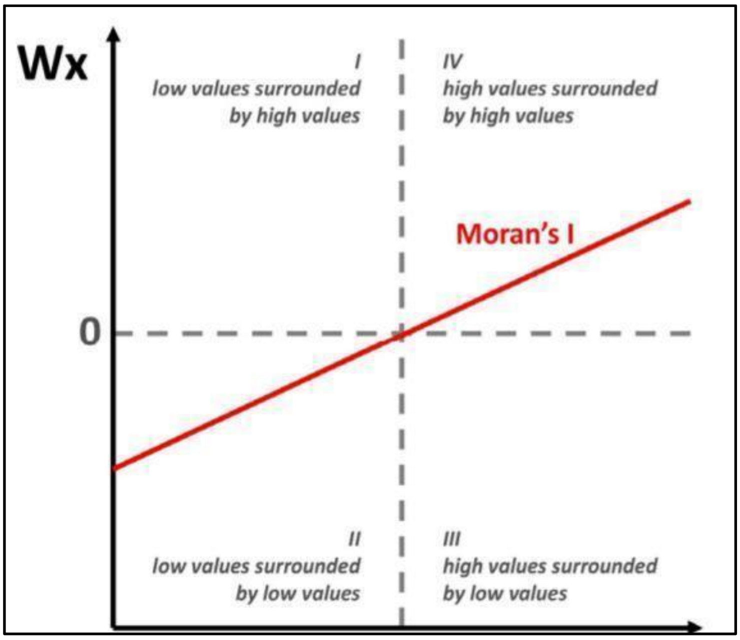


Fig 4.4 *Moran's scatterplot (Scardaccione, 2010)*

The second and fourth quadrants represent areas of values with positive correlations or spatial association of similar values (both values above or below the mean) while the first and third quadrants represent areas with negative correlation, spatial association of dissimilar values (one value above and one value below the mean). The Moran Scatter plot gives no information on the significance of spatial clusters, but it permits to identify outliers present in the statistical distribution by observing their distance from the mean and the row-standardised spatial weights (Scardaccione, 2010).

[2] The Queen contiguity definition was preferred over (for example) 'K Nearest Neighbours' and 'Fixed Distance Neighbours' due to consistent size and distribution of polygons (ESRI, 'no date').

4.2.5 Getis and Ord's Gi (and Gi*)

The family of Moran indices does not discriminate between hot spots and cold spots. The Gi* index is therefore more suitable because it can locate unsafe regions on a global scale and discern cluster structures of high- or low-value concentration among local observations (Songchitruksa & Zeng, 2010; Fig 4.5).

$$G_i^* = \frac{\sum_{j=1}^{n} w_{ij} x_j}{\sum_{j=1}^{n} x_j}$$

where

G_i^* = statistic that describes the spatial dependency of incident i over all n events,

x_j = magnitude of variable X at incident location j over all n (j may equal i), and

w_{ij} = weight value between event i and j that represents their spatial interrelationship.

Fig 4.5: *Equation of Gi**

Gi* statistics may vary according to the selection of d. A close-to-zero Gi* value implies random distribution of the observed spatial events. Conversely, positive, and negative Gi* statistics with high absolute values correspond to the clusters of high- and low-valued events, respectively. The negative Gi*, however, indicates a tendency of clusters of events with short incident durations (Songchitruksa & Zeng, 2010).

4.2.6 Bonferroni Test

The Bonferroni test ensures that the p value for each test must be equal to its alpha divided by the count of the total tests undertaken (Armstrong, 2014). It minimises the likelihood of misidentification of spatial dependency. In its simplest form, it is the confidence level (α) divided by the number of tests. While this becomes conservative as N becomes larger, coefficients can be factored into the adjustment to correct the α level and prevent this conservatism (Songchitruksa & Zeng, 2010).

4.3. Spatial Regression

4.3.1 Linear Regression

Linear regression is a method used to model the relationship between two variables by fitting a linear equation to observed data (Weisberg, 2013). The general form of a linear regression is the following[3]:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_i +,...,+ \beta_p x_{ip} + e_i$$

[3] where yi is the i^{th} observation of the dependent variable, y; i = [1, 2,…,n] with n being the number of observations; xip is the i^{th} value of the independent variable p, where p = [1, 2, …, m], such that m is the number of independent variables; ei is the residual error and p is the p^{th} parameter to be estimated; 0 is an intercept term defining where the regression line crosses the y-axis when x=0.

When fitting a linear regression, the crude association between two variables is not enough to adequately capture the relationship, so confounders and effect modifiers must be accounted for. Confounders are variables that associate with both the outcome and exposure and do not lie on the causal pathway. Effect modifiers are variables that associate with either exposure or outcome and elicit different outcome effects between stratified groups (Kirkwood & Sterne, 2010). For this analysis, the effect modifier of interest is ethnicity and confounders will be assessed using a correlation matrix and individual regression coefficients. Correlations from a matrix greater than 0.10 or less than -0.10 were considered notable enough to test for potential confounding and variables were considered actual confounders if a deviation from the crude association was observed in the crime coefficient (Kirkwood & Sterne, 2010).

Linear models have four key assumptions: 1) linearity between the independent and dependent variables, 2) constant variance of residuals (homoscedasticity), 3) normality of residuals and 4) independence of residuals (multicollinearity; Bender, 2009). To test these assumptions, linearity will be checked with Residual vs fitted plots, homoscedasticity with scale-location plots, normality with QQ-plots and multicollinearity with residuals vs leverage plots. If all these tests pass, the linear regression would need no further adjustment. However, since this is spatial data, it is hypothesised that multicollinearity will be violated due to spatial autocorrelation.

4.3.2 Testing for Autocorrelation

This analysis used Moran's I and the Lagrange Multiplier (LM) to evaluate autocorrelation within the linear model (Darmofal, 2015). Moran's I is used to capture the *presence* of spatial autocorrelation in the data, whereas the LM tests are designed to test which *type* (lag or error) of spatial regression model is most appropriate for the dataset.

4.3.3 Spatial Regression

Spatial regression models typically account for the presence of spatial autocorrelation in one of three ways: 1) Including spatially lagged values of the dependent variable in the model; 2) Including a spatially lagged error term; and 3) Accounting for both lags and error terms. The model most appropriate for the dataset at hand was determined by autocorrelation results, which indicated that a Durbin spatial regression was required. This spatial lag model assumes the presence of autocorrelation in one or more independent variables, as well as the dependent variable (Darmofal, 2015) and is formulated as[4]:

$$y = \rho W y + X\beta + WX\theta + \epsilon$$

To compare the spatial regressions with the linear model, Nagelkerke pseudo-R^2 will be used as an approximate compare parameter. The Rho p-value will be used to test

[4] where y is the observation vector and are autocorrelation parameters W is a spatial weight matrix and is the vector of independent errors. The term ρWy includes the sum of observations y_j that are spatially adjacent to y_i multiplied by i. The term $WX\theta$ is the effect of creating a weighted sum of the independent variables that are adjacent to location y_i and multiplied by autocorrelation .

whether the addition ρ significantly improves the model fit and the Wald test p-value will further test for spatial dependence. The LM test for residual autocorrelation will determine whether the model adequately accounts for spatial autocorrelation in the data.

5. RESULTS

5.1 SA Analysis: Crime [Pratibha]

5.1.1 Global Moran's I (Randomisation): For Global Moran's I statistic (Fig 5.1.1), the null hypothesis states that the attribute being analysed is randomly distributed and the spatial processes resulting in observed patterns are due to a chance. Here, the Moran's I statistic is 0.2924. This indicates that the crime type variable is positively autocorrelated. In other words, the crime data is spatially clustered. The p-value is small, and this implies that the results are statistically significant.

```
Moran I statistic standard deviate = 12.974,
p-value < 2.2e-16
alternative hypothesis: greater
sample estimates:
Moran I statistic    Expectation      Variance
0.2924911825      -0.0015408320    0.0005136137
```

Fig 5.1.1: *Output of Global Moran I's (Randomisation)*

5.1.2 Global Moran's I (Monte Carlo Simulation): Here, the observed rank is 1000, which means that the observed value of Moran's I was higher than any of the 999 random permutations (Fig 5.1.2). The p-value gives the statistical significance of the result. The value of 0.001 means that there is a 0.1% probability of the observed Moran's I statistic being due to chance. Thus, results are not due to a chance(random) and the null hypothesis can be rejected. In other words, Crime data is spatially correlated.

```
number of simulations + 1: 1000
statistic = 0.29249, observed rank = 1000, p-value = 0.001
alternative hypothesis: greater
```

Fig 5.1.2: *Output of Global Moran's I: Monte Carlo Simulation*

5.1.3 Monte Carlo Simulation Density Plot: The curve of this plot indicates the values of Moran I statistics that would be expected had crime data be randomly distributed (Fig 5.1.3). The vertical line lies on the right side of the curve, suggesting clustering of crime data. The observed statistics have a value of 0.2924.

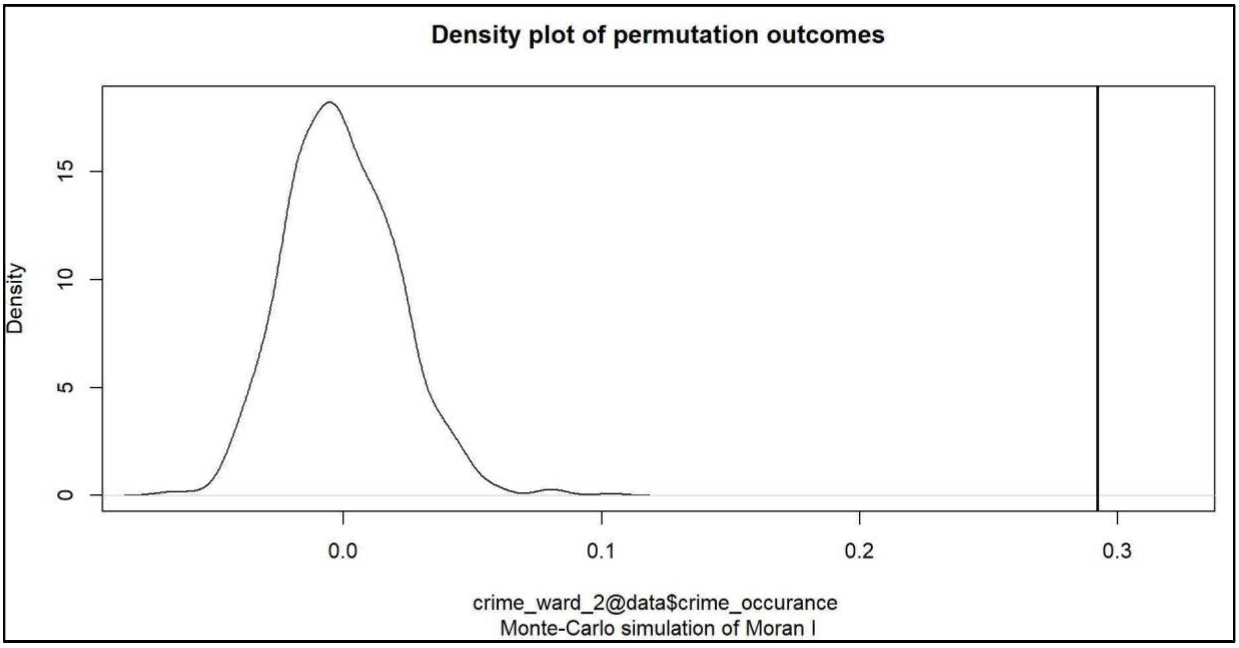


Fig 5.1.3: *Density plot of permutation outcomes*

<u>5.1.4 Randomised Distribution:</u> The observed crime occurrences are shown along with randomized distribution of crime (Fig 5.1.4). The observed data shows higher levels of crime occurrences concentrated in central London and less in the outer districts; however, this is not the case in the randomized distribution (Fig 5.1.5).

