Spatial Analysis of Crime Patterns in London

Ng Jia Wen & Junju Ng

28/10/2018

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Figure 1: Boroughs of London

1 Introduction

Crime (and the prevention of and response to crime) is associated with significant social and economic costs. In England and Wales, the total cost of crimes against individuals and businesses is ?50.1 billion and ?8.7 billion respectively in 2015/16 alone (Brand and Price 2014). A significant portion of these costs are incurred in London, given that about 20% of crimes in England and Wales occurs in London (Mayor of London 2016).

Consequently, much work has been done to understand the occurrence of crime, and to predict crime. To date, the spatial concentration of crime in cities is well-established in the literature (Malleson and Andresen 2016). (Sherman, Gartin, and Buerger 1989)'s seminal analysis of predatory crime in Minneapolis revealed that 50% of police calls come from 3% of street segments, indicating that crime hotspots, down to the street level, are present within cities. Recent works have thus focussed on trying to improve spatial analysis techniques for crime. Specifically, (Chainey, Tompson, and Uhlig 2008) examined the use of different hotspot mapping techniques to predict spatial patterns of crime in Camden and Islington local authority district areas in London. Other workers (e.g.(Cheng and Williams 2012)) have been working on developing techniques to examine spatial-temporal patterns of crime, in order to understand how crime develops and evolves to improve crime prediction.

Given that a significant portion of crimes in England and Wales occurs in London and the occurrence of crime is non-random, this study will therefore examine spatial crime patterns in London. Specifically, this study aims to answer two main questions: 1) where do crime types occur? 2) what factors are associated with the occurrence of different types of crime?

Study area

London is a thriving metropolis in the United Kingdom with a population of 8.8 million. However, beyond the large residential population, London also attracts a huge number of visitors, with more than 56 million overnight stays from tourists in 2016 (Mayor of London 2016).

London consists of 33 local government districts (32 London Boroughs and the City of London). The City of London Police is the police force responsible for law enforcement within the City of London while the Metropolitan Police Service is reponsible for policing the Greater London region, excluding the City of London. Greater London can be split into 4835 geographic regions known as lower layer super output areas(LSOAs) for the purposes of reporting small-area statistics. These LSOAs will form the basis of the analysis.

2 Data description

Official geocoded crime data from London is required to analyse spatial patterns of crime. To this end, crime data in London for a 1-year period (1 January 2017 to 31 December 2017) from the Metropolitan Police and the City of London Police was used for this study. These data are taken from the Metropolitan Police and the City of London Police because they are the two police forces covering the London and Greater London area. The data was obtained via the police.uk website as a CSV file. Whilst most crimes are geocoded, some reported crimes do not have a location and are therefore excluded from the analysis. The effect on excluding crimes without locations from the analysis is anticipated to be minimal, as these crimes only form a small proportion of reported crimes (5.3% for the City of London Police, and 1.2% for the Metropolitan Police).

The geocoded crime data are categorised into 14 crime types: anti-social behaviour, bicycle theft, burglary, criminal damage and arson, drugs, other crime, other theft, possession of weapons, public order, robbery, shoplifting, theft from a person, vehicle crime, and violence and sexual offences. In addition, geomasking techniques were applied to the data to reduce their spatial accuracy for privacy purposes. Specifically, each crime is mapped to its nearest map point on the master list of map points kept by the Home Office (Home Office 2019a). However, analysis by (Tompson et al. 2015) reveals that at the lower super output area (LSOA) level, 85% of areas exhibited no statistically significant difference between the masked and raw crime data. Hence, analysis of patterns in crime will predominantly be conducted at the LSOA level in this study.

Industrial landuse areas are also obtained from OpenStreetMap using the overpass API as a polygon dataset. This is to observe if trends between the occurrence of crimes and industrial areas exist. The information is crowd-sourced, and not created by geospatial experts. Thus, some discrepancies may be present in the dataset (Basiri et al. 2016). However, corroboration of the information with aerial imagery and street imagery from Google Maps shows that the data is generally accurate, and therefore suitable for broader-scale exploratory analysis.

2011 census data at the LSOA level was also obtained from the London Datastore, to examine the demographic factors that may contribute to the occurrence of crimes. Specifically, information about the total resident population in each London LSOA was obtained.

Also have pubs data, transport data.

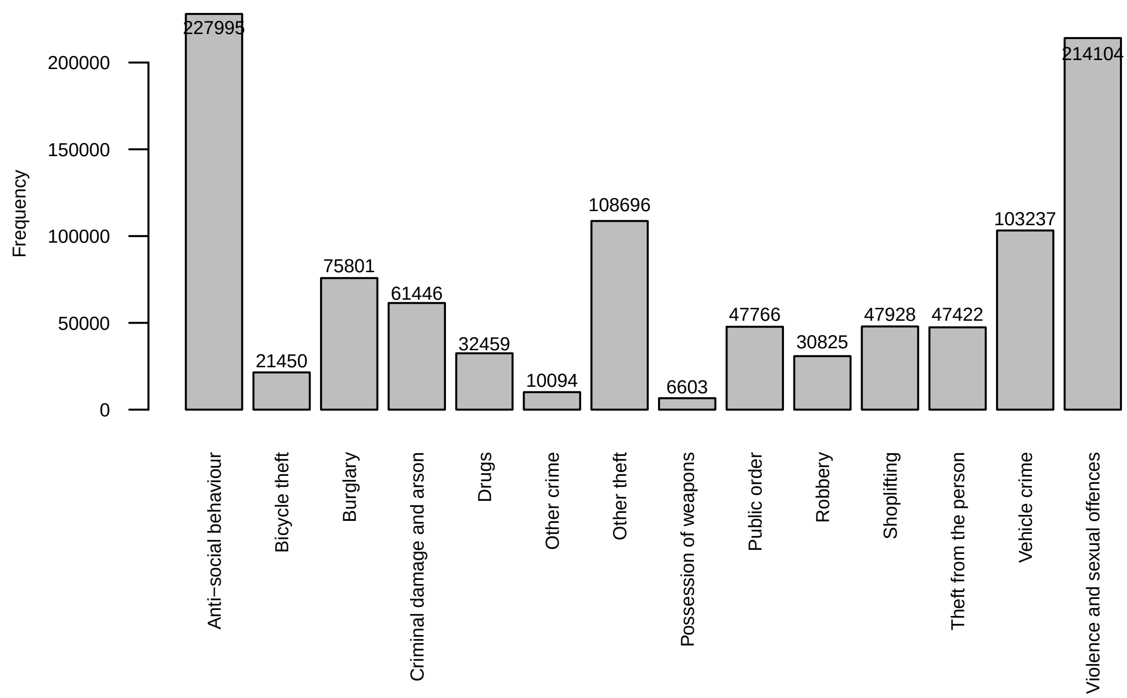


Figure 2: 2017 London crime counts by crime type

3 Exploratory Spatial Data Analysis

An exploratory analysis of the crime data will be conducted in this section.

A total of 1,048,712 crimes were reported in 2017. Of these crimes, 1,035,826 (98.7%) have a location. As discussed previously, only the geocoded crimes will be used in the analysis.

Variations in Crime by Type

The barplot below depicts the frequency of crimes by crime type in London in 2017 (Figure 2). Over 40% of reported crimes in London come from 2 categories - antisocial behaviour (22.0%) and violence and sexual offences (20.7%). The next two most significant crime types making up 20% of crimes are other theft (10.5%) and vehicle crime (10.0%). The remaining 10 crime types make up the remaining 36.9% of crimes. As such, different types of crimes are reported at different frequencies, with antisocial behaviour and violence and sexual offences being the most commonly reported crimes, followed by vehicle crime and other theft.

Variations in Crime by Type and Month

A line graph of crime count by type and month (Figure 3) is plotted to examine temporal patterns in crime in London across the year. Figure 4 depicts a similar graph, without anti-social behaviour and violence and sexual offences, in order to better observe trends in the other crime types.

From Figure 3, it is evident that the frequency of some crime types varies throughout the year. For instance, reports of anti-social behaviour appear to peak in July and August. Burglary reports appear to increase between October and January, while bicycle theft reports appear to increase between May and October (Figure 4).

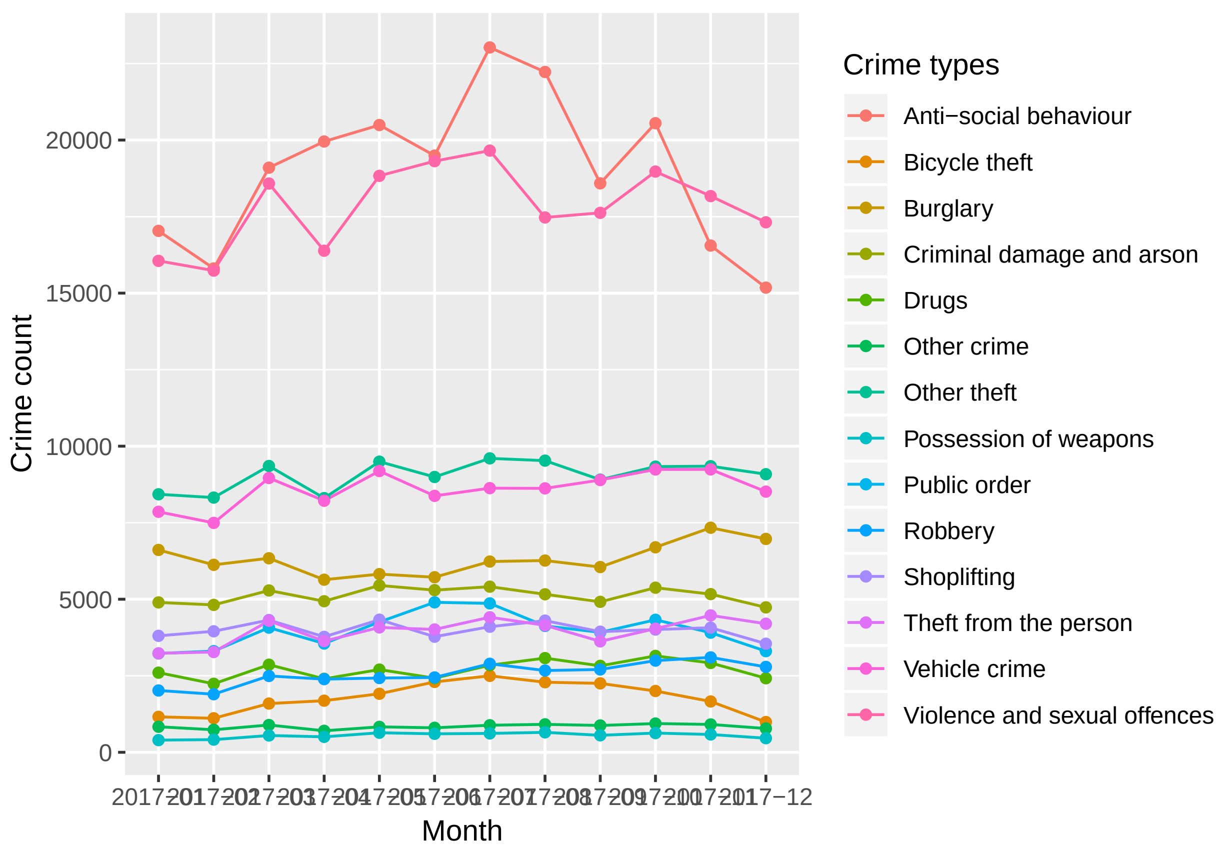


Figure 3: 2017 London crime count by type and month

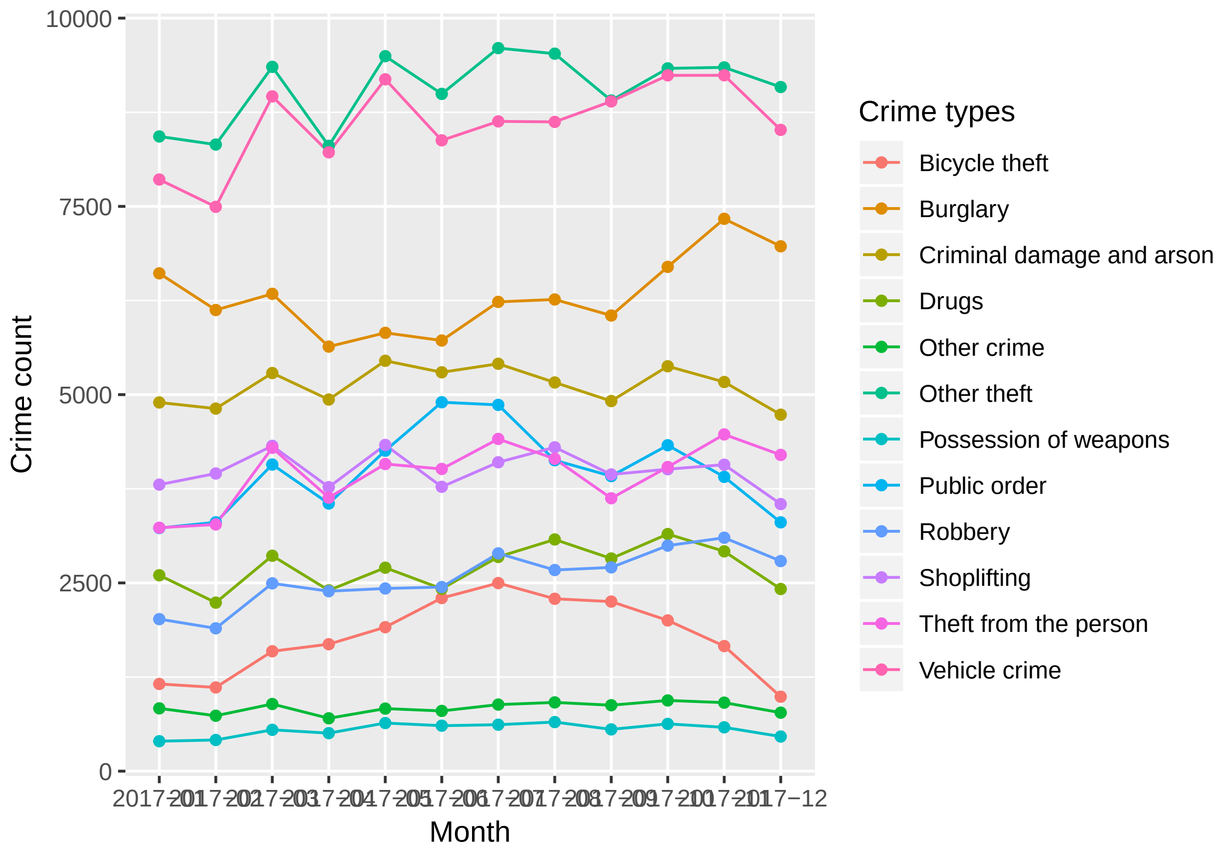


Figure 4: 2017 London crime count by type and month (excluding anti-social behaviour and violence and sexual offences

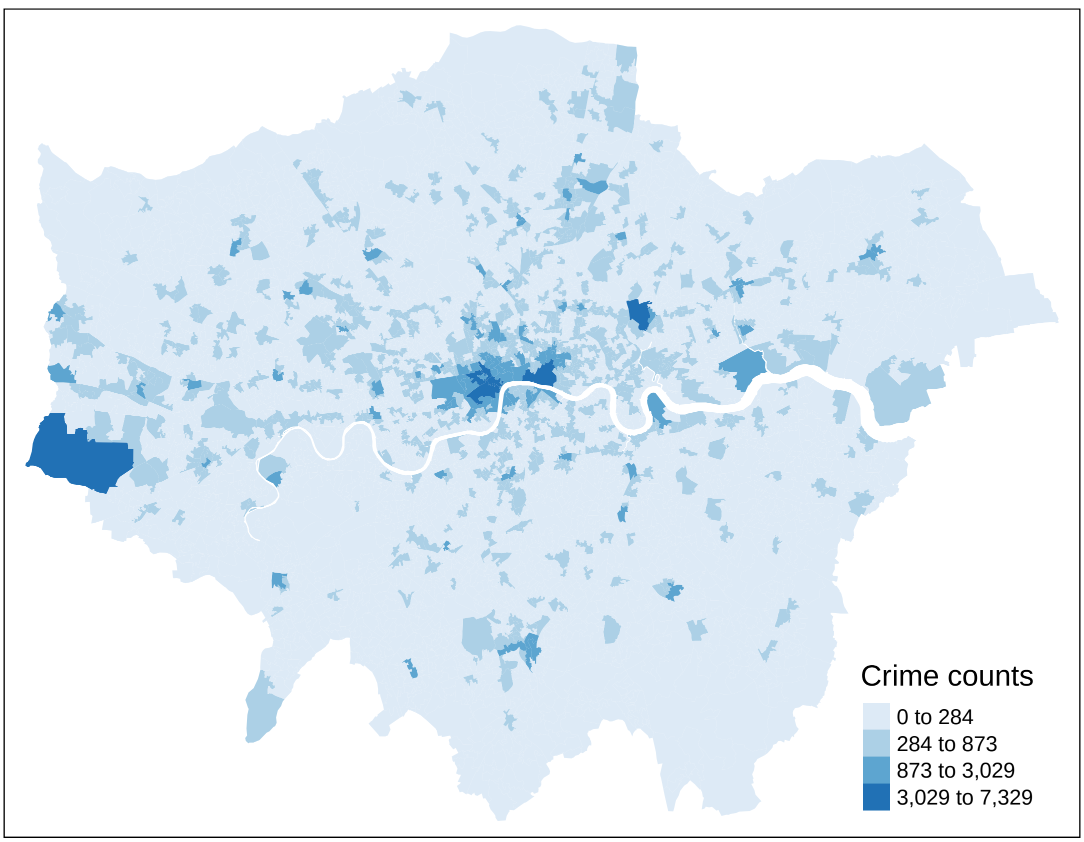
Table 1: Crime Count Statistics by LSOA

	Value
Minimum	1.0
1st Quartile	64.0
Median	127.0
Mean	175.3
3rd Quartile	211.0
Maximum	7329.0