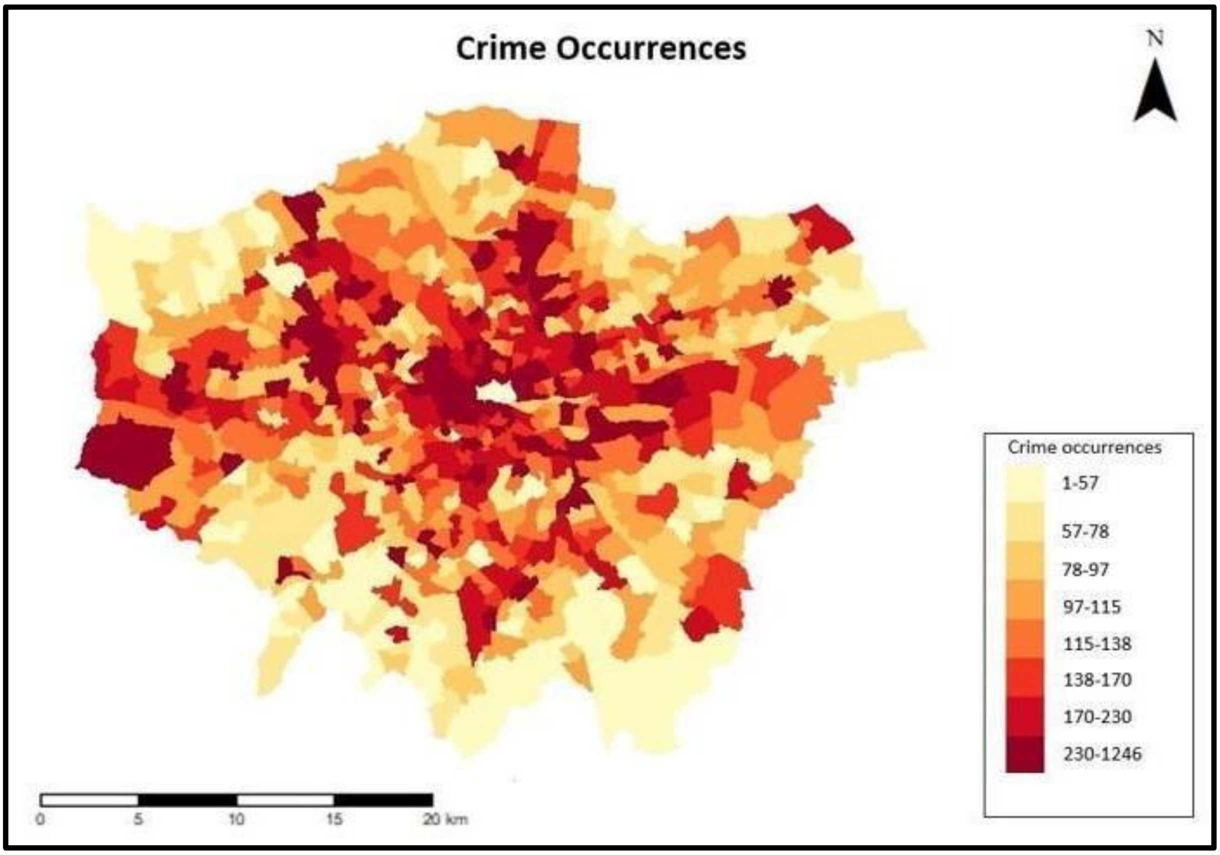


Fig 5.1.4: *Observed Distribution of crime occurrences*

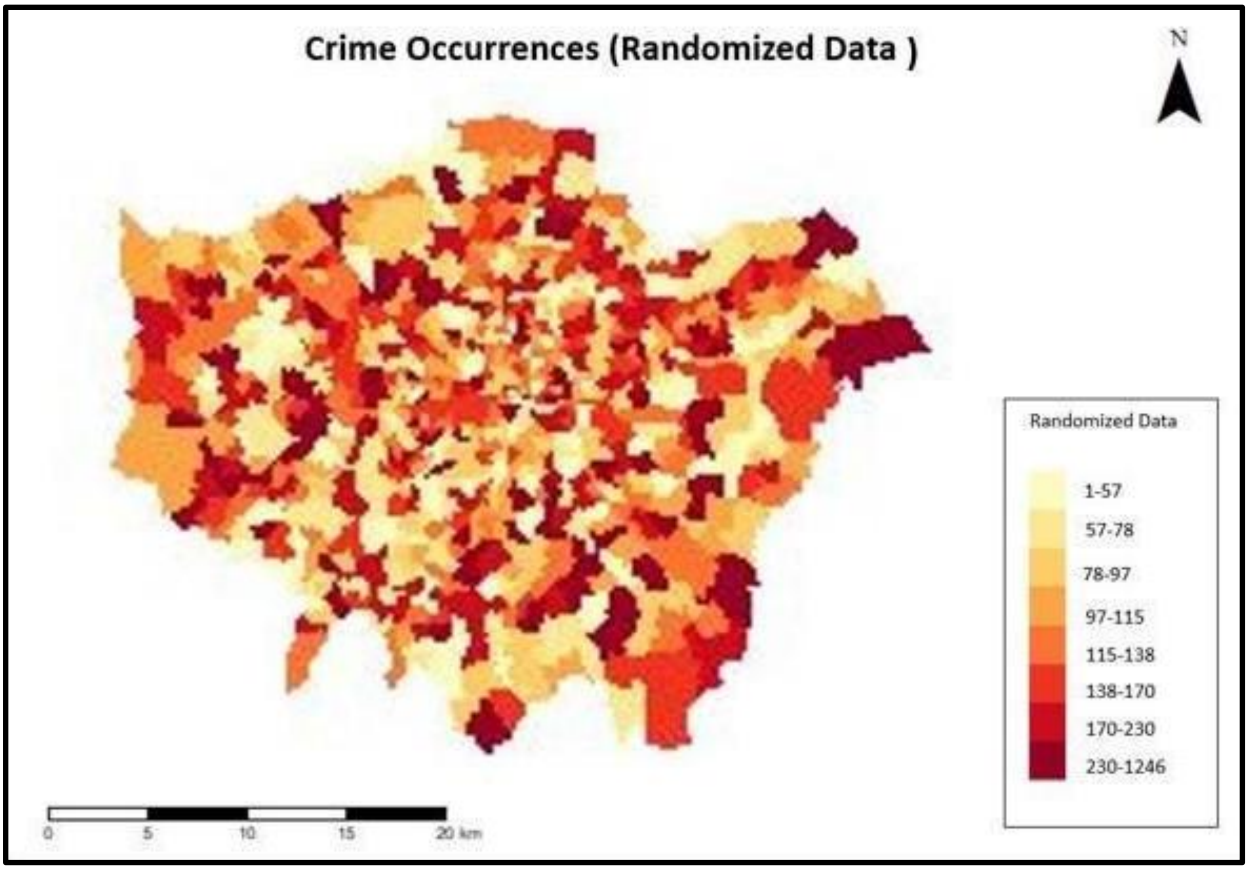


Fig 5.1.5: *Randomised distribution of crime occurrences*

<u>5.1.5 Getis-Ord General G:</u> The Getis Ord General G null hypothesis states that there is no spatial clustering of feature values (Esri, 2019). With a positive z-score of 7.9617 and a significant p-value, the null hypothesis can be rejected (Fig 5.1.6). This is also demonstrated by the difference between the expected and observed General G statistics. There is less than a 1% likelihood that the pattern observed could be the result of chance.

Observed General G = 0.0061671
Expected General G = 0.001541
Variance = 0.000000, z-score = 7.961703, p-value = 0.000000

Fig 5.1.6: *Output of Global G*

<u>5.1.6 Moran Scatterplot :</u> This is the Moran scatterplot of the crime occurrences at the lowest spatial level (area: ‘Name’; Fig 5.1.7). From the scatterplot, areas of high crime occurrence that are neighboured by other areas of high crime occurrence are West End and St James's. This indicates that there may be some clusters of high crimes in West End and St James's. Contrastingly, areas such as Abbey and Heathrow Villages

have a high crime occurrence but are not neighboured by areas with similarly high levels of occurrence.

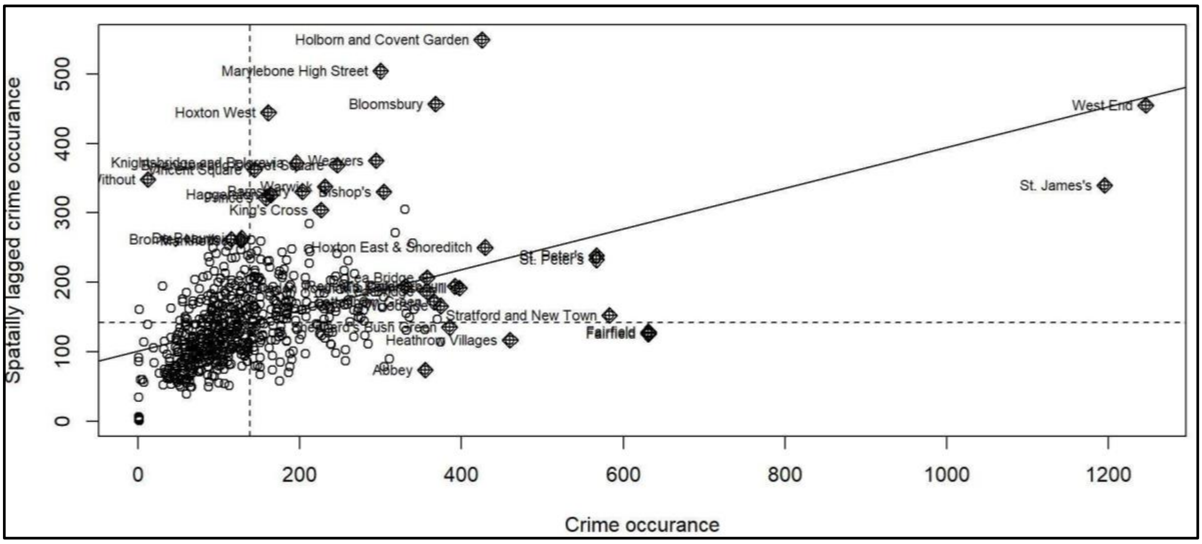


Fig 5.1.7 *Moran scatterplot at ward level*

<u>5.1.7 Getis-Ord Gi* statistics</u>: The results for Getis-Ord G* was done using ArcMap. These results were generated using a neighbour distance of 3000m (Fig 5.1.8). Most of the area has cold spots with 90% confidence. Hotspots with a confidence of 99% are in Central London (St. James's, West End etc.), East of the centre towards Stratford and New Town and in West London (Heathrow villages). This result is not unexpected as from the results above it was found that the crimes are high in Central London.

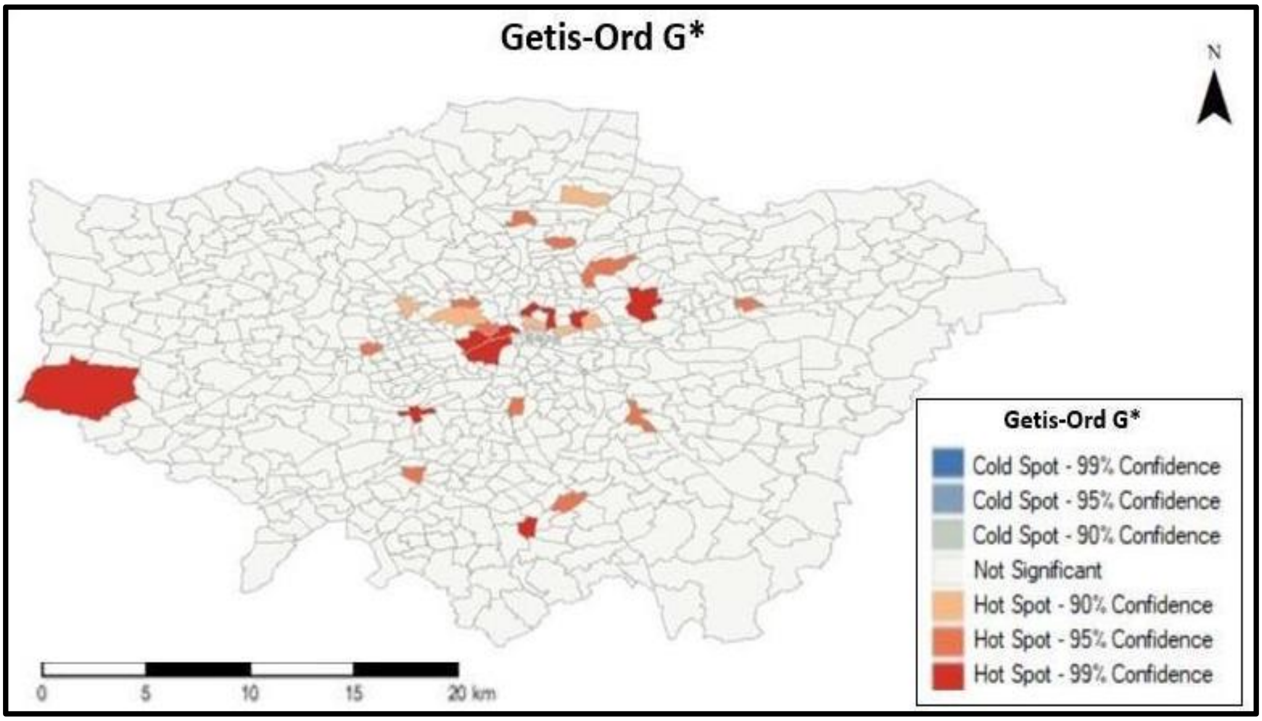


Fig 5.1.8: *Getis-Ord G* Analysis*

<u>5.1.8 Local Moran's I:</u> It is evident that the magnitude and frequency of positive values are more, in comparison to negative values, indicating that the area has more clustering effect than dispersion (Fig 5.1.9). The areas showing high clustering include St James's and West End. It shows positive local Moran I statistics (Fig 5.1.10)with p- values less than 0.05, which is at a significance level of 95%. It indicates that a feature has neighbouring features with similarly high or low attribute values and thus forming a cluster. It forms a cluster in Central London including the areas of West End, St James's, Holborn and Covent Garden, Marylebone High Street, Bloomsbury, Regent's Park, etc. Equivalent results were found in the Moran Scatterplot. Negative Moran I statistic (Fig 5.1.11) indicates that a feature has neighbouring features with dissimilar attribute values and thus forming an outlier. It includes areas such as Farringdon without, Wandsworth common, King's Park etc.

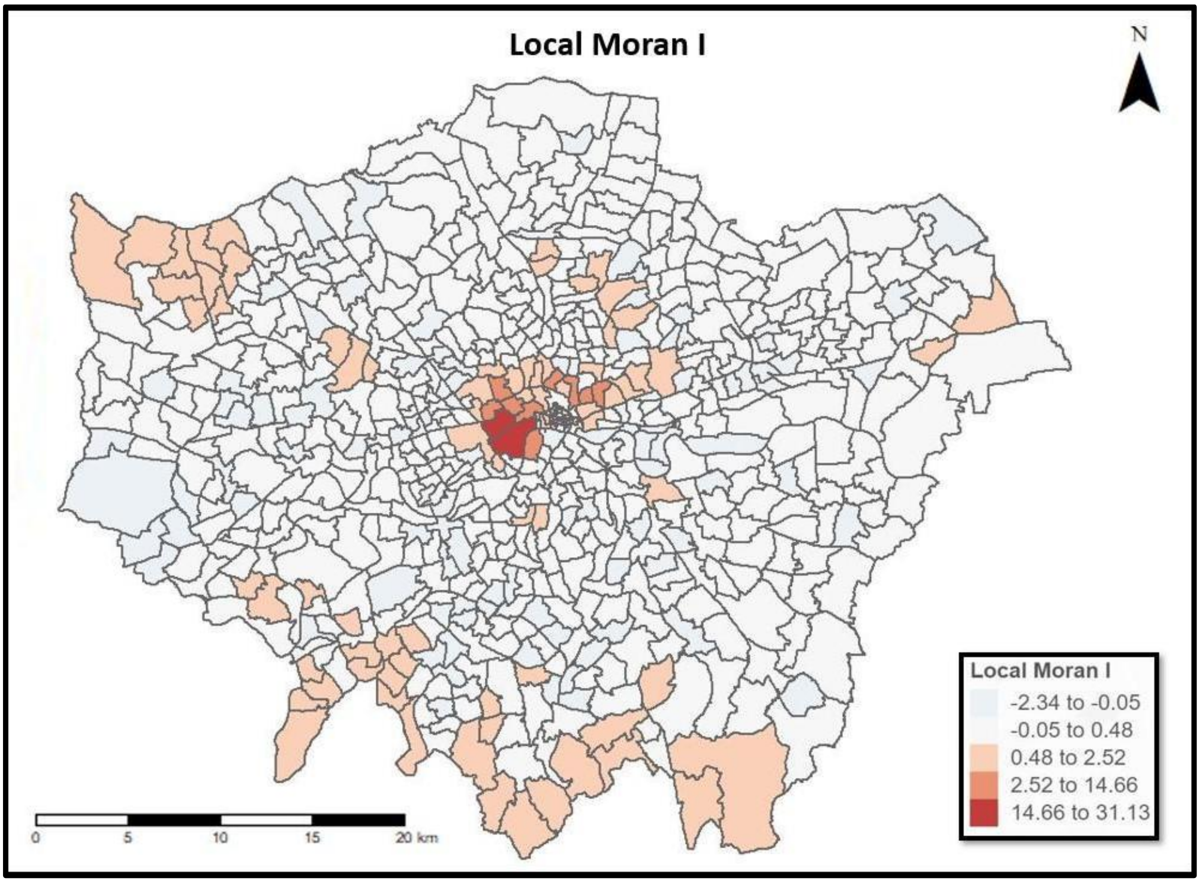


Fig 5.1.9: *Local Moran I analysis*

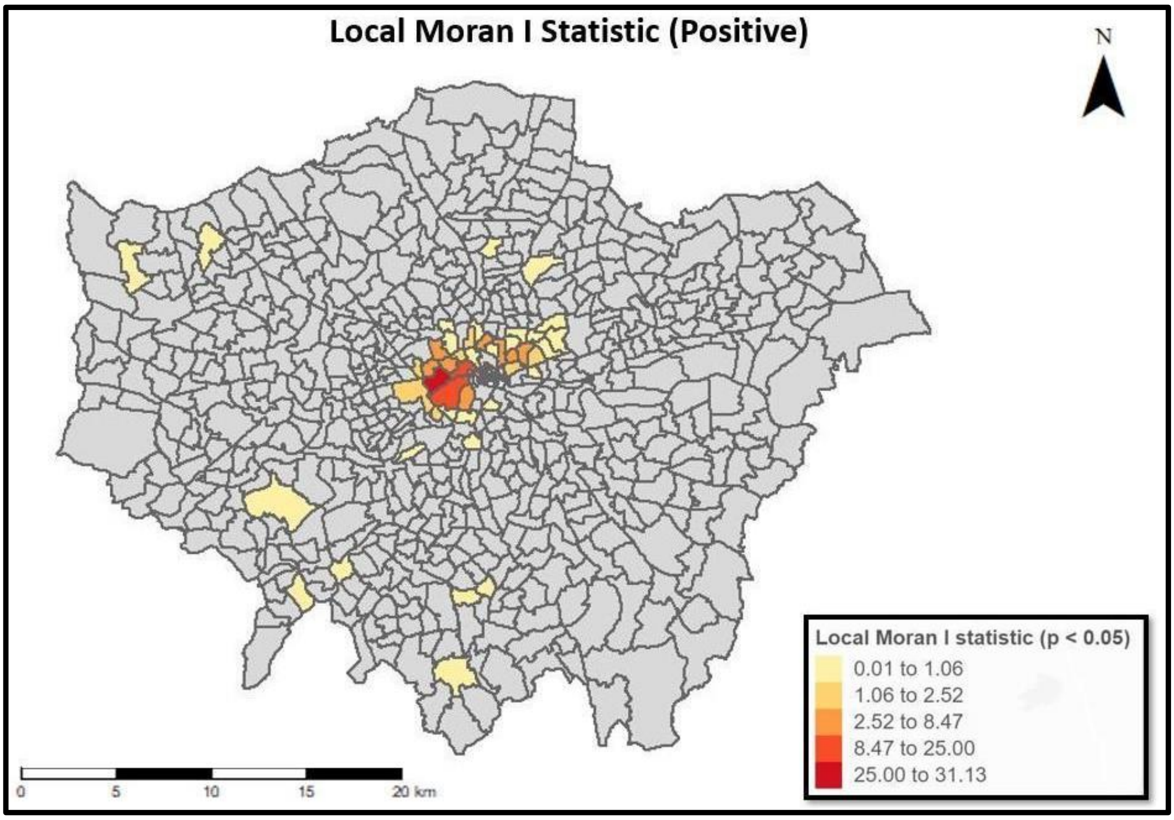


Fig 5.1.10: *Positive Local Moran I Statistic*

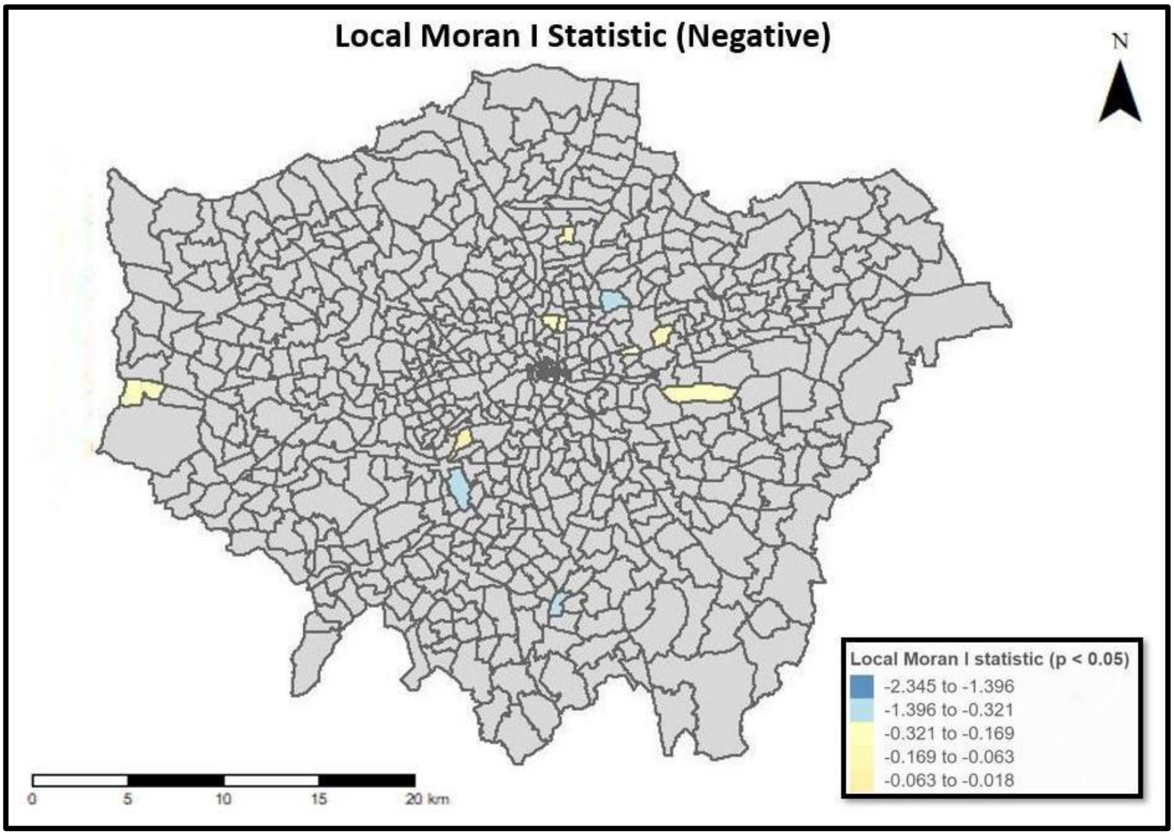


Fig 5.1.11: *Negative Local Moran I Statistic*

<u>5.2.3.1 Significant Local Moran I Statistics and Benferroni Adjustment: F</u>igure 5.1.12 shows all the wards with local Moran I at a significance level of 95%. There are 589 wards that are classified as non-significant and 61 as significant. The clustering is still significant in Central London. The London wards consist of a small number of spatial units and therefore the likelihood of false positives in the results must be accounted for (Armstrong, 2014). After applying the Bonferroni adjustment (Fig 5.1.13), the number of wards that are statistically significant is reduced to 32 from 61. However, the pattern remains same i.e., clustering is significant in the centre of London (West End, St James's, Holborn and Covent Garden, Marylebone High Street, Bloomsbury, Regent's Park, Weavers, Haggerston etc.). One distinct ward seen in figure is Selhurst.

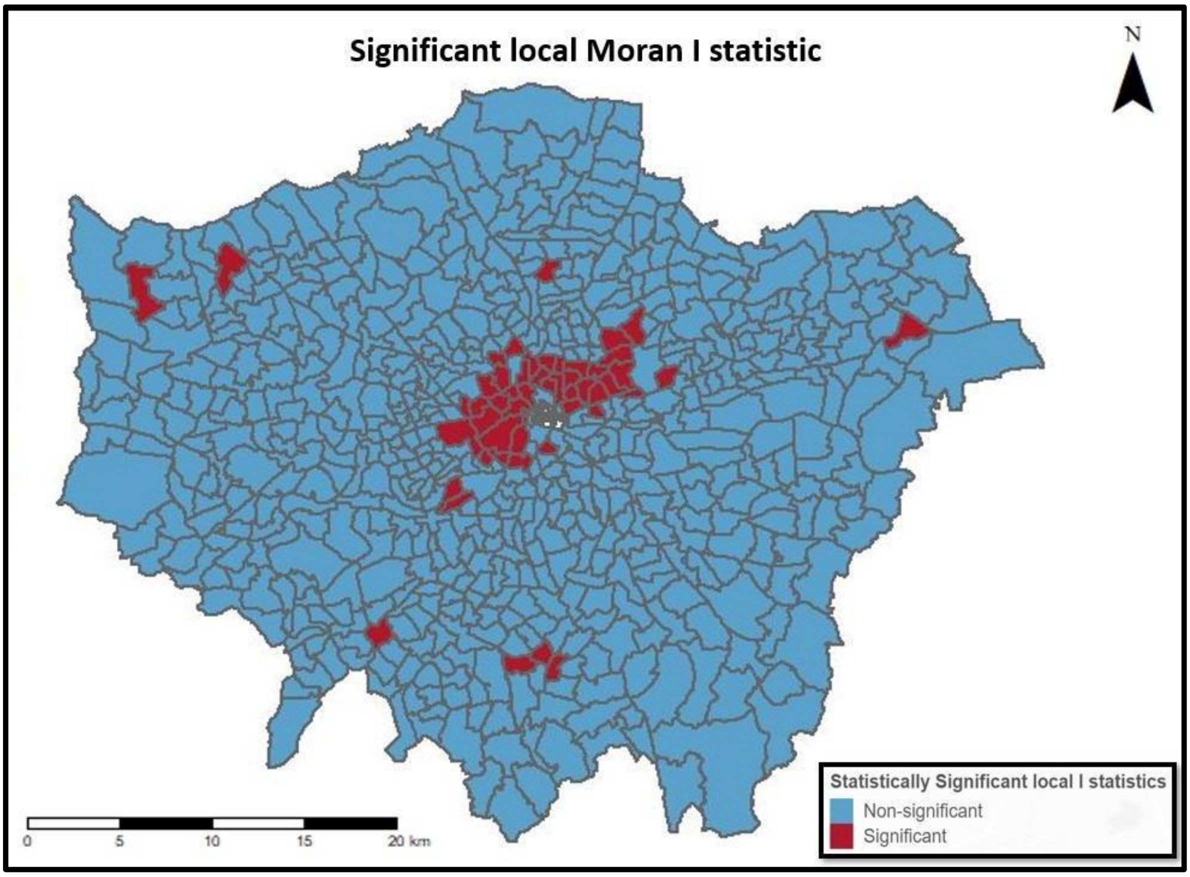


Fig 5.1.12: *Significant Local I statistic*

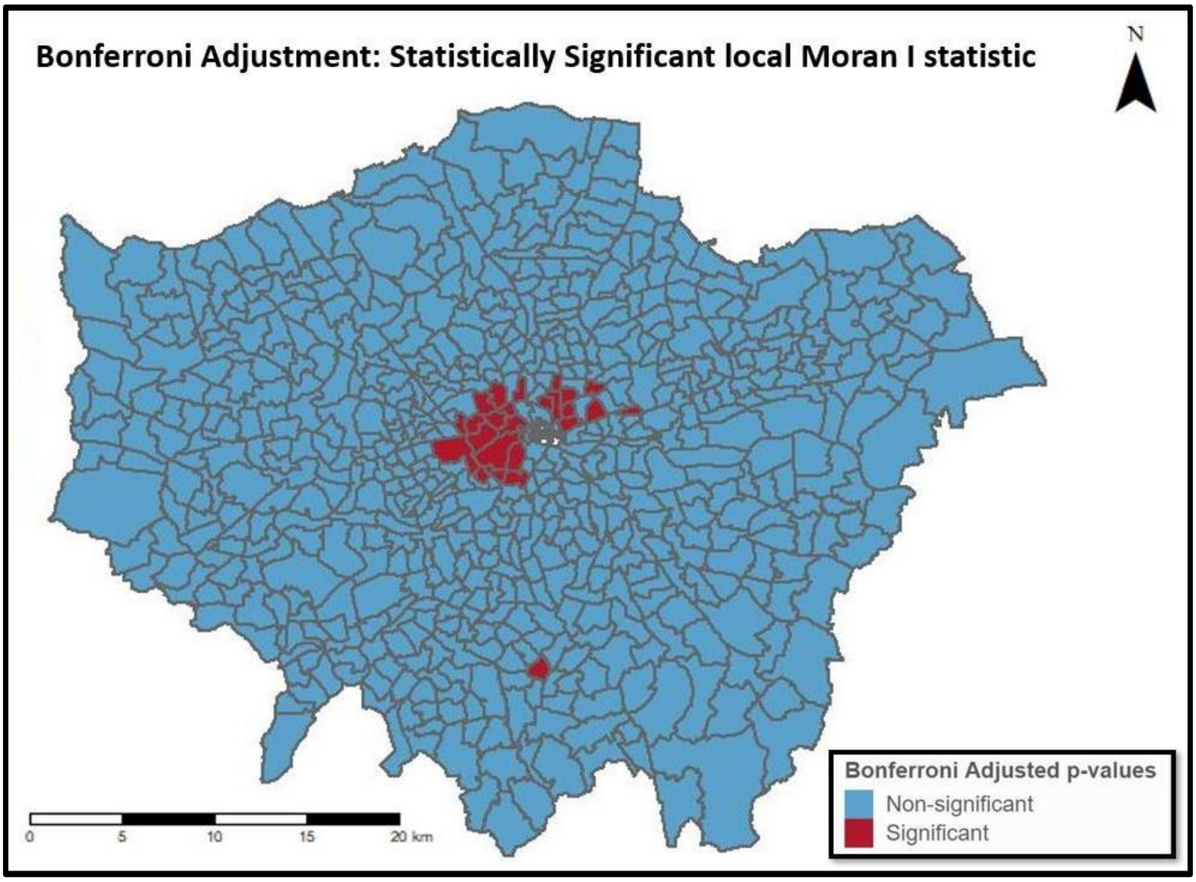


Fig 5.1.13: *Benferroni adjusted local I statistic*

5.2 SA Analysis: SS [Danni]

As shown in Fig 5.2.1, if the data exhibited characteristics of CSR, a Moran I statistic of -0.0016 would be expected. This contrasts greatly to the returned Moran I statistic of 0.2767 whose direction and magnitude indicate positive spatial autocorrelation throughout the dataset. The returned p-value of < 2.2e-16 suggests that while the data is not perfectly clustered (I = +1), the clustering present is significant and the null hypothesis should be rejected (Bellefon, 2018).

```
GLOBAL MORANS I (under randomisation):
Moran I statistic standard deviate = 11.571
p-value < 2.2e-16
alternative hypothesis: greater

sample estimates:
Moran I statistic      Expectation       Variance
0.2767138176        -0.0016313214    0.0005786173
```

Fig 5.2.1: *Results of Global Moran's I (under randomisation) for SS data.*

The previous Moran's I analysis is faster than that of the Monte Carlo (MC) simulation but may be sensitive to irregularly distributed polygons (Gimond, 2019). The MC simulation aims to address how, even with CSR, some degree of clustering is likely to occur by random chance by generating permutations of the data. Fig 5.2.2 shows that the MC simulation results are identical to that seen previously to provide additional confidence that the data is clustered to this degree. An observed rank of 1000 indicates that the Moran's I statistic was higher than any of the simulated results. The results are significant at a 99.9% confidence interval.

```
number of simulations + 1: 1000
Statistic = 0.27671, observed rank = 1000,
p-value = 0.001
alternative hypothesis: greater
```

Fig 5.2.2 *Results of the Global Moran's I under Monte Carlo simulation*

Fig 5.2.3 is a density plot of the MC simulation whose curve shows the values of the Moran I statistic that would be expected in random spatial dispersion. The vertical line at 0.2767 falls significantly to the right demonstrating the unlikeliness of this result in CSR. Additionally, Fig 5.2.4 shows higher rates of ss occurrence in central London however this trend is not evident in the randomised data.

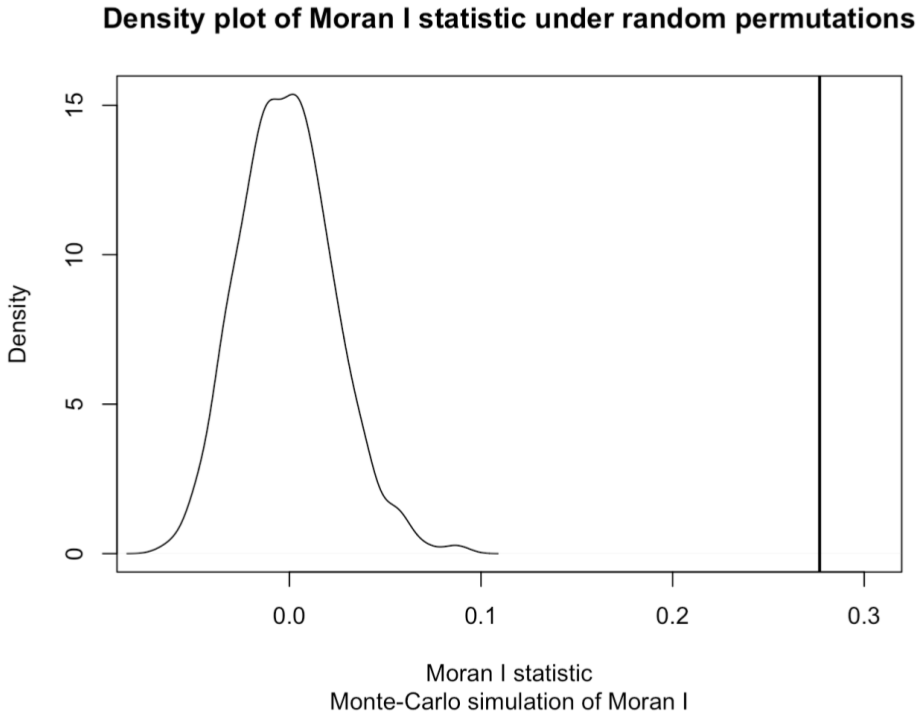


Fig 5.2.3: *Density plot of Moran I statistic under random permutations compared to calculated test statistic.*

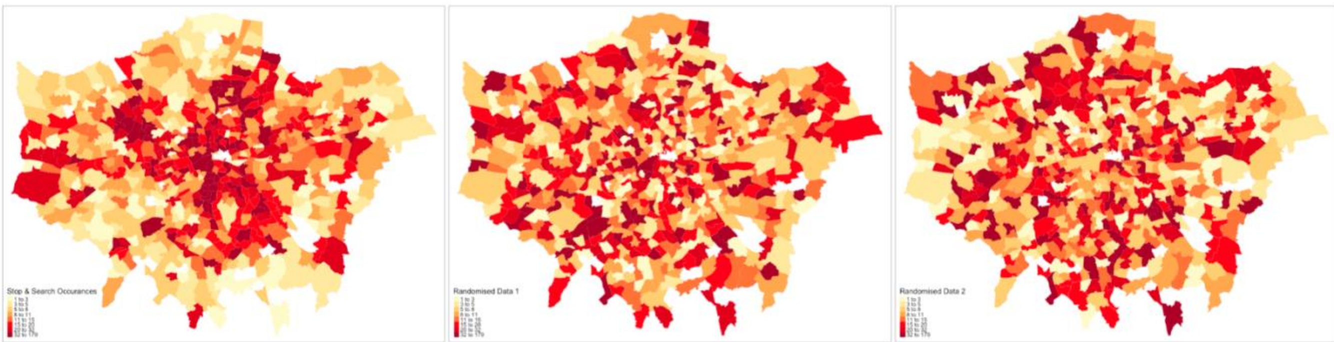


Fig 5.2.4 *The real SS occurrences are plotted alongside two visuals of spatially randomised data. (Far left: SS occurrence data per ward. Centre and Right: randomised data)*

The Moran Scatterplot (Fig 5.2.5) allows for the identification of spatial heterogeneity; a characteristic not present in the global measures. The graphic highlights areas of high SS occurrence that are neighboured by other areas of high ss occurrence. Examples of this include Coldharbour, St James's and West End. At the district level the scatterplot highlights Lambeth, Brent, Lewisham, and the City of Westminster as the key regions of spatial autocorrelation.