Variations in Crime by LSOA

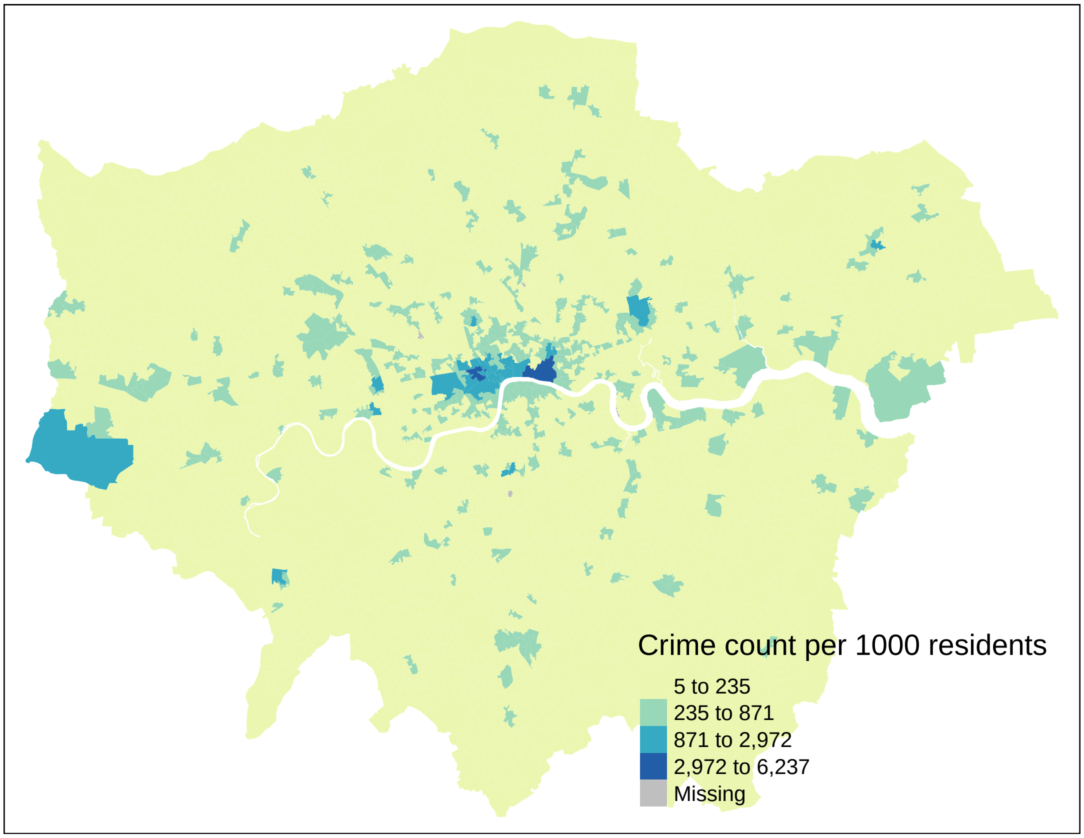
Crime counts are also examined by LSOA, in order to study the distribution of crime in London. From Table 1, it is evident that crime counts vary significantly between LSOAs. Few LSOAs have extremely high crime counts, while 50% of LSOAs have crime counts between 64 and 211. Consequently, the jenks classification scheme will be used to map the distribution of crime counts across London, to minimise the variation within each class but highlight differences between classes.

Crime count maps are plotted to visualise the spatial distribution of crime across London. The crime count map (Figure **??**) illustrates the total number of reported crimes in each LSOA in 2017. This allows for the visualisation of regions with the highest number of crimes. By visual inspection, crime counts are highest in central London, although some regions with higher crime counts are present along the river Thames in East London, along the Lea Valley and in Hillingdon. However, as crime counts do not consider that LSOAs have unequal areas, and thus do not give an accurate representation of crime density.



Consequently, a crime rate map (Figure **??**), derived by taking the crime count divided by the resident population in the corresponding LSOA and then multipled by 1000 (i.e. crime count per 1000 residents), is plotted, to obtain an estimate of crime density. These crime rate maps allow for the assessment of the risk of crime in each LSOA (Brantingham and Brantingham 1997). However, it is to be noted that residential populations are used to calculate crime rate. Thus, regions with a low residential population (but high pedestrian population e.g. commercial areas) would have an inflated crime rate.

Visually, although there are some differences between the crime rate and crime count maps, the regions with the highest crime counts are also the regions with the highest crime rates. However, a number of regions outside of central London with slightly higher crime counts (284 to 873) have lower-than-expected crime rates. This indicates that residential population does not have a significant influence on crime counts, except when crime counts are slightly elevated and occur in LSOAs outside central London (presumably with a higher residential population).



4 Methodology

Vehicle data was first mapped in terms of crime count and crime count per 1000 resident population. These choropleth maps were produced using the jenks classification scheme, to accentuate the variance between classes, and minimise the variance within each class. Visual inspection of the maps suggests that vehicle crime rates appear to concentrate in regions. Thus, the Moran's I was used to test for spatial autocorrelation.

The Moran's I (Moran 1950) is a weighted correlation coefficient that measures if the spatial data sampled at adjacent locations are correlated with one another. It measures a single average spatial autocorrelation across the entire area. The Moran's I is calculated using the following equation:

$$I = \frac{n}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2}$$

Where n is the number of LSOAs, w_{ij} is the element of a spatial weight matrix W giving the spatial weight between LSOAs i and j,
x_i and x_j are the vehicle crime rates measured at LSOAs i and j respectively and $i, j = 1, 2, ..., n$,
$\bar{x}$ is the mean of x (i.e. the mean LSOA vehicle crime rate)

A expectation of I under a null hypothesis is $\frac{-1}{n-1}$. Values greater than that indicate a positive spatial autocorrelation, while values smaller than that indicate a negative spatial autocorrelation.

A local Moran's I (Anselin 1995), I_i, was subsequently calculated for each LSOA, to determine the spatial autocorrelation between a given LSOA and its adjacent LSOAs. This is to observe if variations in spatial autocorrelation exist. The local Moran's I can be calculated using the following equation:

$$I_i = \frac{z_i}{m_2} \sum_j w_{ij} z_j$$

Where $z_i = x_i - \bar{x}$, $z_j = x_j - \bar{x}$, $m_2 = \frac{1}{n} \sum_i z_i^2$, $\bar{x}$ is the mean vehicle crime rate, x, at n LSOAs and $i = 1, 2, ..., n$

The expectation of I_i is $\frac{-w_i}{(n-1)}$, where $-w_i = \sum_j w_{ij}$. Local hotspots of positive or negative autocorrelation will be present if vehicle crime rates are spatially heterogeneous.

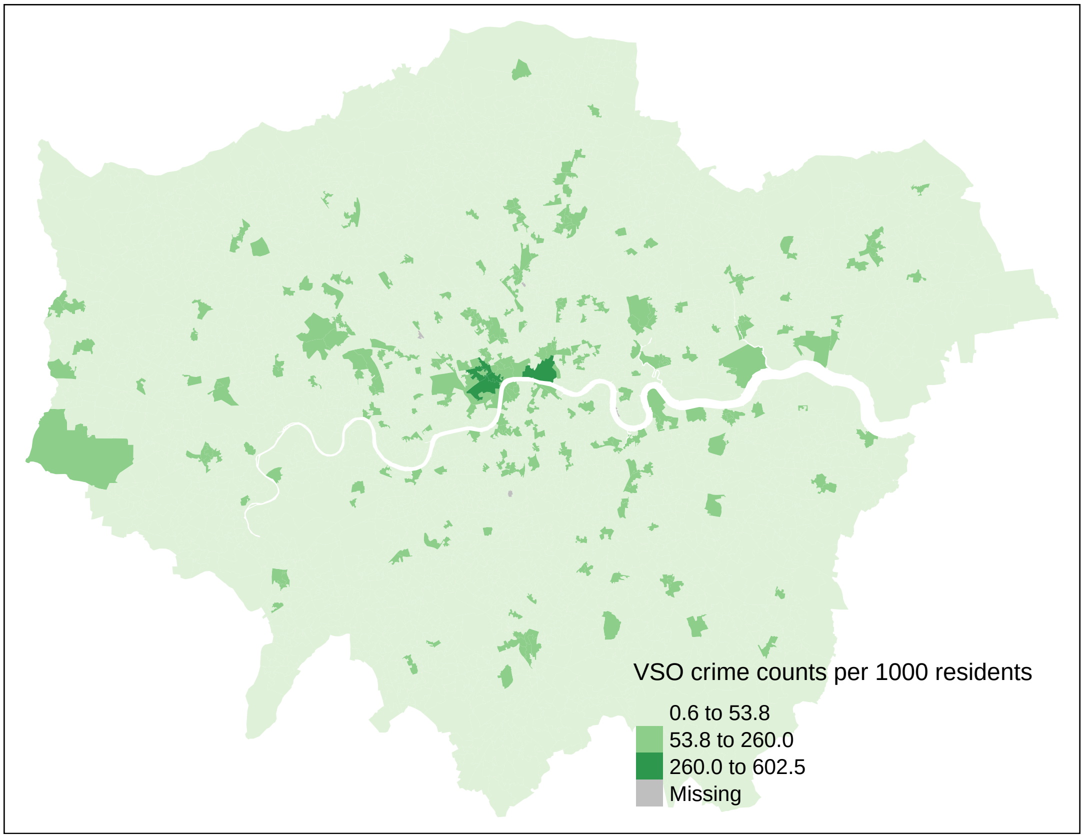
The areas with high vehicle crime rates and which are statistically significant high-high clusters are then analysed using Google Map imagery. Further analysis is also conducted with industrial landuse data from OpenStreetMap. # Results and discussion

Two crime types, violence and sexual offences, and vehicle crime have been used for further analysis. Examination of violence and sexual offences will be conducted, as it is one of the most commonly reported, as well as more severe crimes that bring about damage to people and property. Vehicle crime is chosen for further analysis as it is one of the more commonly reported crimes (excluding violence and sexual offences). The nature of vehicle crime is also different from that of violence and sexual offences, as vehicle crime relates to the theft of and/or from vehicles (Flatley 2017). Consequently, vehicle crime can be committed without direct contact with the victim, unlike violence and sexual offences which often requires direct contact with the victim.