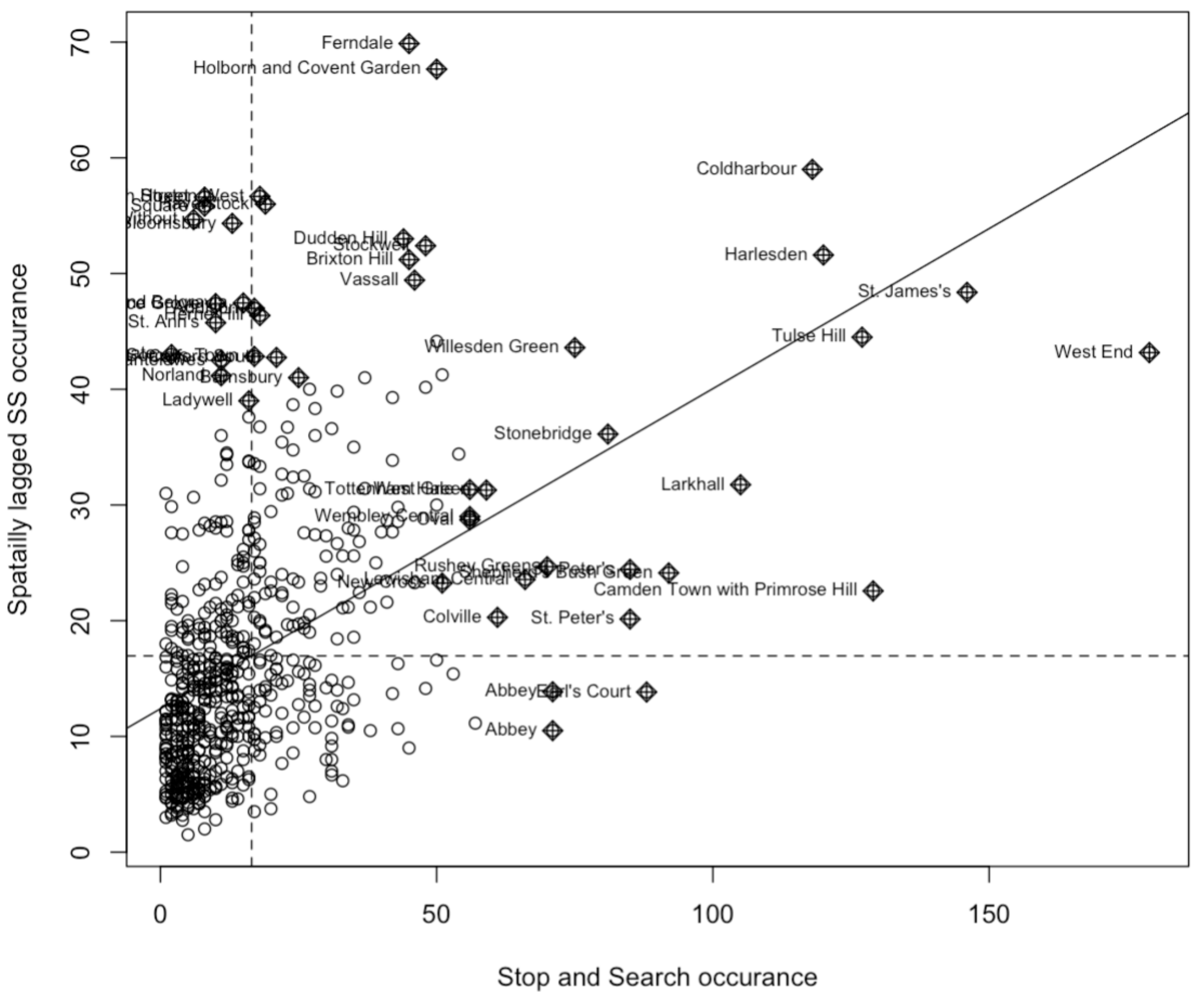


Fig 5.2.5: *Local Moran's I scatter plot*

The Getis Ord General G analysis was performed using the ArcGIS Pro 'High / Low Clustering' software and produced the output shown in Fig 5.2.6. The Gi and Gi$*$ statistics measure how similar values are clustered across the study region to make hot and cold spots. The 'Zone of indifference' option was chosen to conceptualise spatial relationships in ArcGIS as it combines the Inverse Distance and Fixed Distance band models (ArcGIS Desktop, 2021) and prevents the imposition of sharp boundaries. A threshold of 1.5km was chosen to ensure that each polygon had a neighbour. With a z-score of +9.77 and a significant p-value, the null hypothesis can be rejected and the spatial distribution of high values in the dataset can be considered more spatially clustered than would be expected of a truly random distribution. This is also demonstrated by the difference between the expected and observed General G statistic. There is less than 1% likelihood that the pattern observed could be the result of chance.

Observed General G: 0.002391
z-score: 9.771527
p-value: 0.000000

Given the z-score of 9.771526602675104, there is a less than 1% likelihood that this high-clustered pattern could be the result of random chance.

Observed General G:	0.002391
Expected General G:	0.001631
Variance:	0.000000
z-score:	9.771527
p-value:	0.000000

Fig 5.2.6 *Getis Ord General G results (produced using ArcGIS Pro)*

Fig 5.2.7 shows the results of the Getis Ord Gi* analysis which breaks down G into the contribution of each spatial unit. For consistency the same parameters were chosen for all Getis Ord analyses. The Gi* analysis has deemed most of the London wards as a cold spot with a (relatively low) 90% confidence level. Contrastingly, the highly significant (99% confidence) hot spots such as St James's, Coldharbour and West End nearly all congregate in central London and support the findings of the Local Moran scatterplot.

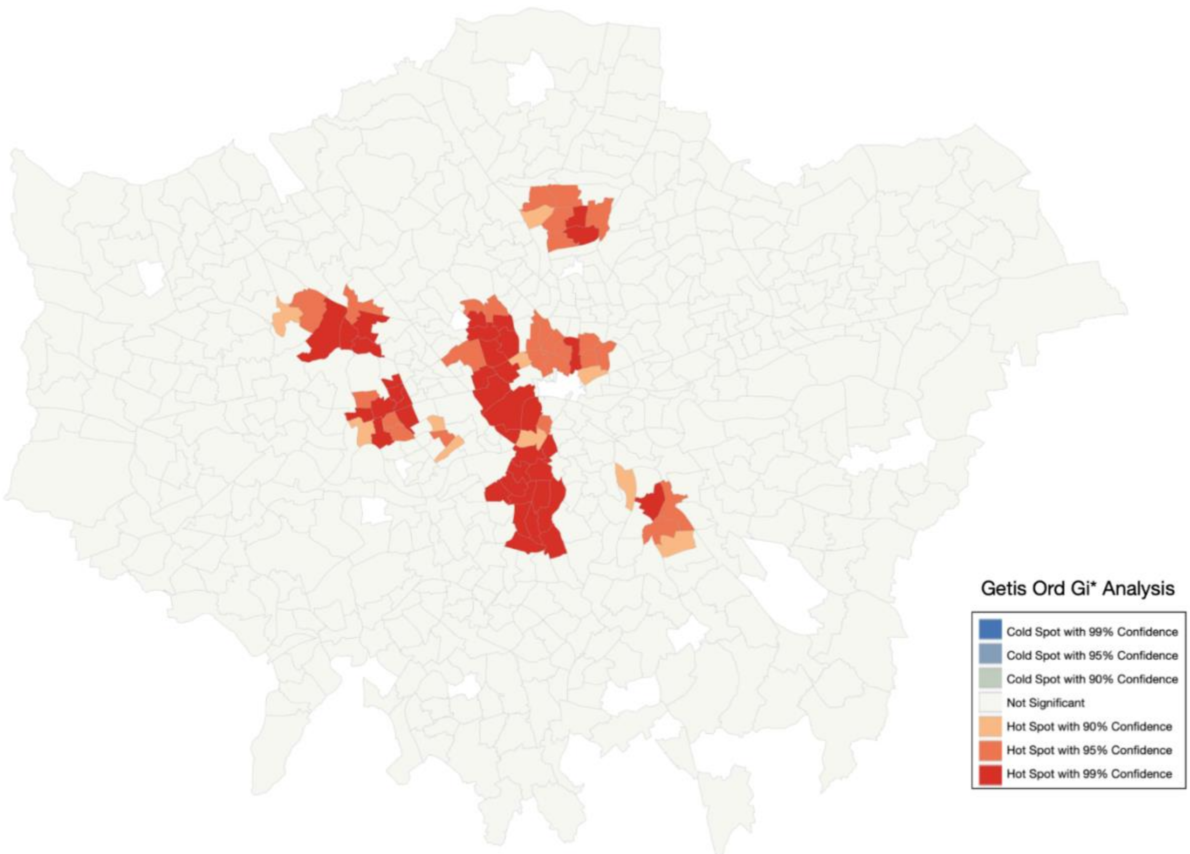


Fig 5.2.7: *Getis Ord Gi* results.*

The Local Moran I identify local clusters or outliers to understand their contribution to the 'global' clustering as calculated by the GMI (AURIN, n.d.). The expected statistics for the London wards (following a random spatial distribution) are shown in Fig. Visually, this contrasts to Fig 5.2.8 where the real test statistics are shown. High test statistics indicate that the region has neighbours with similarly high/low attribute values and are therefore part of a cluster. Consistent with the results of the Moran Scatterplot, St James's exhibits spatial clustering and is a hot spot. Fig 5.2.9 shows the spatial distribution of the local Moran but does not account for the associated p-value. Fig 5.2.10 and 5.2.11 show the regions of low and high clustering at the $p<0.05$ significance level. The positive Local Moran I statistics are larger in magnitude and more frequent than the negative values which indicate that the effects of clustering are more severe and frequent than that of dispersion.