As the nature of violence and sexual offences, and vehicle crime differs, examination of the spatial distribution of the two crime types in London will also allow for better understanding of the factors influencing the occurrence of these two crimes.

4.1 Analysing Violence and Sexual Offences

By plotting the occurrence of violence and sexual offences per 1000 people on a chloropeth, we get the following map below:



This map shows us that VSO crimes are mainly concentrated in central london, with a few LSOAs having mid-range crime density dispersed across london.

Ranking the LSOAs by crime density, we obtain the following rank table, showing the top 20 LSOAs with the highest crime rates (crime count per 1000 people):

We select the City of London 001F (COL001F) to do our analysis as it has the highest crime density.

4.1.1 Analysing Violence and Sexual Offences in City of London 001F

```
## OGR data source with driver: ESRI Shapefile
## Source: "C:\Users\Junju\Desktop\Masters\Term 1\Spatial Analysis and Geocomputation\Geocomputation\bo
```

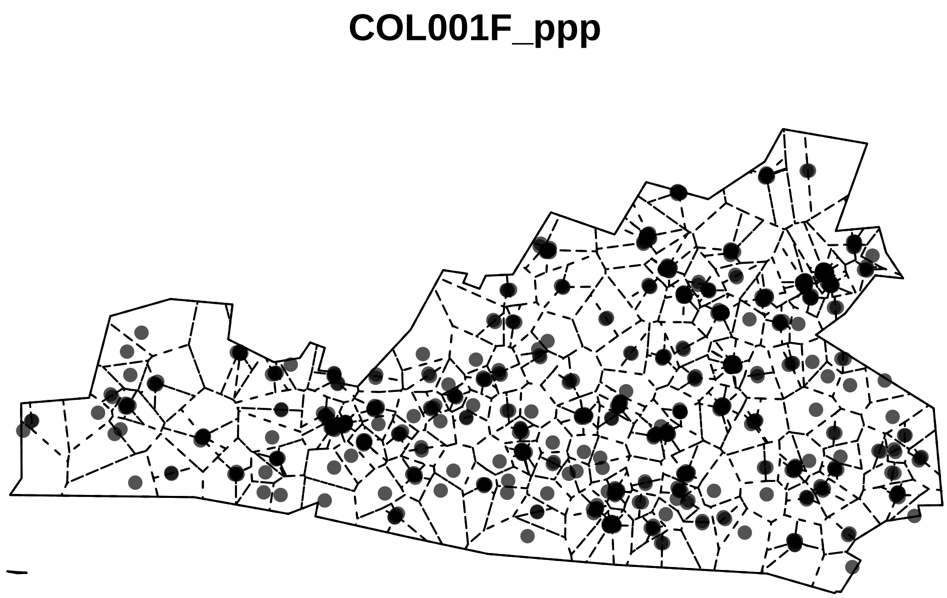
Table 2: 20 LSOAs with the highest crime rates

LSOA name	Crime Rate
City of London 001F	602.4904
Westminster 013E	594.0426
Westminster 018A	520.2840
Westminster 018C	342.8899
Westminster 013B	304.1843
Camden 021A	259.9595
Hackney 027G	254.5341
Lambeth 011B	244.0074
Kingston upon Thames 009C	214.7472
Hillingdon 031A	195.8538
Havering 013C	193.6538
Islington 004B	186.2427
Newham 013G	184.6803
Croydon 027B	183.4756
Sutton 012D	183.0226
Greenwich 004E	173.0580
Westminster 013F	165.9919
Westminster 018B	164.5708
Hammersmith and Fulham 004A	162.2313
Greenwich 036B	161.7647

```
## with 4303 features
## It has 8 fields
```

By plotting the spatial distribution of the crimes on a map, we can make our first hypothesis:
H1. VSO crimes are randomly distributed in the City of London 001F LSOA

To test for H1, we employ the use of quadrat counting. In our case, as our area of interest is in the shape of the LSOA itself (not a regular shape), the quadrats are determined by dirichlet tessallation.

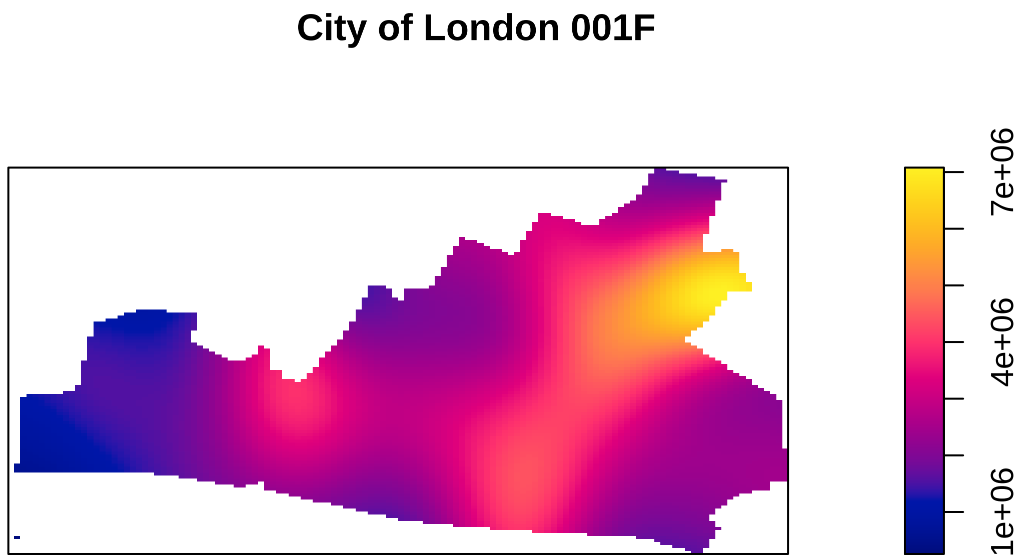


A chi-sq test gives the following results:

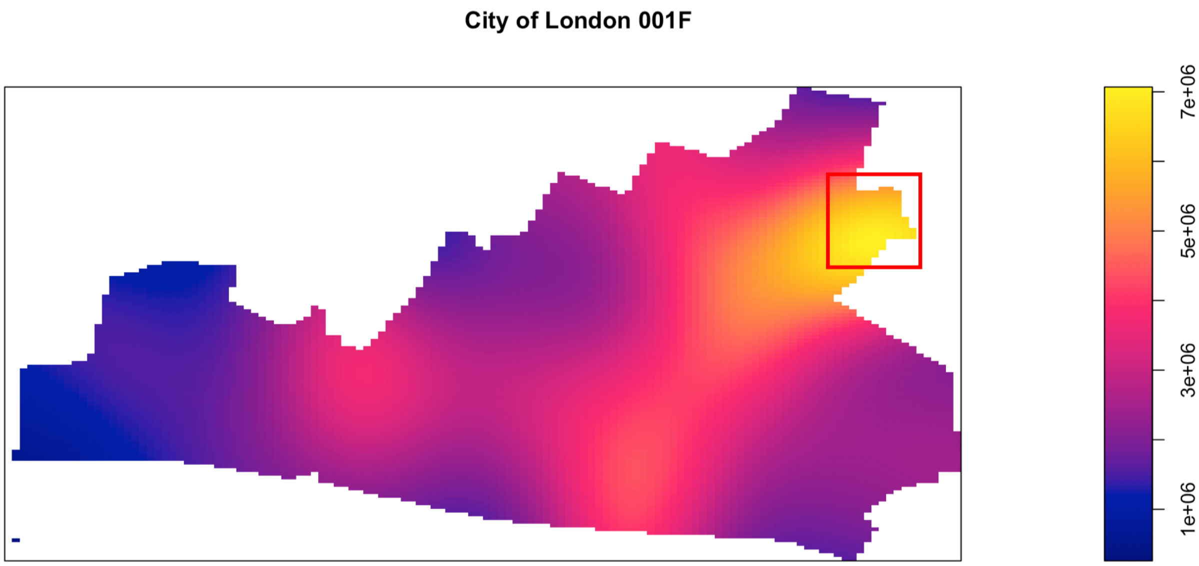
```
##
##  Chi-squared test of CSR using quadrat counts
##  Pearson X2 statistic
##
## data:  COL001F_ppp
## X2 = 34882, df = 617, p-value < 2.2e-16
## alternative hypothesis: two.sided
##
## Quadrats: 618 tiles (irregular windows)
```

As the p-value is less than 0.05, it rejects the null hypothesis that the crimes are homogeneous.

Next, we use the Kernel Density Estimation to visualise the different intensities of the VSO crime on the map.



From the map, clusters of VSO crime seem to occur North-East of City of London 001F. To understand why this is so, we can study the area in more detail (red box).



The street level view reveals a hotspot of 67 VSO crimes in the region.

Based on visual inspection alone, the offences seem to congregate around public entertainment outlets (orange markers above). Here, we construct a third hypothesis.

H2: The location of VSO crimes correlate with the location of entertainment outlets.


67 offences occurred
in this region for the
year 2017
Bishopsgate
A10
New St
Catherine Wheel Alley
Middlesex St
Rose Alley
Cock Hill
Liverpool St
Devonshire Row
Alderman's Walk
Dirty Dicks
Sartoria
East End Cosmetics
Urban Stay Abbotts
Chambers Serviced...
McGregor
Boyall Associates
Honest Burgers
- Liverpool St
Caffè Nero
Pret A Manger
Wasabi Sushi & Bento
The Astronomer
Estee Lauder
City of London Police
Ten Health & Fitness City
By Samanta
Sweet Chariot
Doddle
KFC
Clarendon
Business Centres...
Square Repair
Polo Bar
Debt Explained
London Steakhouse
Co - City
WHSmith
Carphone Warehouse
Taylor St
Baristas - New St
Wrap It Up!
Liverpool Street Serviced
Apartments, thesqua.re
Bishopsgate
Capital Limited
Robust IT Training
The Temple
Fish Market
New Street Wine
Tesco Metro
Grenson
Andaz London
Liverpool Street
Dirty Martini
Trendy 2 Bed
moments from...
Hinde Capital
The Magpie
SRG London (Clinical)
Miyako
New Street Grill
Cinnamon Kitchen City
The Bull
Fernando's Pasta
& Salad Bar
Fitness First,
Devonshire Square
WeWork
Metro Bank
Henderson & Jones
Blue Arrow London City
GIA Building
Consultancy
Coopers' Hall
Subway
Bossington Partners
Tate Recruitment
- London
Natilik
Arrendt & Medernach
Planet Organic
Bank of Ceylon (UK)
Kenza Restaurant
& Lounge
Owen Reed
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Map data ©2019 Google
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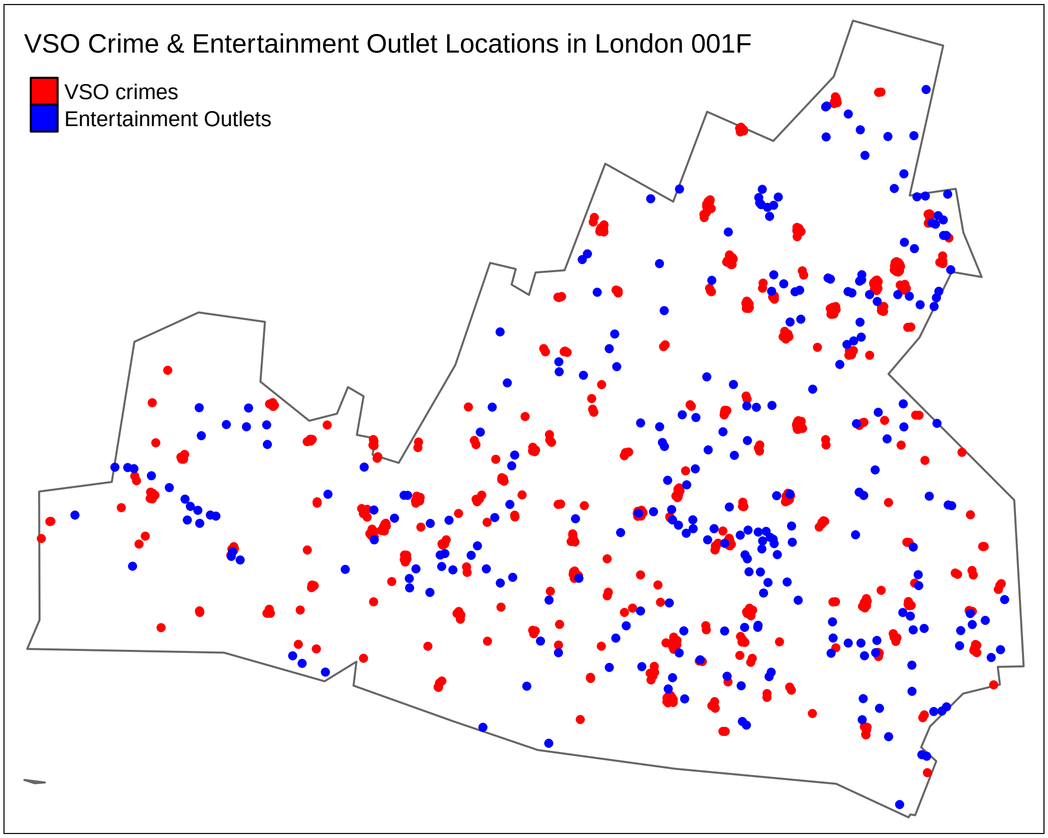
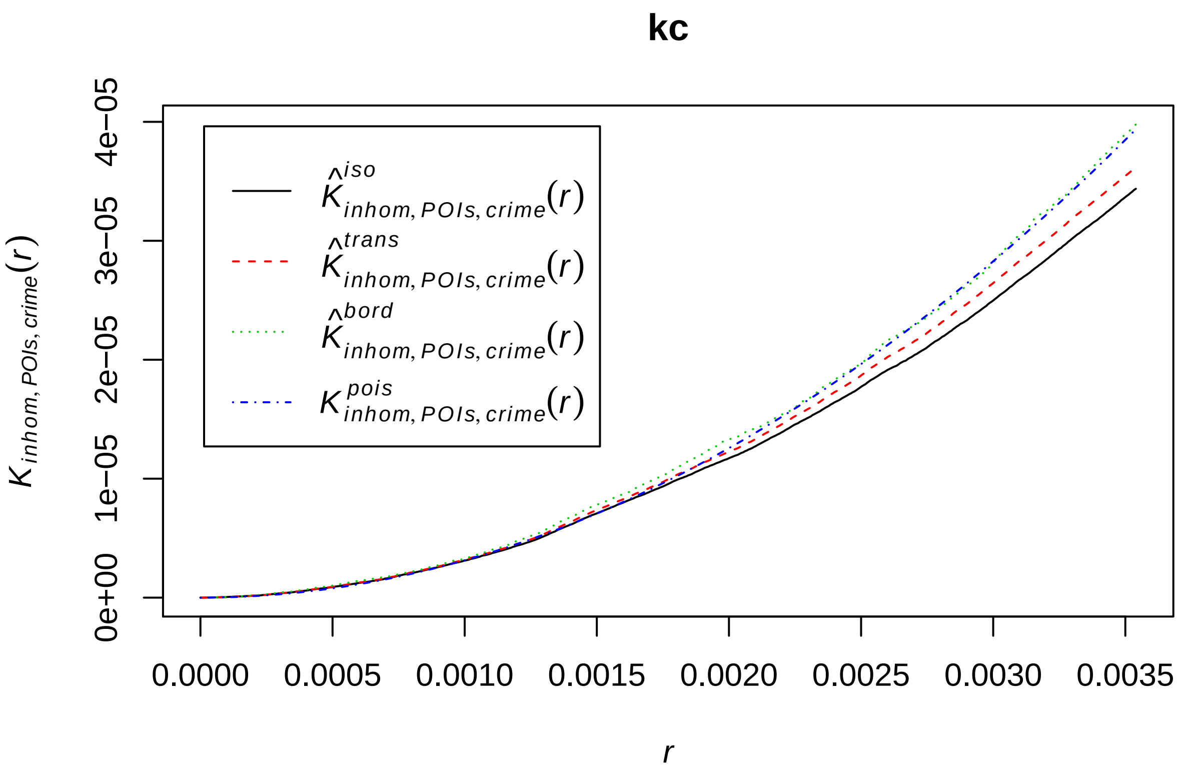
Figure 5:

We define entertainment outlets here to be: restaurants, bars and pubs. With open street map, we can extract the locations of these outlets and visualise them on a map, alongside the VSO crimes:



Visually, the map seems to agree with our hypothesis. VSO crime locations seem to correlate with locations of entertainment outlets. We can perform an inhomogeneous kcross function to determine their spatial relationship.