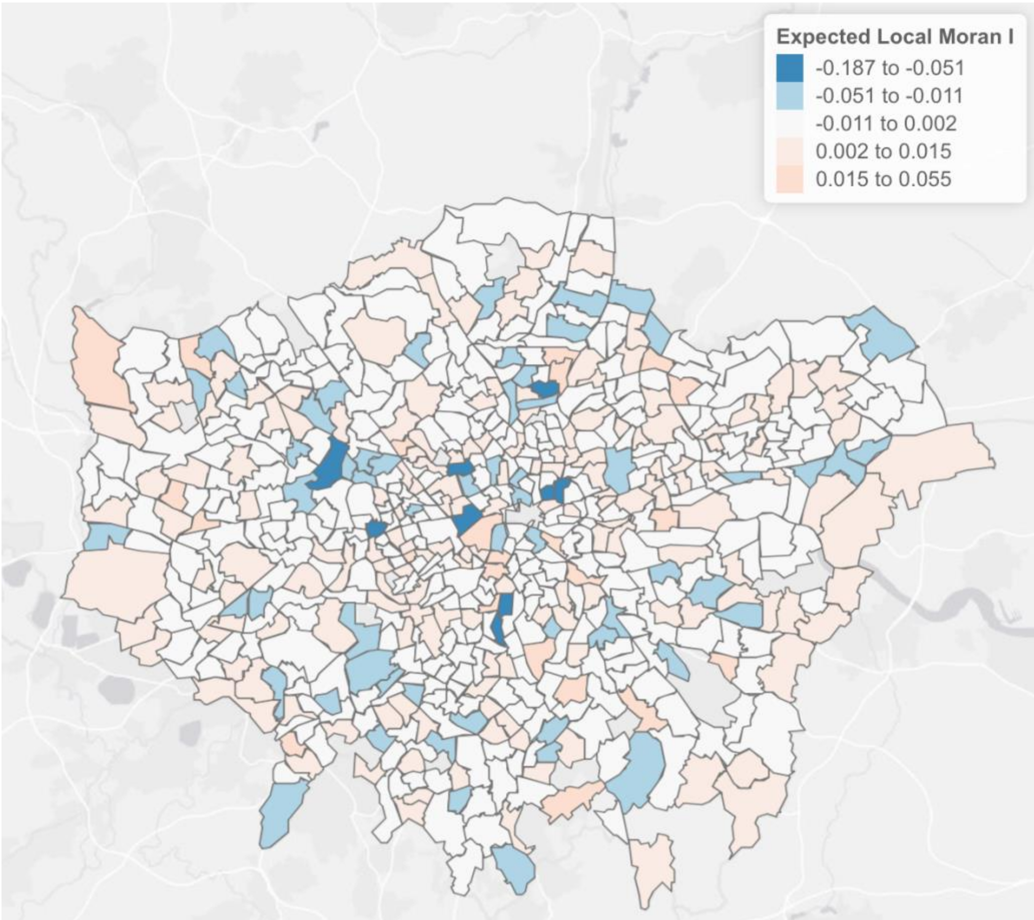


Fig 5.2.8: *Local Moran I: Expected statistic*

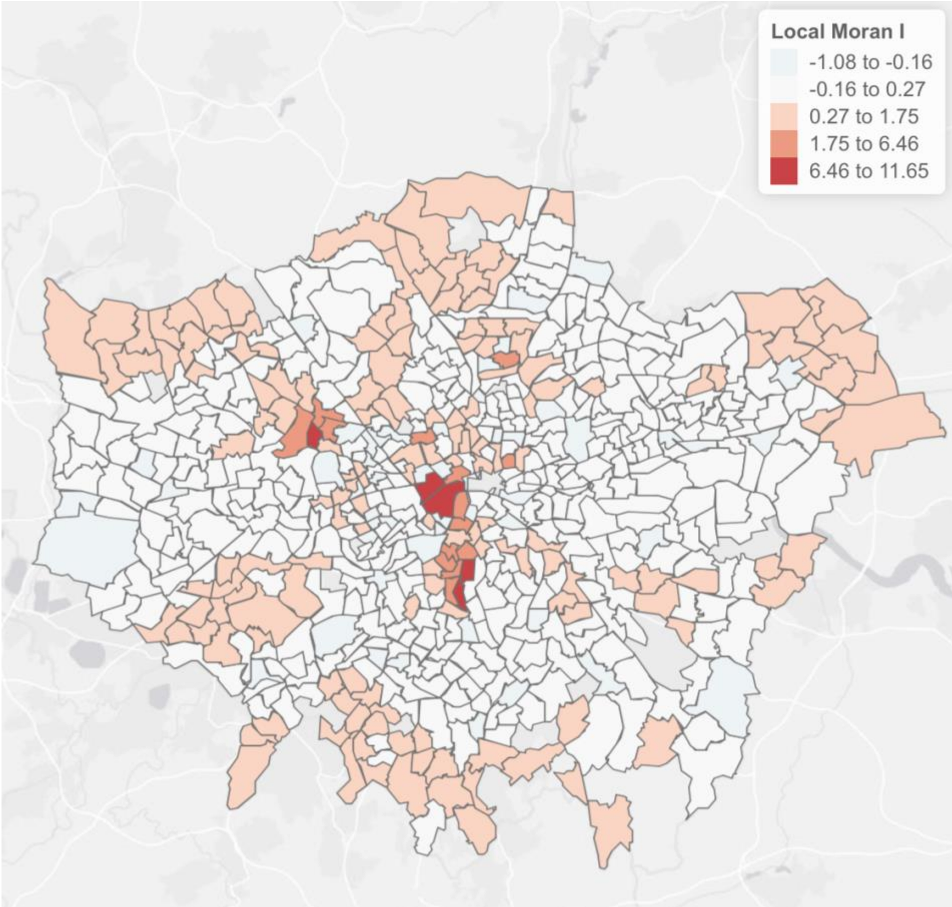


Fig 5.2.9: *Local Moran I: test statistics*

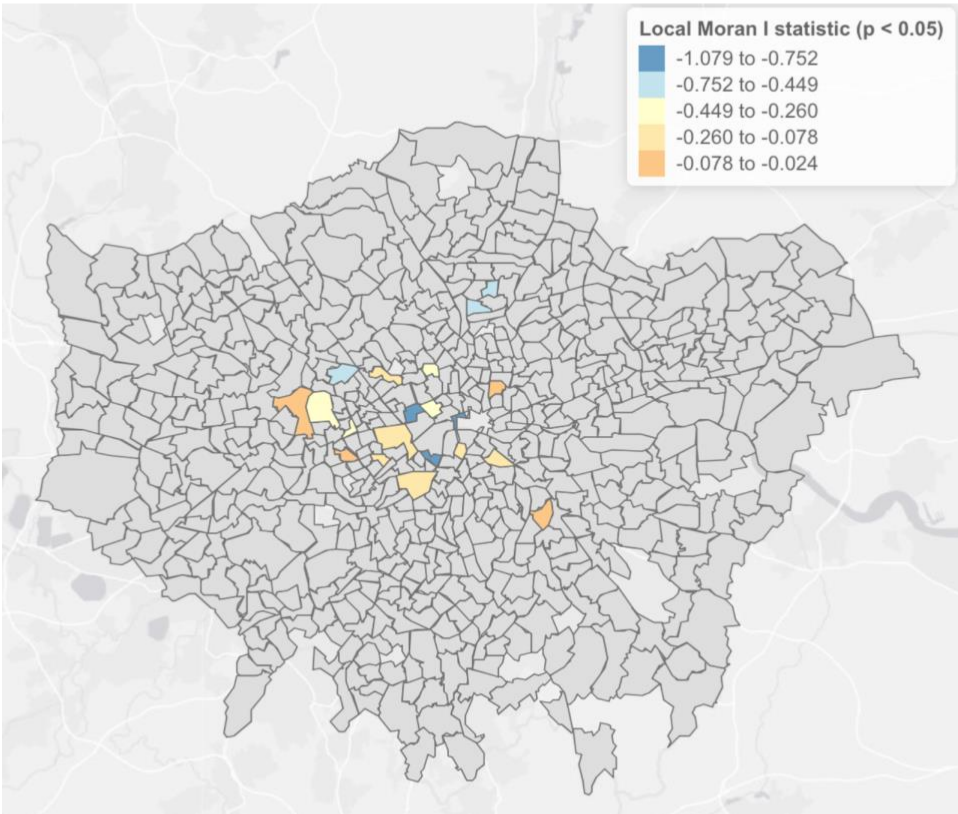


Fig 5.2.10: *Local Moran I: Regions of spatial dispersion ($p < 0.05$)*

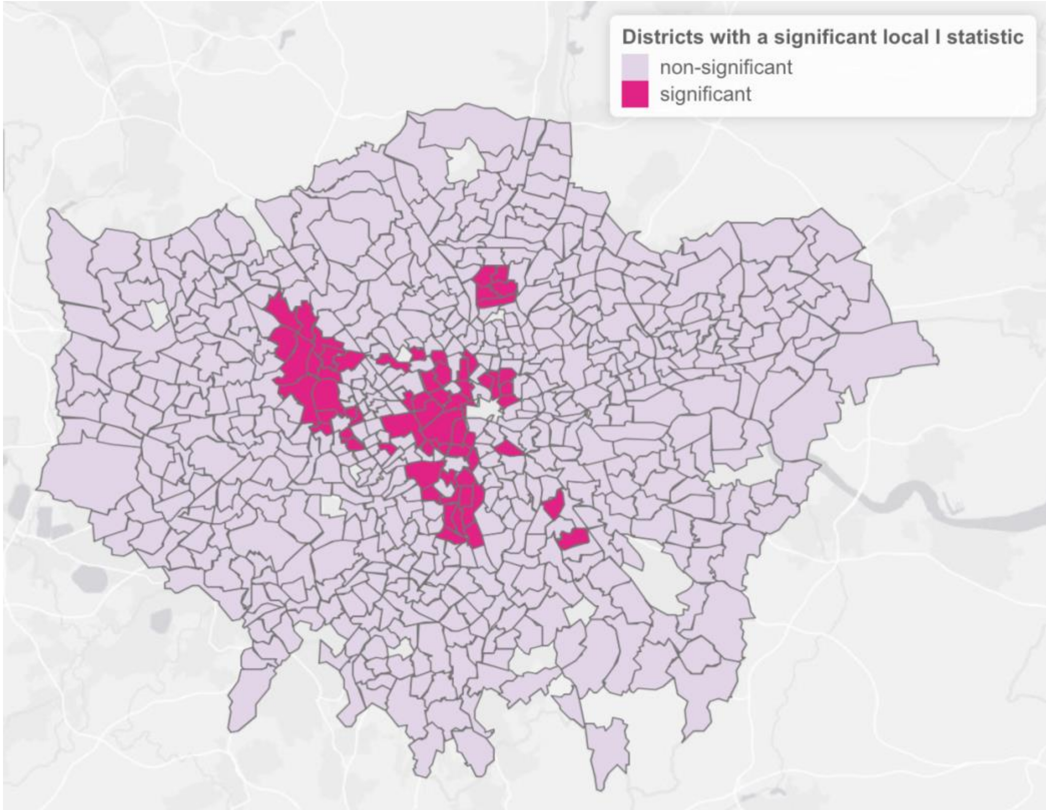


Fig 5.2.11: *Local Moran I: London Wards which had a significant I statistic before Bonferroni adjustment.*

The London wards consist of a relatively small number of spatial units and therefore the likelihood of false positives in the results must be accounted for. The Bonferroni test ensures that the p-value for each test must be equal to its alpha divided by the count of the total tests undertaken (Armstrong, 2014). While this form of correction can be overly conservative (Jafari, 2018), it allows for extra confidence when determining which wards are significant. Numerically, the unadjusted local Moran analysis produces 63 wards that are statistically significant (Fig 5.2.11) but this falls to 38 following the Bonferroni adjustment (Fig 5.1.12).

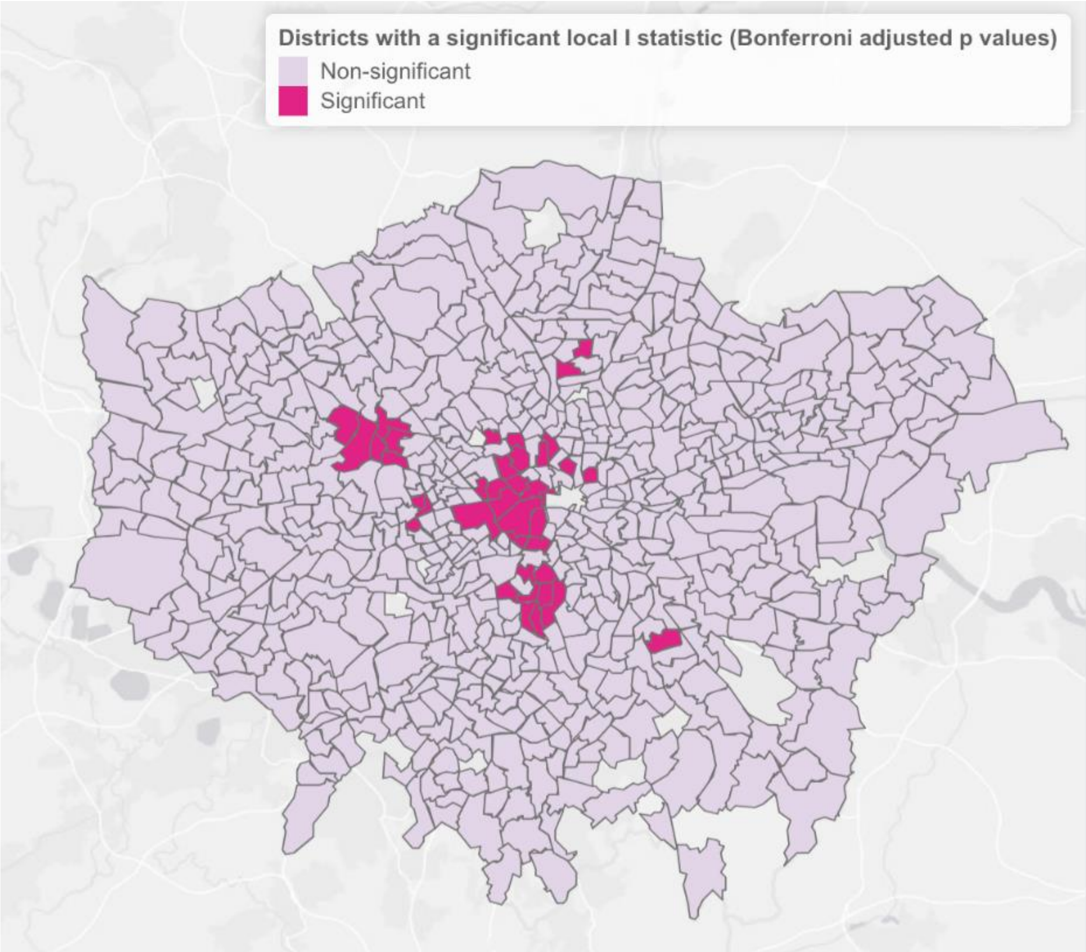


Fig 5.2.12: *Local Moran I: London Wards which had a significant I statistic after Bonferroni adjustment.*

5.3 SA Analysis: PP [Tommy]

5.3.1 Preliminary Assessment: The neighbourhood assessment (Fig 5.3.1) confirmed a small number of viable regions and links that justify autocorrelation testing, albeit with the caveat that a small sample would reduce the confidence level (z-value) and increase margin of error.

	SWM Summary
Number of regions	27
Number of nonzero links	96
nonzero weights (%)	13.16872
Average number of links	3.555556

Fig 5.3.1: *Neighbourhood Assessment, where PP was aggregated to the borough-level (32 regions) and a subset was omitted due to poor neighbourhood coverage (27 regions).*

5.3.2 Global Moran's I (GMI): Two instances of GMI were deployed to test against the null hypothesis that the encoded 'Fair S&S' values were randomly distributed across the study area; Randomised (Fig 5.3.2) and Monte Carlo (Fig 5.3.3) methods.

In Fig 5.3.2 The positive observed statistic (Ii) is positive (0.388566), which indicates that the PP variable is positively correlated and exhibits higher degree of spatial clustering than expected if the spatial process was random. The positive value for z (2.977071) and the small number of p indicates statistically significant results (0.1% probability of randomness).

Given the irregularities in distributed polygons described in the preliminary assessment, the MC was deemed the most suited GMI test (Fig 5.3.3). The observed rank (999) indicated that LMI statistic was greater than 998 permutations of the test and offers confidence that the observed statistic (0.38857) is valid. As with the Randomised Method, this showed positively correlated spatial clusters that are statistically significant (0.1% probability of randomness).

The curve (Fig 5.3.4) depicts expected LMI PP values in the scenario of random distribution. The vertical line of the observed statistic (0.38857) in the >0 territory indicates PP values are clustered.

	Summary
Observed Statistic	0.388566
Expected Statistic	-0.03846
Variance	0.020575
Z-Value	2.977071
P-Value	0.001455
Pattern	Clustered
Alternative Hypothesis	Greater

Fig 5.3.2: *Randomisation Method based on Queen Neighbours Definition.*

	Summary
Simulations (n)	1: 1000
Observed Statistic	0.38857
Observed Rank	999
P-Value	0.001
Pattern	Clustered
Alternative Hypothesis	Greater

Fig 5.3.3: *Monte Carlo Simulation Method based on Queen Neighbours Definition.*

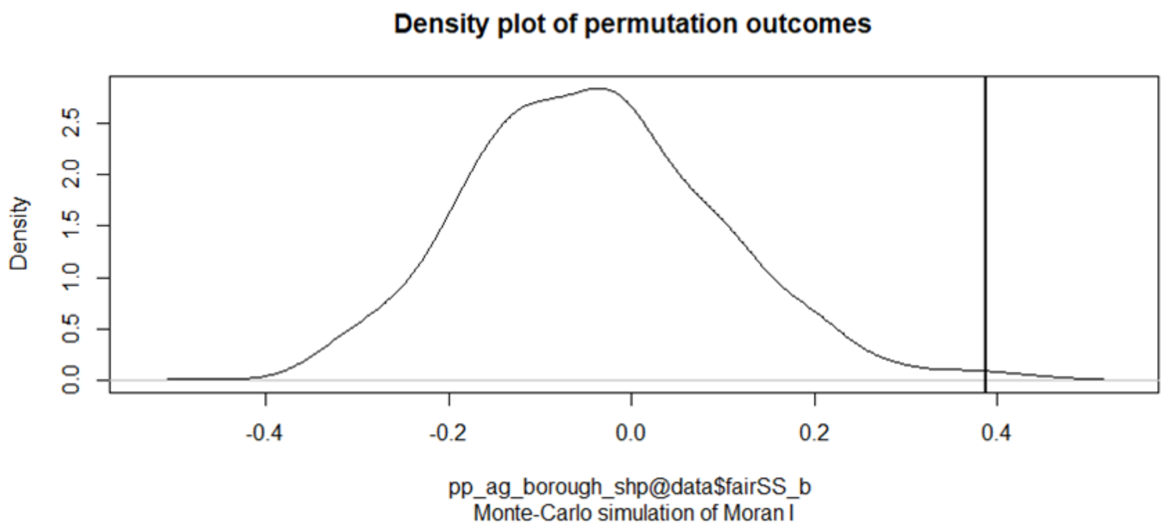


Fig 5.3.4: *GMI MC Density plot of Permutation Outcomes*

<u>5.3.3 Getis-Ord General G:</u> Getis Ord General G tests (Fig 5.3.5) on numerous suitable neighbourhood definitions detected a random distribution across the study area, which contests clustered patterns observed in GMI tests. While the Observed Statistic points to positive autocorrelation, the null hypothesis could not be rejected

because the z-value is negative, and the p-value is not significant. The results therefore infer a version of Complete Spatial Randomness (CRS).

	Queen	**Fixed Distance**	**Zone of Indifference**
Observed General G	0.038165	0.038320	0.038315
Expected General G	0.038462	0.038462	0.038462
Variance	0.000000	0.000000	0.000000
z-score	-0.688850	-0.386759	-0.422808
p-value	0.490917	0.698935	0.672435
Pattern	Random	Random	Random

Fig 5.3.5: *Getis Ord General G Statistics*

<u>5.3.4 Local Moran Scatterplot:</u> The graphical representation of spatial heterogeneity (Fig 5.3.6) shows a sparse plot of observations impacted by the aggregation process. Nonetheless the results distinguish a cluster in the 'low values neighbouring low values' quadrant (e.g., Hackney, Camden).