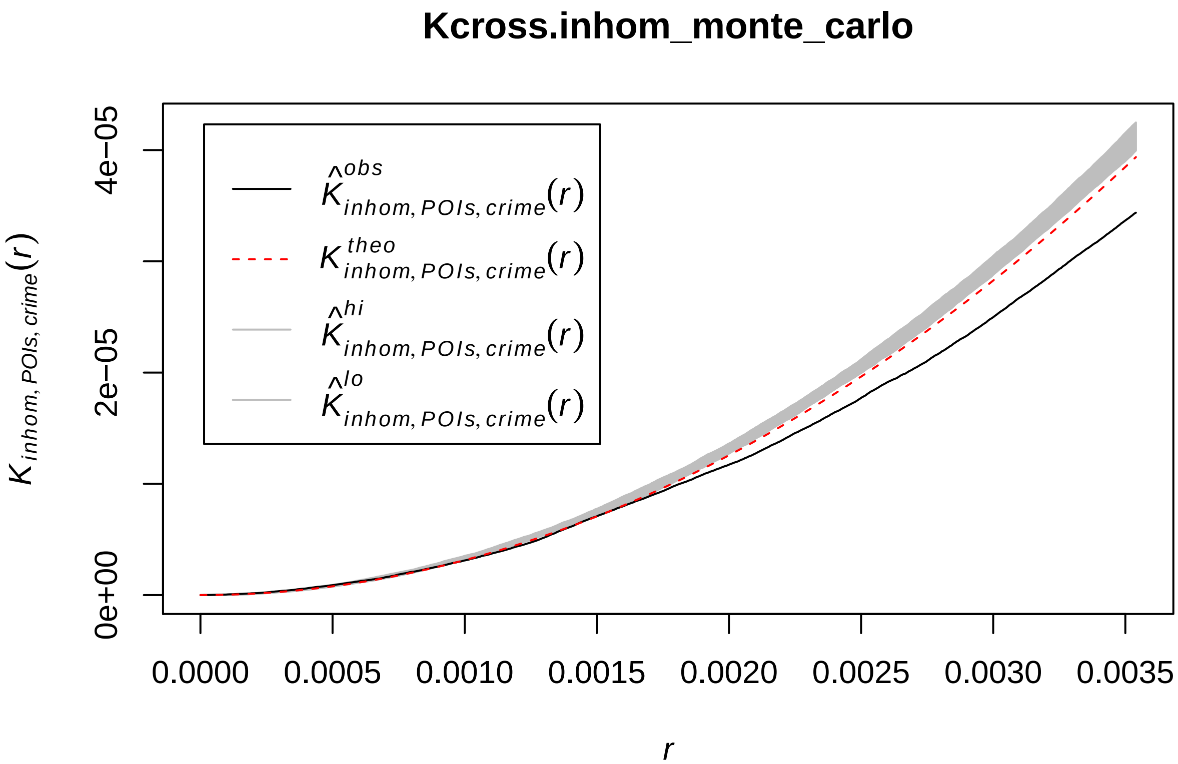
The inhomogeneous kcross function tells us that there is in fact, a repulsive spatial relationship between the location of VSO crimes and the location of entertainment outlets (lines below the blue line) – VSO crimes do not cluster around entertainment outlets.

Running a monte-carlo simulation tells us whether this observation is statistically significant:

```
## Generating 100 simulations of CSR  ...
## 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28
## 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 6
## 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99,  100.
##
## Done.
```

Table 3: Points on the streets

points_on_roads	Freq
FALSE	247
TRUE	371



The observed *Kcrossinhom* line lies below and outside of the acceptance region. This means that the null hypothesis that the 2 variables are independent is rejected. The results also indicate a dispersive relationship between the 2 variables.

This finding is surprising because we expected the 2 variables to be attractive. We may be able to explain this finding though, that the inhomogeneous Kcross function accounted for the the inhomogeneity in the spatial point pattern, brought about by private buildings and parks (random empty spaces on the map).

So although the 2 variables seem to be occurring in the 'same place', they are in fact brought together because of the spatial structure of the environment. The presence of parks and buildings 'forces' the points to go along in a particular direction. This means if we plot other variables on the map as well (for example: other crimes or locations of supermarkets, etc.), their spatial locations may appear similar too – avoiding the spaces that can't be occupied (parks, private spaces and buildings) and occupying the spaces that can be.
Just out of curiosity, we can do simple tabulation of the number of VSO crimes that happen on the streets.

60% of VSO crimes happen on the streets.

The repulsive relationship between VSO crimes and entertainment outlets (bars, pubs and restaurants) is still surprising though and we are uncertain why this is so. Perhaps these are places people usually go to with a group of friends of family and hence it is more difficult for perpatrators to commit VSOs? These are also places with high visibility therefore perpatrators do not dare to commit VSOs? VSOs at bars and pubs are also likely to go unreported, because of the nature of their environments? Or perhaps it could be because of a related variable that causes this repulsive relationship. Clearly, more analysis and research is needed in this area.

4.2 Analysing Vehicle Crime

Vehicle crime refers to any theft, tampering, or interference with motor vehicles (Home Office 2019b). It is chosen for further analysis as it has one of the relatively higher crime rates. The nature of the crime also contrasts that of violence and sexual offences, as it does not require direct contact with the victim.

4.2.1 Spatial distribution of vehicle crime by LSOA

Figure 6 and Figure 7 show the spatial distribution of vehicle crime counts and vehicle crime rates by LSOA respectively. Under normal circumstances, if the relatively high crime counts are due to a large resident population, the crime rates in these LSOAs should be relatively lower after accounting for the size of the resident population.

However, the spatial pattern between the two maps is generally similar. Thus, regions with the highest vehicle crime counts have the highest vehicle crime rates, and vice versa. This can be due to two possibilites:
1) Vehicle crime count is inversely proportional to resident population size. If this is true, LSOAs with relatively high crime counts have a small resident population, thus crime rates are also relatively high. On the other hand, LSOAs with relatively low crime counts have a large resident population, thus crime rates are also relatively low.
2) The size of the resident population in each LSOA does not have a significant effect on the likelihood of the occurrence of vehicle crime.

Further analysis of the spatial patterns in the occurrence of vehicle crime will be made using the crime rate map, as this is slightly more accurate than using crime counts - the size of LSOAs varies, hence taking crime counts alone will conflate results; crime rates attempt to account for the variation in LSOA size. Several generalised observations made from the crime rate map (Figure 7) are described below:
1. Majority of LSOAs with the highest crime rates are located north of the river Thames 2. LSOAs with the highest crime rates tend to be found along the river Thames
3. LSOAs in (2) can be grouped into 4 main areas: East London (e.g. Newham, Creekmouth, Rainham, Greenwich), (commercial) Central London (e.g. City of London, Westminster), (residential) Southwest London (e.g. Kensington, Knightsbridge), West London (e.g. Heathrow, Acton, Hammersmith, Chiswick)

4.2.2 Spatial autocorrelation of vehicle crime

Earlier observations of the spatial distribution of vehicle crime rates suggests that LSOAs with high crime rates can be grouped into regions. Thus, this section will investigate this further, by examining spatial autocorrelation of vehicle crime at the LSOA level based on regions with contiguous boundaries.

A Moran's I value of 0.36013 suggests that a positive autocorrelation in vehicle crime counts exist on average across the entire area. Results for the Moran's I test using randomisation and the Monte-Carlo simulation using 999 simulations both produce small p-values of 2.2e-16 and 0.001 respectively, suggesting that the calculated Moran's I value is highly statistically significant. Thus, at the LSOA level, frequency of vehicle crimes display, on average, a significant positive autocorrelation in London.

Local spatial autocorrelation

Local variations in spatial autocorrelation are also examined, in order to determine if levels of autocorrelation vary due to spatial heterogeneity. A map of the local Moran's I values at each LSOA is presented in figure 8.

LSOAs with local Moran's I values that are statistically significant at the 95% confidence interval were then calculated and mapped. Figure 9 shows that spatial autocorrelation is non-significant across most of London. It is however noteworthy that the LSOAs with the highest crime rates also tend to form statistically significant high-high clusters. Specifically, high-high clusters are present in West London, central London and East London along the river Thames. This confirms the earlier hypothesis that there is a concentration of

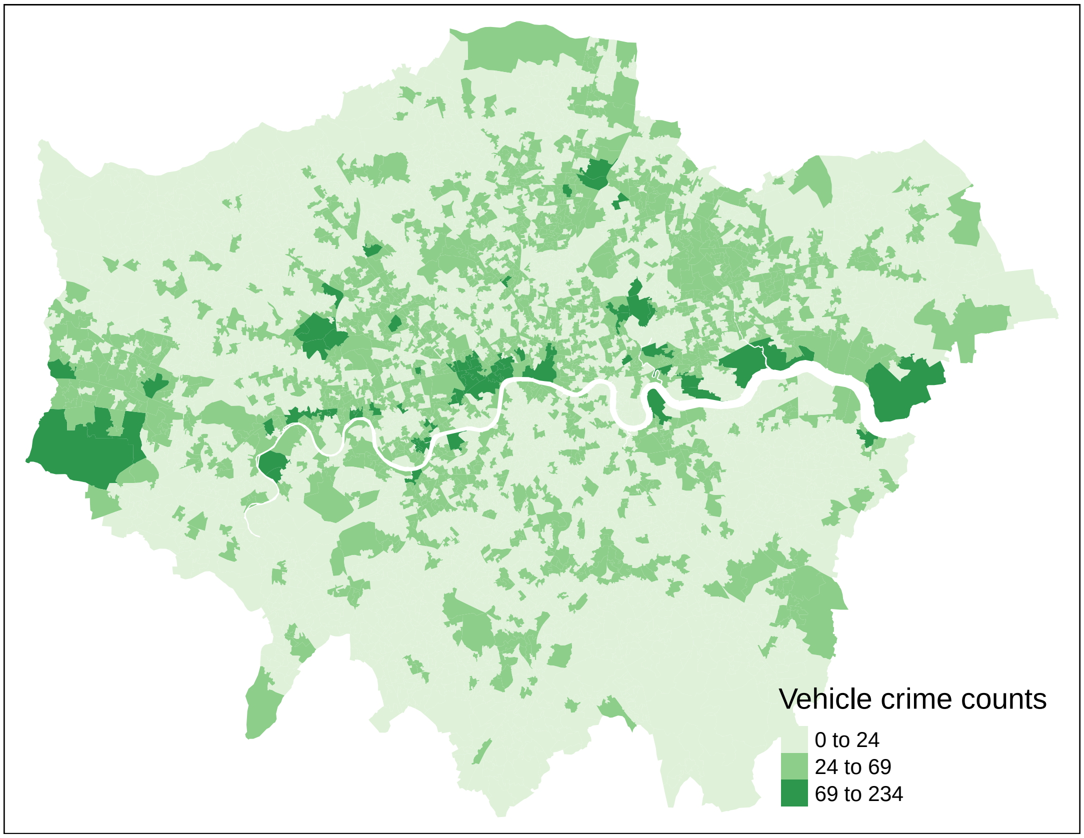


Figure 6: 2017 London vehicle crime counts by LSOA

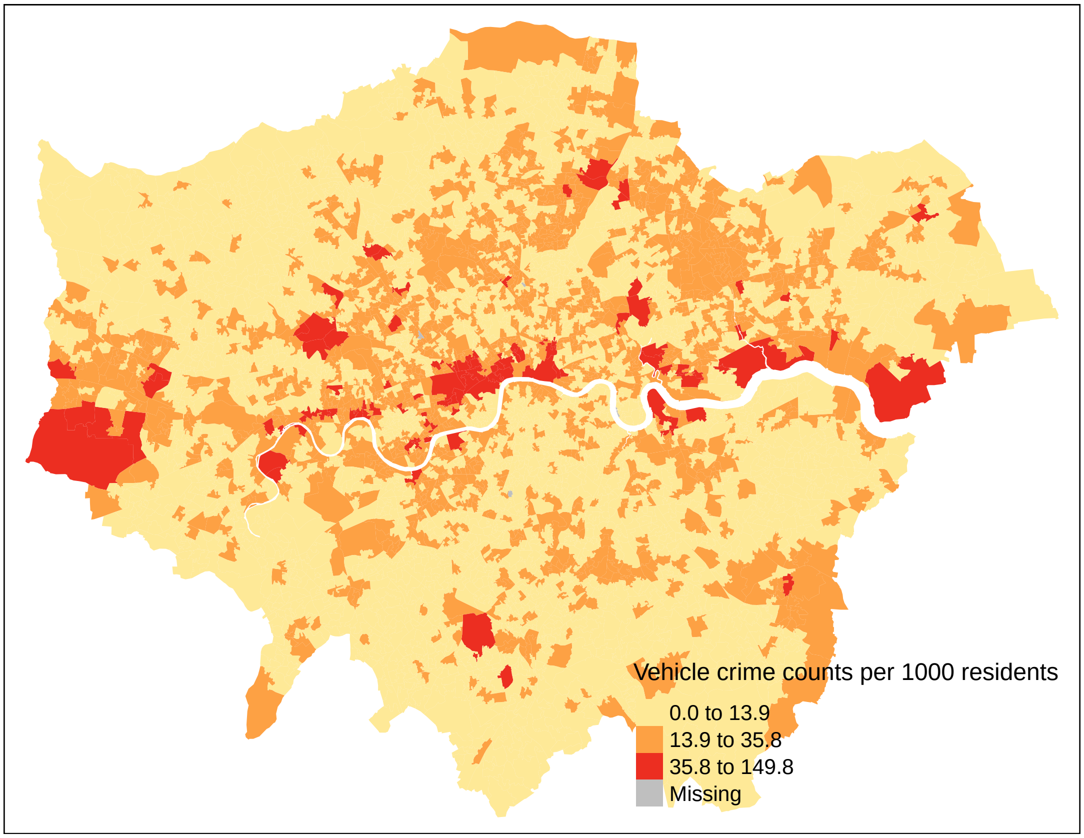


Figure 7: 2017 London vehicle crime rate map by LSOA

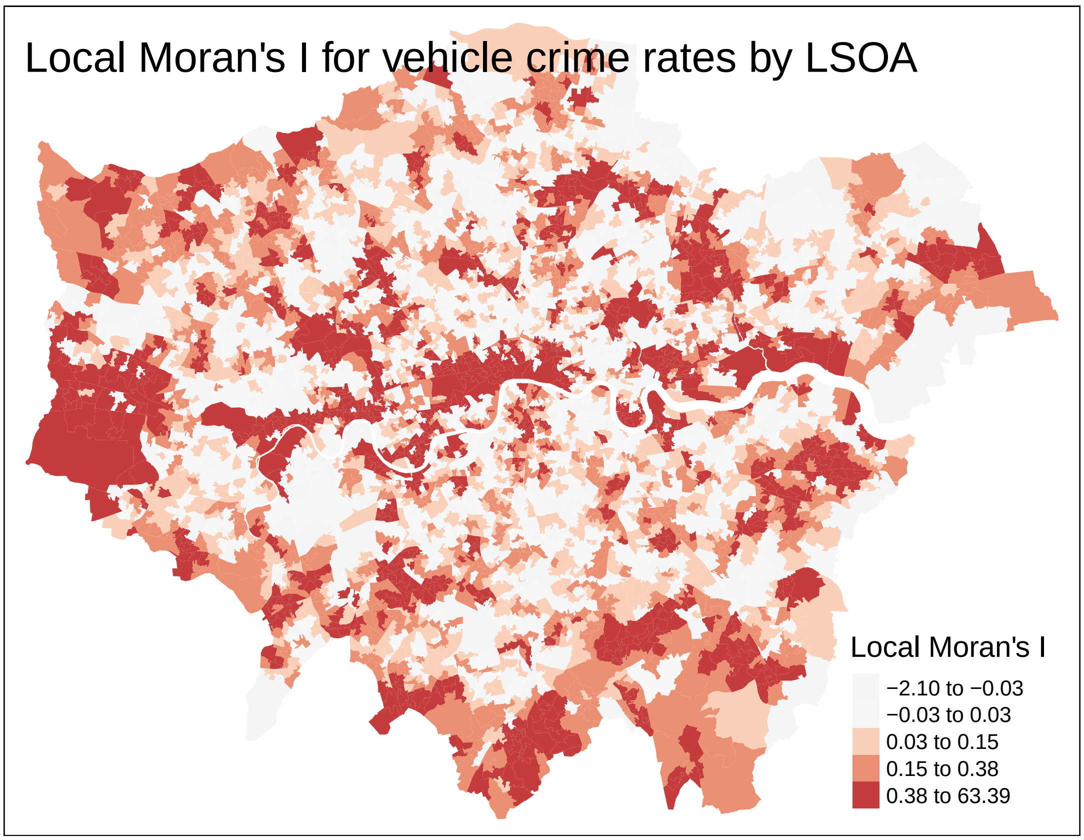


Figure 8: 2017 London vehicle crime rates local Moran's by LSOA

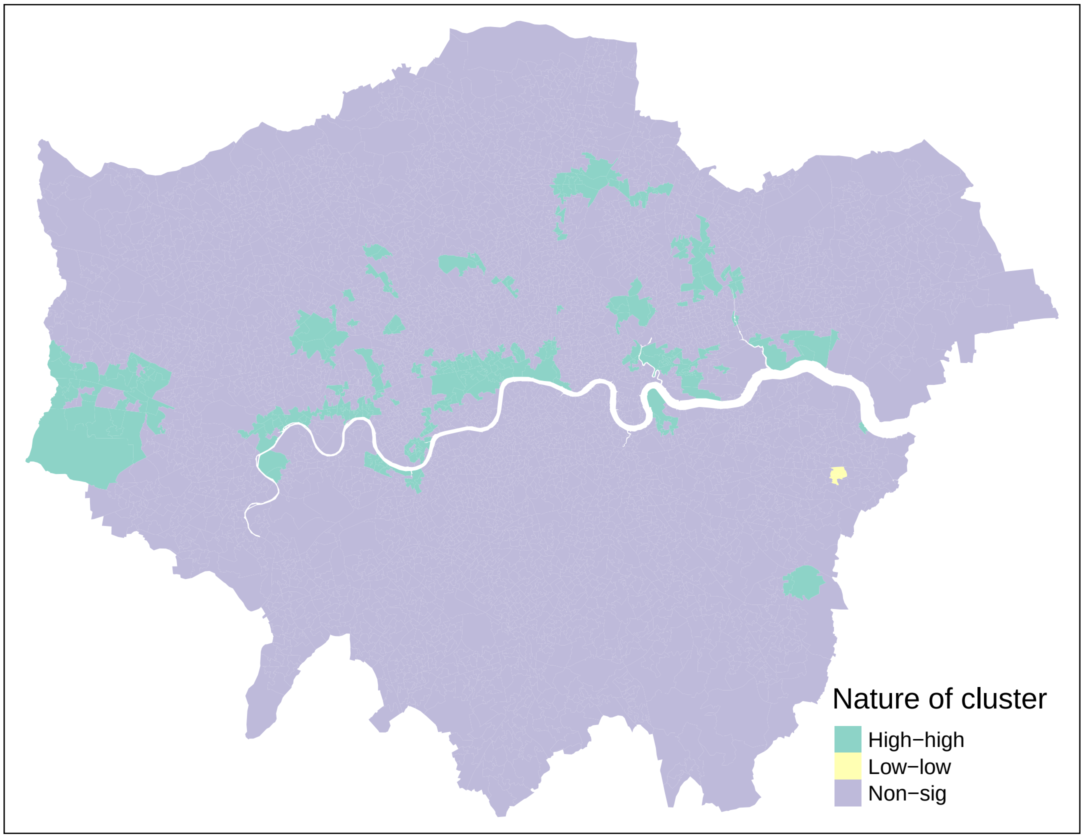


Figure 9: LSOAs with statistically significant local Moran's clusters for vehicle crime

crimes on a local level in different regions of London. It is also notable that several other LSOAs (that do not have relatively high vehicle crime rates) also have high-high clusters, indicating that spatial autocorrelation is not only restricted to regions with high vehicle crime rates. This may be related to characteristics of the region or criminal behaviour. Interestingly, a single low-low cluster is observed in south London, in the Bexley region.