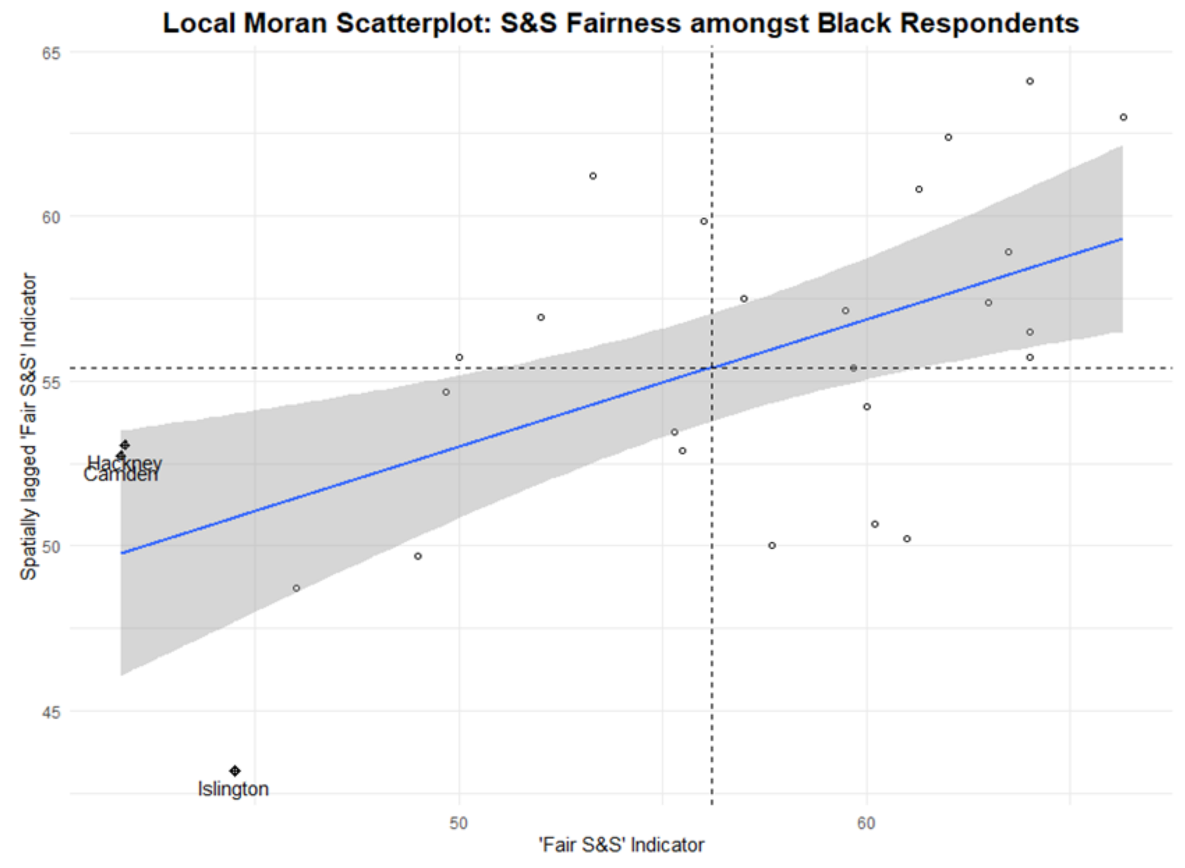


Fig 5.3.6: *Distribution of local cluster using Moran's Scatterplot*

5.3.5 Local Moran's I (LMI; Fig 5.3.7): All observed LMI statistics (top-right) were distinctly higher in frequency and magnitude than the corresponding expected LMI statistic (top-left). All observed values were >0, which indicates the presence of local autocorrelation across the study area. High statistics in east (e.g., Barking & Dagenham), central-north (e.g., Camden) and south-west (e.g., Wandsworth) London indicate 'hot spots' of spatial clusters that share similar attributes. As these clusters show positive z-values (bottom-left) and small p-values (bottom-right), the LMI statistics are statistically significant.

The most significant clusters (Fig 5.3.8) were distinguished by applying the p-value threshold of 95% for determining test significance ($p<0.05$); revealing a small cluster of 3 significant boroughs (left). A greater number of clusters could be identified by diverging from the project's significance threshold of <0.05. Given the small number of polygons, there is a high chance of false detection of clusters. The Bonferroni adjustment was subsequently applied as an additional form of correction that reduced the significant cluster to 2 adjacent boroughs: Haringey and Islington.

The ArcMap flavour of LMI was utilised to integrate quadratic definitions into the visualisation of significant clusters, which detected clusters in the High-High Cluster category in East London (Fig 5.3.9). Since ESRI have not published a precise methodology for executing LMI, the results can only contextualise existing findings.

Group B6

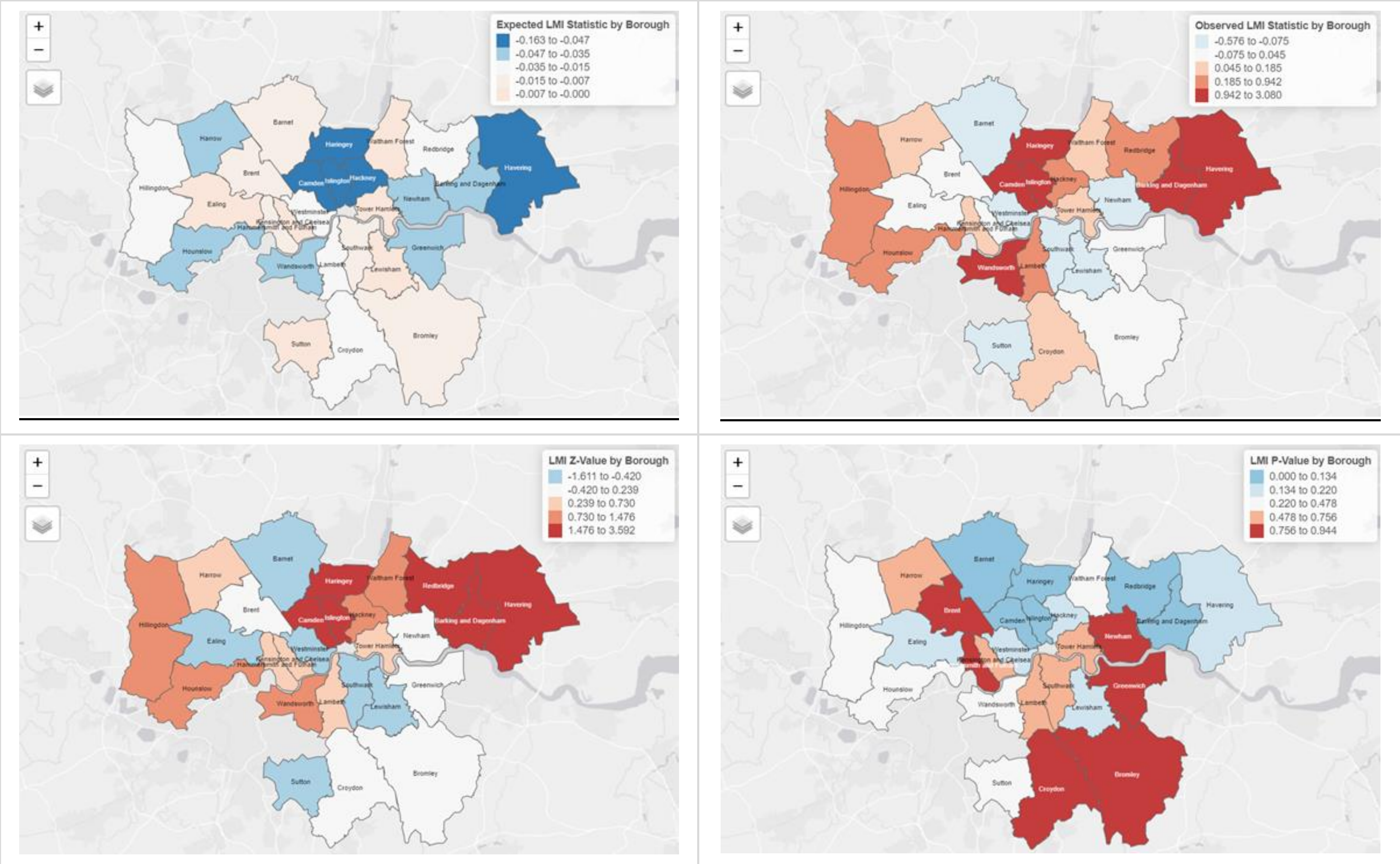
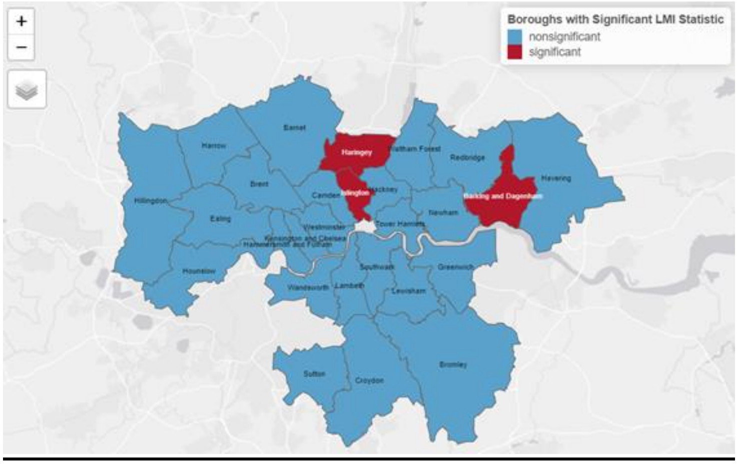
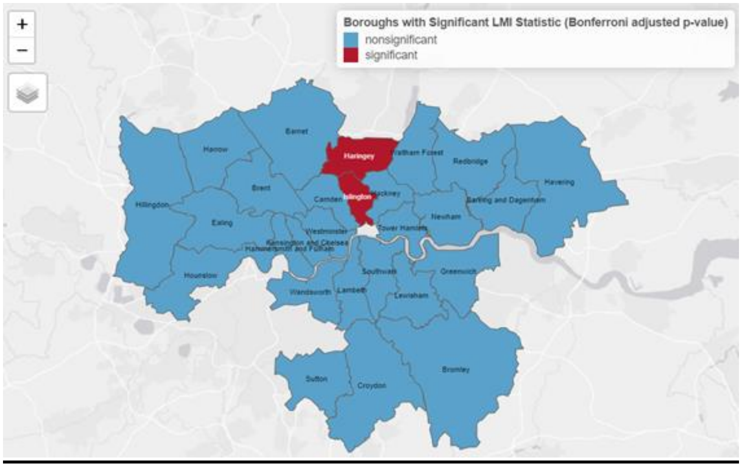


Fig 5.3.7: *Distribution of LMI Indices by Borough*



Unadjusted p-value



Bonferroni Adjusted p-value

Fig 5.3.8: *Significant LMI Statistics by Borough with adjusted p-values*

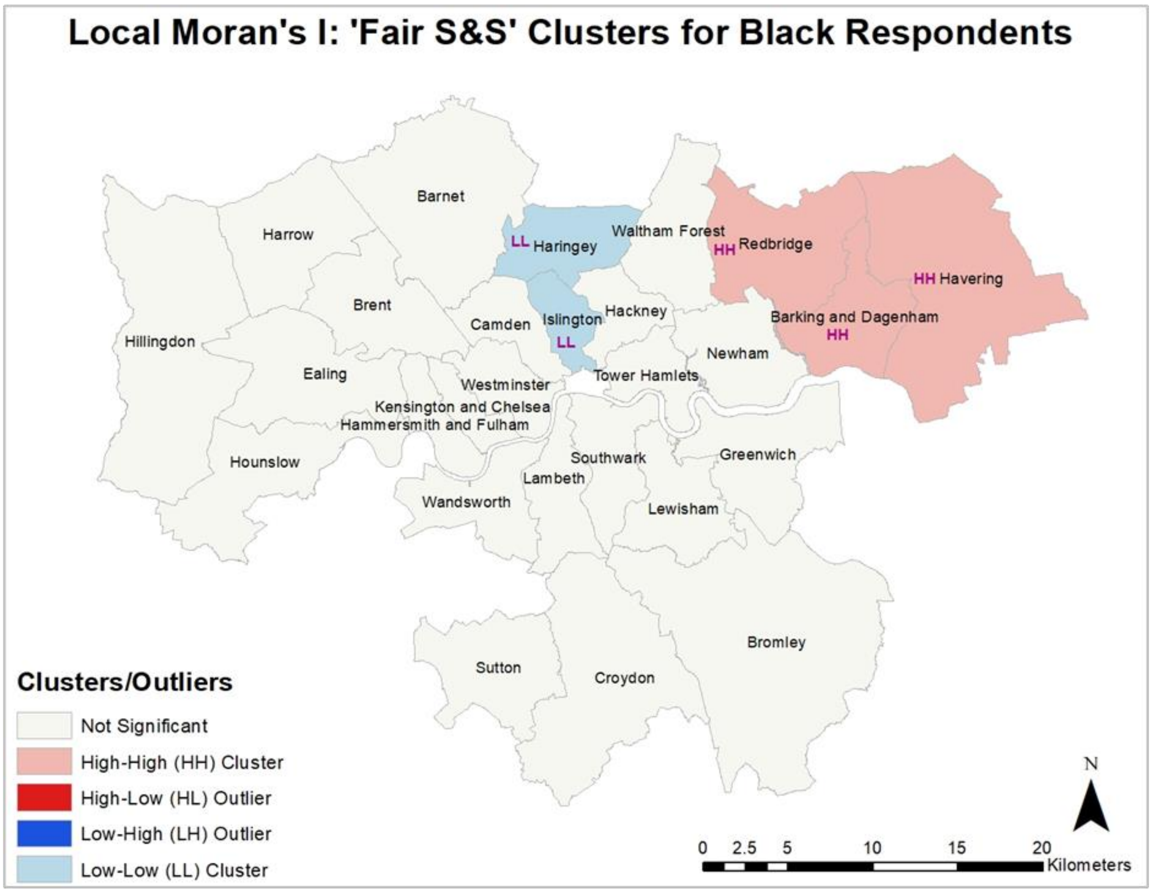


Fig 5.3.9 *LMI Alternative: ArcMap Randomised Two-Sided LMI Test Results*

<u>5.3.6 Getis-Ord Gi* (Fig 5.3.10):</u> Where G is decomposed into contributions from each polygon, hot and cold spots are distinguished at the local level. The highly significant hot spots (>95%) concentrate around central-north boroughs, whilst cold spots cover

East London boroughs. With positive z-score and significant p-values, the null hypothesis can be rejected.

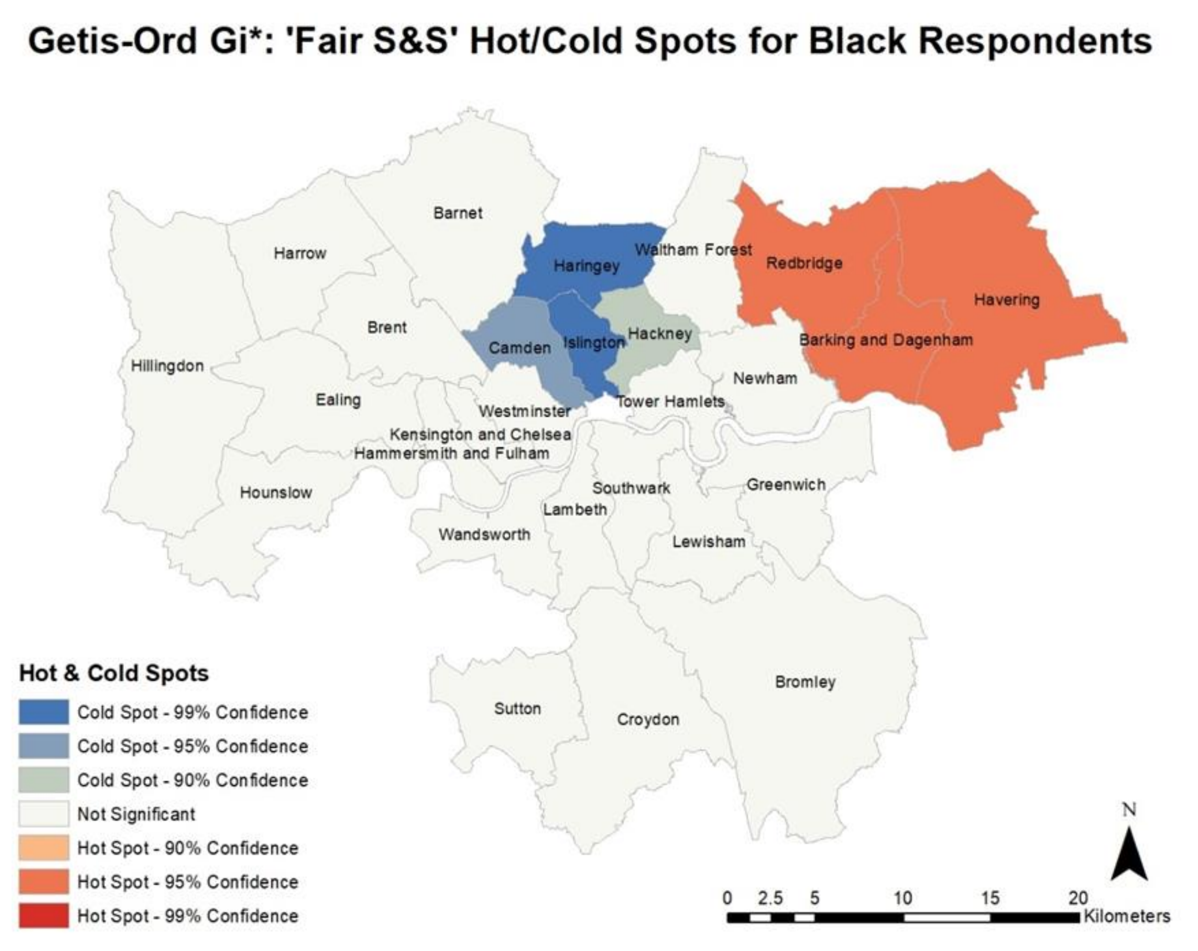


Fig 5.3.10: *Getis-Ord Gi**

<u>5.3.7 Interpretations:</u> Global measures of spatial autocorrelation provided variable results. Both Randomisation and Monte Carlo instances of GMI results concurred that the PP variable was positively correlated, exhibited spatial clusters and statistically significant (0.1% chance of randomness). The Getis-Ord General G test results instead inferred a Complete Spatial Randomness. Second, Local measures were successful in revealing clusters that share similar high/low attributes. Moran's Scatterplot, LMI and Getis-Ord Gi* tests consistently distinguished clusters of cold spots in Central-North London (e.g., Haringey, Islington) where neighbours shared negative responses of S&S. Applying a p-value threshold (95%) and the Bonferroni adjustment pinpointed significant areas of concern where the black community feel S&S practises are being used unfairly. It must however be reiterated that all such spatial-statistical tests would have been impacted by the input size. Getis-Ord General G recommends a minimum number of 30 spatial units, compared to the 27 for PP. Also, aggregating values to boroughs would have changed the pattern of links, whilst omitting unviable boroughs would have removed borders and links that exist in the real world. All such factors frame the project outcomes.

5.4 Spatial Regression [Claudia]

Prior to model building, the data was cleaned to remove all missing data and spatial weight matrix was extracted using queen's neighbourhood methods set to zero policy, so that polygons with no neighbours could be included. While removing missing values was not ideal, it was necessary for the running of these models.

5.4.1. Linear Regression

The crude association between SS and crime provides an intercept of -1.90 (p=0.10), a crime coefficient of 0.13 (p<0.001) and adjusted-r^2 of 0.49. This suggests that for every SS occurrence, there is 0.13 times more crime and that the model accounts for 49% of variance in data. With the crude association and ethnicity as the effect modifier, intra-variable associations were then explored using a correlation matrix. Variables that did not meet thresholds were removed from subsequent analyses. Overall, 12 variables were identified as being potential confounders and were then tested using linear regression (Table 5.4.1).

Table 5.4.1: *Correlation Matrix Results for SS and Crime Occurrences*

Variables	SS (All)	SS (White)	SS (Black)	SS (Asian)	Crime (All)
SS (All) - OUTCOME	1.000	0.860	0.854	0.426	0.703
SS (White)*	0.860	1.000	0.533	0.280	0.695
SS (Black)*	0.854	0.533	1.000	0.188	0.463
SS (Asian)*	0.426	0.280	0.188	1.000	0.404
Crime (All) - EXPOSURE	0.703	0.695	0.463	0.404	1.000
Crime (Anti-social)	0.617	0.577	0.389	0.501	0.900
PP All (mean)	0.023	0.133	-0.118	-0.023	0.068
PP Black (mean)	-0.107	-0.070	-0.139	0.023	-0.042
PP Asian (mean)	-0.047	0.004	-0.069	-0.122	-0.048
PP White (mean)**	**-0.157**	-0.064	**-0.203**	**-0.110**	**-0.100**
PP White (fairness)**	**-0.282**	**-0.198**	**-0.276**	-0.080	**-0.216**
PP Black (fairness)**	**-0.221**	**-0.162**	**-0.222**	-0.001	**-0.164**
PP Asian (fairness)**	**-0.182**	**-0.152**	**-0.137**	**-0.142**	**-0.144**
Mean Population Age (2013)**	**-0.241**	-0.078	**-0.280**	**-0.259**	**-0.300**
Population Density (2013)**	**0.239**	0.092	**0.231**	**0.183**	**0.152**
Mortality Ratio (2013)**	**0.136**	0.053	**0.162**	**0.142**	**0.159**
Life Expectancy (2013)**	-0.096	-0.009	**-0.139**	**-0.137**	**-0.134**
Median House Prices (2013)**	**0.135**	**0.207**	0.005	**-0.014**	**0.162**
Mean Household Income (2013)	0.006	0.116	-0.114	-0.098	0.020
Total Crime Rate (2013)**	0.607	0.705	0.347	0.181	0.797
Ethnic Group White (2013)	-0.105	0.019	-0.097	-0.318	-0.060
Ethnic Group Asian (2013)	-0.044	-0.120	-0.074	0.390	0.053
Ethnic Group Black (2013) **	**0.341**	0.099	**0.526**	**0.020**	**0.223**
Police Stations (2013) **	**0.161**	**0.186**	**0.116**	0.009	**0.268**

** Identified as effect moderator*
***Identified as potential confounder*
*NB: correlations greater than 0.10 or less than -0.10 are marked in **bold***

Linear model building showed that the mean PP (white), fairness PP (white, black, Asian), mean population age, population density, total crime rate and number of black ethnic group for each ward were significant confounders in the relationship between SS and crime occurrences (Table 5.4.2) and thus included in the final model.

Table 5.4.2: *Model building for linear model between all SS and crime occurrences (only reporting variables identified as potential confounders)*				
Models	**Intercept**	**Coeff (P)**	**Adj. R^2**	**F-stat. (P)**
Crude (unadjusted)	-1.904	0.130 (<0.001)	0.493	475.9 (<0.001)
Adj. for PP White (mean)*	23.145	0.129 (<0.001)	0.499	244.8 (<0.001)
Adj. for PP White (fairness)*	28.556	0.125 (<0.001)	0.510	255.0 (<0.001)
Adj. for PP Black (fairness)*	16.907	0.127 (<0.001)	0.503	248.5 (<0.001)
Adj. for PP Asian (fairness)*	24.141	0.128 (<0.001)	0.498	243.8 (<0.001)
Adj. for Mean Population Age (2013)*	6.736	0.128 (<0.001)	0.493	238.4 (<0.001)
Adj. for Population Density (2013)*	-6.227	0.127 (<0.001)	0.510	255.1 (<0.001)
Adj. for Mortality Ratio (2013)	-4.039	0.130 (<0.001)	0.492	238.1 (<0.001)
Adj. for Life Expectancy (2013)	-1.581	0.130 (<0.001)	0.492	237.5 (<0.001)
Adj. for Median House Prices (2013)	-2.529	0.130 (<0.001)	0.492	237.9 (<0.001)
Adj. for Total Crime Rate (2013)*	-1.557	0.112 (<0.001)	0.498	243.1 (<0.001)
Adj. for Ethnic Group Black (2013)*	-5.673	0.122 (<0.001)	0.528	274.0 (<0.001)
Adj. for Police Stations (2013)	-1.820	0.132 (<0.001)	0.492	238.2 (<0.001)
** Identified as confounder*				

The final linear model (Table 5.4.3) accounts for 57% of variance in data, which is a significant increase from the crude association. For every increase in SS, crime increases by 0.09, the average population age increases by 1.44, the population increases by 0.001 and ward levels of black ethnicity increase by 0.004. While these results have racial implications, assumptions must be checked before interpreting these results further.

Table 5.4.3: *Final linear model between all SS and crime occurrences*			
Coeff (P)	**Intercept**	**-41.270**	**(0.007)**
	Crime occurrence (All)	**0.092**	**(<0.001)**
	PP White (mean)	-0.329	(0.153)
	PP White (fairness)	0.177	(0.444)
	PP Black (fairness)	-0.033	(0.833)
	PP Asian (fairness)	-0.167	(0.415)
	Mean Population Age (2013)	**1.439**	**(<0.001)**
	Population Density (2013)	**0.001**	**(<0.001)**
	Total Crime Rate (2013)	**0.051**	**(<0.001)**
	Ethnic Group Black (2013)	**0.004**	**(<0.001)**
RSE (df)	13.5 (479)		
F-stat. (P)	73.22 (<0.001)		
Adj-R^2	0.571		
*NB: significant coefficient p-values are marked in **bold***			

5.4.2. Assumption Testing & Autocorrelation

Fig 5.4.1 displays the model assumption checks for linearity, normality homogeneity and multicollinearity. Residual vs fitted plots indicate that the linearity assumption holds. The QQ-plot indicates some deviation from normality due to outliers, but the assumption holds for the most part. However, the scale-location and residuals vs leverage plot indicate that the homoscedasticity assumption is violated, and that multicollinearity exists in the model. When mapping the model residuals (Fig 5.4.2), there appears to be a spatial pattern in the data, thus suggesting that a spatial regression model may be better suited for the data at hand.

Assumption testing for the final linear regression model

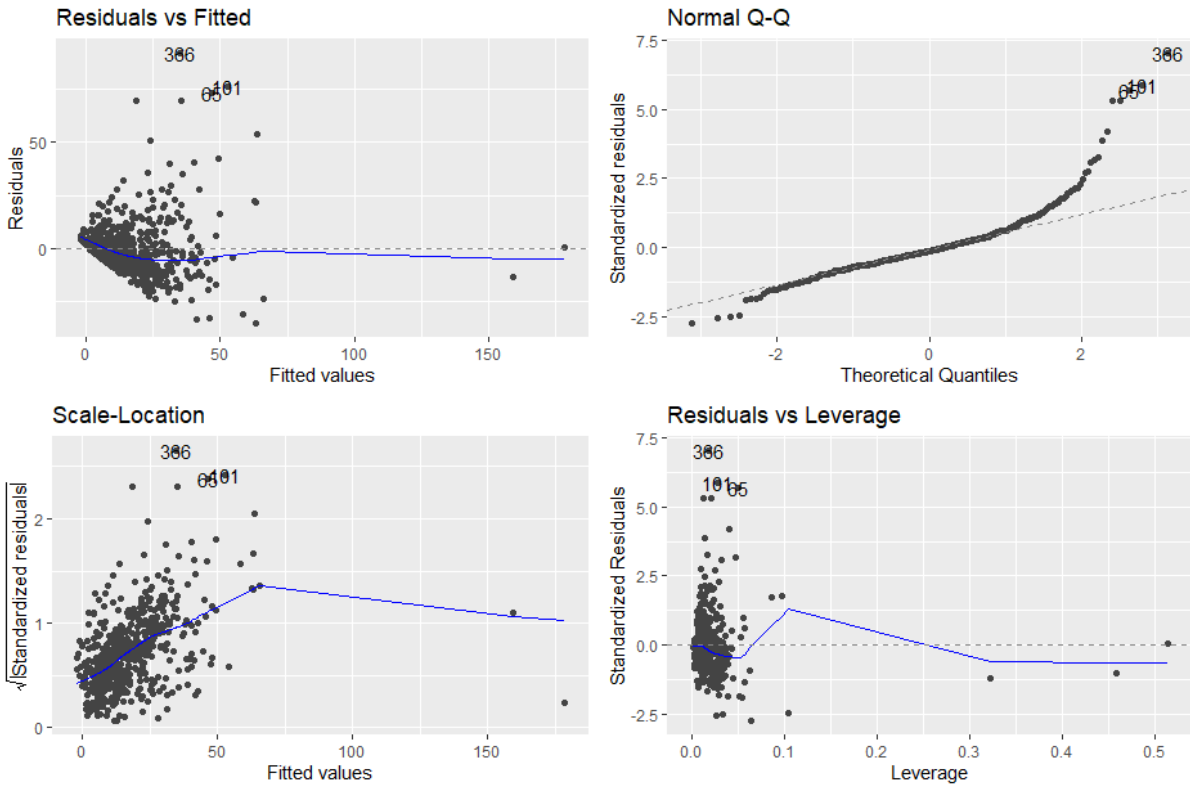


Fig 5.4.1: *Assumption testing for the final linear regression model*

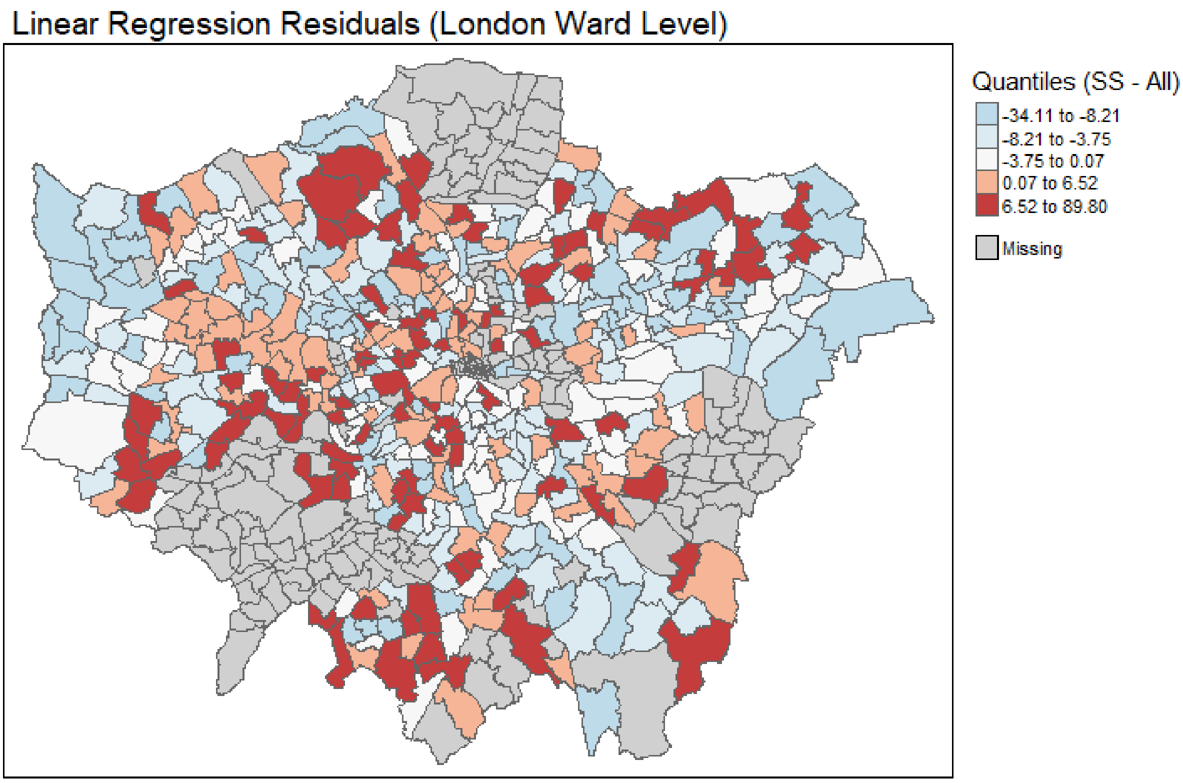


Fig 5.4.2: *Final linear regression residuals, at the London ward level*

To quantify the presence of spatial autocorrelation, the Moran's I test was deployed and returned a value of 6.782 ($p<0.001$) thus indicating significant autocorrelation in the models' residuals. LM tests for spatial lag and spatial error indicated that both were present in the model, with p-values of 0.04 and <0.001 respectively. Thus, a Durbin spatial regression was fit.

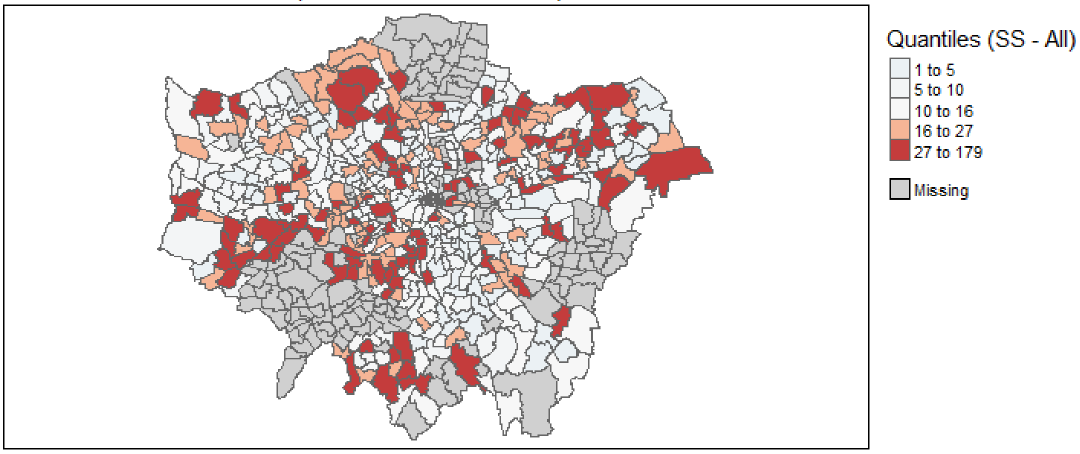
5.4.3. Spatial Regression

A Durbin spatial regression was fit with the same formula from the linear regression model (Table 5.4.4). Spatial lag variables of particular significance were crime, average white PP, black PP of fairness and population density. Furthermore, the pseudo-r^2 indicates that the model accounts for 62% of data variance, which 5% more than the linear model. The Rho autocorrelation parameter suggests that the addition of ρ significantly improves the model fit and this is further supported by the Wald test. The LM test for residual autocorrelation is insignificant ($p=0.24$), so the spatial model effectively accounts for autocorrelation. However, when comparing the actual SS occurrence and the models predicted SS occurrence (Fig 5.4.3), there are discrepancies in the model fit which cause it to over predict SS occurrence. This same model was then stratified by SS ethnicity.

Table 5.4.4. *Final Durbin model between all SS and crime occurrences*

Coeff (P)	Intercept	-43.211	(0.090)
	Crime occurrence (All)	**0.095**	**(<0.001)**
	PP White (mean)	0.434	(0.244)
	PP White (fairness)	0.248	(0.490)
	PP Black (fairness)	**-0.564**	**(0.040)**
	PP Asian (fairness)	-0.365	(0.244)
	Mean Population Age (2013)	**1.150**	**(<0.001)**
	Population Density (2013)	**0.001**	**(0.004)**
	Total Crime Rate (2013)	**0.050**	**(<0.001)**
	Ethnic Group Black (2013)	**0.004**	**(<0.001)**
	LAG Crime occurrence (All)	**-0.046**	**(0.029)**
	LAG PP White (mean)	**-1.102**	**(0.020)**
	LAG PP White (fairness)	0.082	(0.861)
	LAG PP Black (fairness)	**0.696**	**(0.040)**
	LAG PP Asian (fairness)	0.208	(0.612)
	LAG Mean Population Age (2013)	0.419	(0.454)
	LAG Population Density (2013)	**0.001**	**(0.058)**
	LAG Total Crime Rate (2013)	-0.031	(0.251)
	LAG Ethnic Group Black (2013)	-0.001	(0.519)
Rho (P)	**0.353 (<0.001)**		
Wald Stat. (P)	**35.278 (<0.001)**		
AIC (AIC for lm)	3913.8 (3944.9)		
LM Test (P)	1.408 (0.235)		
Psuedo-R^2	0.621		
*NB: significant coefficient p-values are marked in **bold***			

Actual SS Occurance (London Ward Level)



Durbin SS Predicted (London Ward Level)

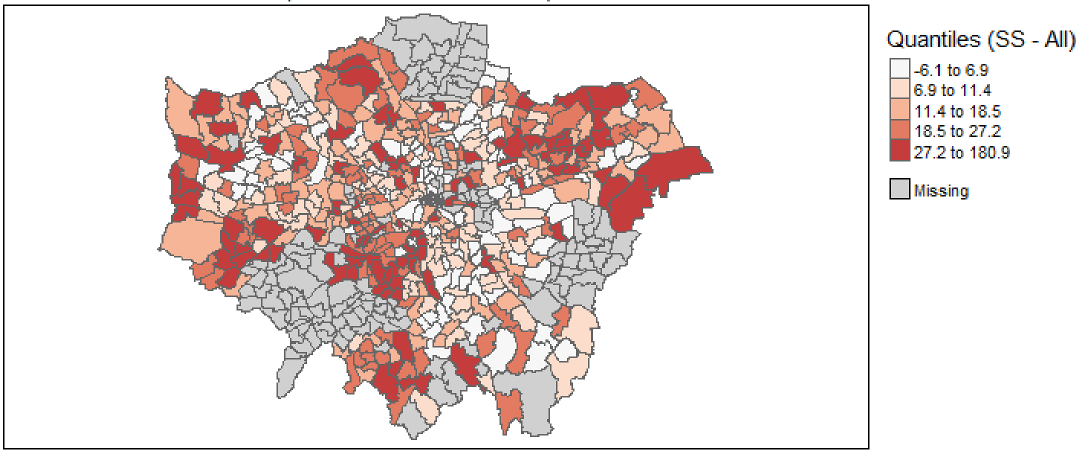


Fig 5.4.3: *Comparing actual and predicted SS occurrences*

SS – White Ethnicity

The White SS model (Table 5.4.5) indicates that spatial lag variables of particular significance were crime occurrence, mean white PP and black PP of fairness. Rho autocorrelation parameter was 0.236 ($p<0.001$) which suggests that the addition of ρ significantly improves the model fit, which is further supported by the Wald test ($p<0.001$). The LM test for residual autocorrelation is insignificant ($p=0.87$), which indicates that the spatial model has fully accounted for spatial autocorrelation in the data. When comparing the actual White SS occurrence and the models predicted

Table 5.4.5: *Final Durbin model between white SS and crime occurrences*			
Coeff (P)	Intercept	-12.680	(0.265)
	Crime occurrence (All)	**0.032**	**(<0.001)**
	PP White (mean)	**0.456**	**(0.006)**
	PP White (fairness)	-0.027	(0.866)
	PP Black (fairness)	**-0.274**	**(0.026)**
	PP Asian (fairness)	**-0.305**	**(0.030)**
	Mean Population Age (2013)	**0.308**	**(0.028)**
	Population Density (2013)	0.000	(0.674)
	Total Crime Rate (2013)	**0.040**	**(<0.001)**

	Ethnic Group Black (2013)	<0.001	(0.252)
	LAG Crime occurrence (All)	**-0.019**	**(0.046)**
	LAG PP White (mean)	**-0.531**	**(0.012)**
	LAG PP White (fairness)	0.018	(0.932)
	LAG PP Black (fairness)	**0.324**	**(0.033)**
	LAG PP Asian (fairness)	0.190	(0.303)
	LAG Mean Population Age (2013)	0.320	(0.199)
	LAG Population Density (2013)	0.000	(0.102)
	LAG Total Crime Rate (2013)	-0.013	(0.300)
	LAG Ethnic Group Black (2013)	0.000	(0.350)
Rho (P)	**0.236 (<0.001)**		
Wald Stat. (P)	**13.548 (<0.001)**		
AIC (AIC for lm)	3122.1 (3133.1)		
LM Test (P)	0.028 (0.866)		
Psuedo-R^2	0.594		
*NB: significant coefficient p-values are marked in **bold***			

SS – Black Ethnicity

The Black SS model (Table 5.4.6) identifies black ethnic group per ward as the only spatial lag variable of significance, suggesting that trends related to population distributions. Rho autocorrelation parameter was 0.375 (p<0.001) which suggests that the addition of ρ significantly improves the model fit, which is further supported by the Wald test (p<0.001). However, the LM test for residual autocorrelation is significant (p=0.007), indicating that the model does not fully account for spatial autocorrelation in the data.

***Table 5.4.6:** Final Durbin model between black SS and crime occurrences*			
Coeff (P)	**Intercept**	**-27.928**	**(0.032)**
	Crime occurrence (All)	**0.024**	**(<0.001)**
	PP White (mean)	-0.126	(0.504)
	PP White (fairness)	0.252	(0.167)
	PP Black (fairness)	-0.252	(0.070)
	PP Asian (fairness)	0.054	(0.734)
	Mean Population Age (2013)	**0.651**	**(<0.001)**
	Population Density (2013)	**<0.001**	**(0.004)**
	Total Crime Rate (2013)	**0.013**	**(0.028)**
	Ethnic Group Black (2013)	**0.003**	**(<0.001)**
	LAG Crime occurrence (All)	-0.011	(0.319)
	LAG PP White (mean)	-0.220	(0.360)
	LAG PP White (fairness)	-0.144	(0.543)
	LAG PP Black (fairness)	**0.310**	**(0.071)**
	LAG PP Asian (fairness)	-0.015	(0.943)
	LAG Mean Population Age (2013)	0.203	(0.473)
	LAG Population Density (2013)	0.000	(0.241)
	LAG Total Crime Rate (2013)	-0.008	(0.547)
	LAG Ethnic Group Black (2013)	**-0.001**	**(0.047)**
Rho (P)	**0.375 (<0.001)**		
Wald Stat. (P)	**41.216 (<0.001)**		
AIC (AIC for lm)	3249.6 (3284.5)		
LM Test	**7.264 (0.007)**		
Psuedo-R^2	0.500		
*NB: significant coefficient p-values are marked in **bold***			

SS – Asian Ethnicity

The Asian SS model (Table 5.4.7) accounts for 37% of data variance and cannot be robustly interpreted due to there only being ~80 samples of Asian SS.

Table 5.4.7: *Final Durbin model between Asian SS and crime occurrences*

Coeff (P)	**Intercept**	**17.534**	**(0.001)**
	Crime occurrence (All)	**0.022**	**(<0.001)**
	PP White (mean)	-0.053	(0.499)
	PP White (fairness)	-0.007	(0.927)
	PP Black (fairness)	0.103	(0.074)
	PP Asian (fairness)	-0.052	(0.425)
	Mean Population Age (2013)	-0.122	(0.063)
	Population Density (2013)	**<0.001**	**(<0.001)**
	Total Crime Rate (2013)	**-0.015**	**(<0.001)**
	Ethnic Group Black (2013)	**-0.001**	**(<0.001)**
	LAG Crime occurrence (All)	**-0.011**	**(0.014)**
	LAG PP White (mean)	-0.132	(0.186)
	LAG PP White (fairness)	**0.254**	**(0.010)**
	LAG PP Black (fairness)	-0.091	(0.201)
	LAG PP Asian (fairness)	-0.095	(0.273)
	LAG Mean Population Age (2013)	**-0.247**	**(0.034)**
	LAG Population Density (2013)	0.000	(0.230)
	LAG Total Crime Rate (2013)	0.005	(0.385)
	LAG Ethnic Group Black (2013)	0.000	(0.254)
Rho (P)	**0.160 (0.019)**		
Wald Stat. (P)	**5.7652 (0.016)**		
AIC (AIC for lm)	2378.1 (2381.5)		
LM Test	1.845 (0.174)		
Psuedo-R^2	0.365		
*NB: significant coefficient p-values are marked in **bold***			

6. DISCUSSION

This analysis highlights the critical importance of capturing spatial autocorrelation in crime models**.** Crime and SS SA analyses found that most data clustered around the centre of London, which was partially attributed to population density. The PP SA analysis found significant spatial differences between white/Asian PP and black PP though the autocorrelation was severely handicapped by a small number of highly aggregated polygons that diminished its purpose beyond providing high-level context**.** The spatial regression answered the research question and illustrated a noticeable relationship between crime and SS when stratified by ethnicity, which is partially explained by PP (fairness) population density and ward ethnicity.

While these analyses were fruitful in revealing spatial patterns, they were undoubtedly hampered by a myriad of factors. In terms of data collection, detecting PP using large-scale structured surveys is problematic since diverse embodied experiences are homogenised into generic categories. Aggregation for all datasets was a difficult process since data trends occurring at a more local level were lost. Moreover, disaggregating PP data back to the ward level skewed final model results and provoked dilemmas relating to MAUP and ecological fallacy. The distance band of 1500m chosen for the Getis Ord analyses was flawed since variation in polygon area would lead smaller wards to have more higher weighted neighbours due solely to more wards fitting in their 1500m radius. Whilst this effect was partially offset using the 'zone of indifference' conceptualisation of spatial relationships in ArcGIS Pro, future research should aim to trial a multitude of distance bands to explore the influence of this factor. Spatial regression assumed that spatial autocorrelation was uniform when SA analyses indicated that was not the case. Geographically weighted regression (GWR; Brunsdon et al., 1998) or Kriging regressions (De Smith et al ., 2007) should be used to explore this further. Despite this, given the topic complexity and project scope, a Durbin regression was maintained.

Future spatial analysis for PP would benefit from access to greater granular-level data across the spatial extent – perhaps borrowing anonymisation techniques adopted by the Crime and S&S datasets. Further research may also choose to investigate the spatial autocorrelation of crime and ss occurrences without aggregation. Crime type would also be interesting to explore as an effect moderator in tandem with ethnicity. Finally, modelling crime over time would give further insight into the magnitude of these stratified effects caused by political events (i.e., Brexit).

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Appendix

Appendix 1 *– Summary of PAS survey questions relating to stop and search*

Q110 (ASK ALL) Including anything you've already mentioned, in the last 12 months have the police stopped you for any reason? (Yes/No/Unsure/Refused)

- *Do you know why you were stopped?*
- *Do you feel that...You were given a reason for why you had been stopped?*
- *Do you feel that...You were told what would happen next?*
- *Do you feel that...You were treated with respect?*
- *Do you feel that...The police were justified in stopping you?*
- *In the last 12 months have the police searched or arrested you?*
- *What was the outcome?*
- *Do you feel that...You were given a reason for why you had been searched/arrested? Read out options except don't know and refused.*
- *You were told what would happen next?*
- *You were treated with respect?*
- *The police were justified in searching you?*
- *The police were justified in arresting you?*
- *Prior to this experience, was your overall opinion of the police....?*
- *As a result of your contact with the police on this occasion (of being stopped and/or searched or arrested), please tell me if your opinion is now better, worse or has not changed?*
- *To what extent do you agree that the Police should conduct Stop and Search?*
- *How confident are you that the Police in this area use their stop and search powers fairly?*