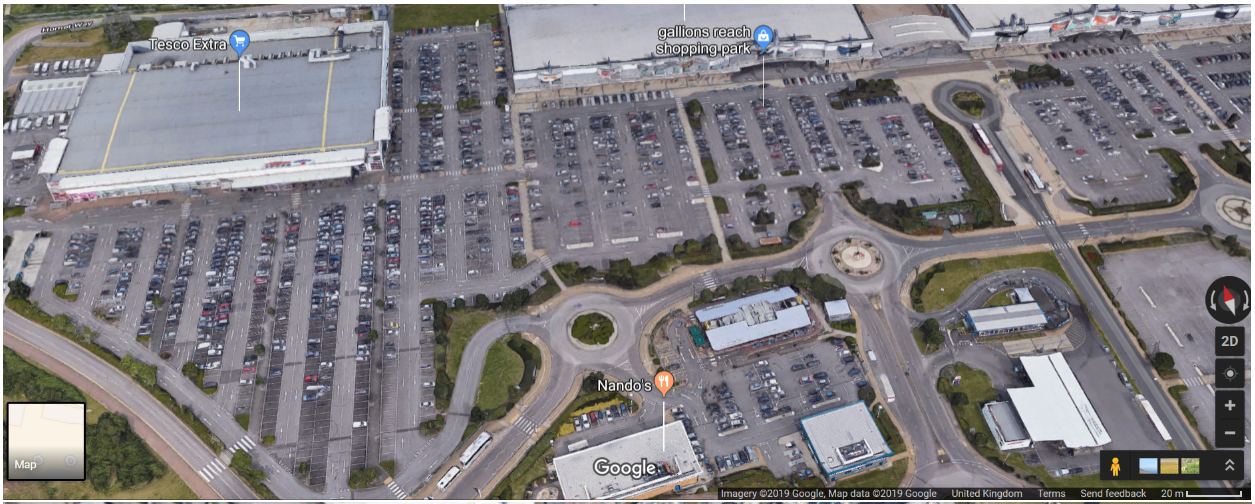
4.2.3 Reasons for vehicle crime rates

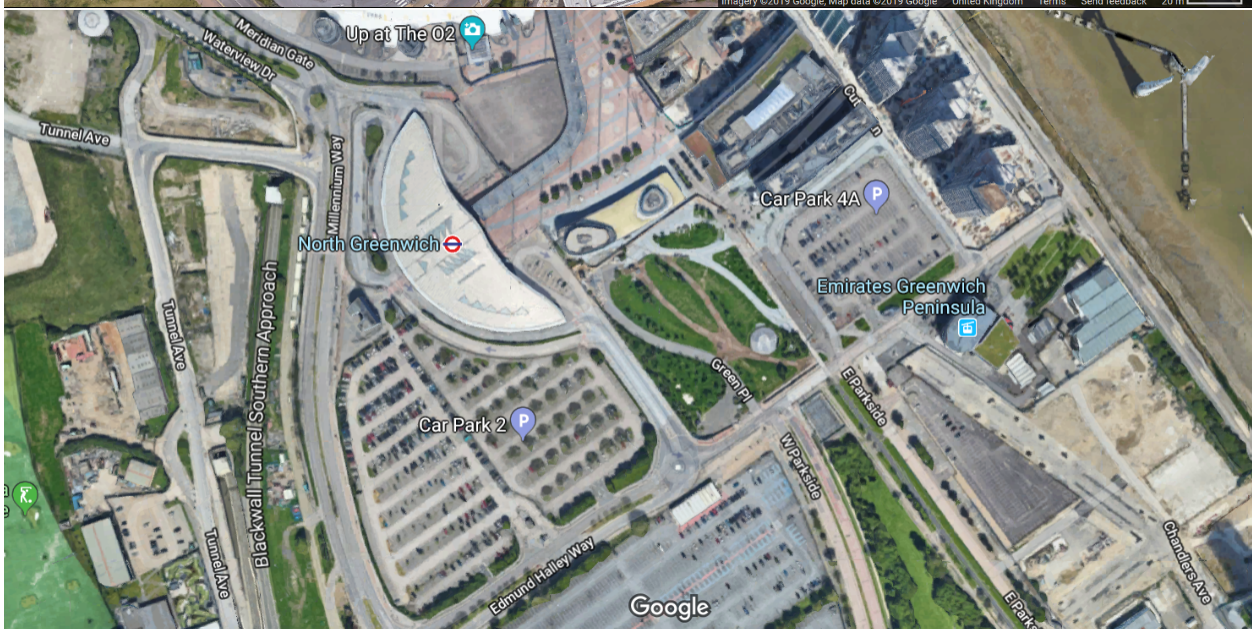
Earlier analysis reveals that elevated crime rates tend to occur in specific regions, and there is spatial autocorrelation at the LSOA level. This may be attributed to either characteristics of the region or criminal behaviour. Therefore, this section will examine regions with high vehicle crime rates (East London, central London, Southwest London, West London), to identify variables that may contribute to high crime rates.

Different shared key characteristics in the regions mentioned above are revealed upon further investigation using aerial and street imagery from GoogleMaps.

East London

In East London, the LSOAs with high crime rates either have 1) industrial parks/scrapyards/depots (e.g. Barking LSOAs, Newham LSOAs) and/or 2) retail parks/leisure parks (e.g. Newham LSOAs, Greenwich LSOAs). For instance, the agglomeration of retail parks in Newham (and the accompanying parking lots), such as the Gallions reach shopping park, Beckton Triangle retail park and Gateway retail park may in contribute to the elevated vehicle crime rates in the LSOA. Likewise, in Greenwich, the presence of leisure parks and the O2 stadium and the accompanying parking lots may contribute to the high vehicle crime rates.





On the other hand, in parts of Creekmouth and Barking, the high vehicle crime rates may be attributed to the presence of industrial parks and scrapyards.

The high rates of vehicle crime at industrial areas/scrapyards is interesting, as the vehicles are often old and/or damaged. This suggests that thieves may steal vehicle parts from these areas. However, industrial areas are be relatively quiet and empty at night, which may mean that the risk of getting caught is lower.

On the other hand, the high vehicle crime rates at retail parks/leisure parks suggests that thieves are likely opportunistic, and target these areas due to the high volume of vehicles parked in these areas.

West London

Interestingly, the other patterns are different in West London and two main patterns can be identified, and can be linked to either carparks or car dealers. High rates of vehicle crime near Heathrow airport may be attributed to the large volumes of parked vehicles, whether it be at the short-stay or long-stay carparks. Criminals may therefore choose to operate near the airport, particularly at the long-stay carparks which are likely used by individuals travelling abroad.

The high crime rates in Chiswick may also be linked to the presence of large numbers of parked cars, as the LSOAs with the highest crime rates tend to have either carparks associated with supermarkets or car dealers. These observations are consistent with the hypothesis that thieves are opportunistic, and pick areas with

Figure 10: Industrial area in Barking

more parked vehicles to increase their likelihood of success.

However, there is no evidence of large numbers of parked vehicles in some parts of west London with high crime rates, such as Hammersmith and parts of Hounslow, both of which appear to be predominantly residential. It may be possible that these LSOAs have high crime rates as they are in the vicinity of other hotspots, such as those in Chiswick.

Vehicle crime rates are also high in Richmond, and may be linked to the presence of multiple carparks and the affluent demographic of the area.

Southwest London

In contrast to other regions, where high crime rates are associated to industrial/commercial areas, in southwest London, high vehicle crime rates occur in residential areas. These include regions such as Kensington, Chelsea and Knightsbridge. Unlike other areas, the volume of parked vehicles is not exceptionally high - there are no carparks/industrial areas/car dealers. However, there are numerous luxury vehicles parked in these areas, as they are affluent neighbourhoods. Hence, it is likely that vehicle crime rates are high in these region, as thieves operating in these areas specifically target high-value vehicles.

Central London

It is not clear why vehicle crime rates are high in central London, particularly in the City of London and Westminster. However, it is also interesting that some parts of the City of London (e.g. Moorgate, Barbican) have low vehicle crime rates - this may be due to the presence of secure parking in underground carparks.

4.2.4 Discussion

More detailed examination of regions with high vehicle crime rates suggests two main modes of operation for criminals:
1) Criminals may operate in areas with large numbers of parked vehicles (e.g. industrial areas, large car parks) [quantity over quality]
2) Criminals may operate specifically in affluent areas to target high-value vehicles [quality over quantity]

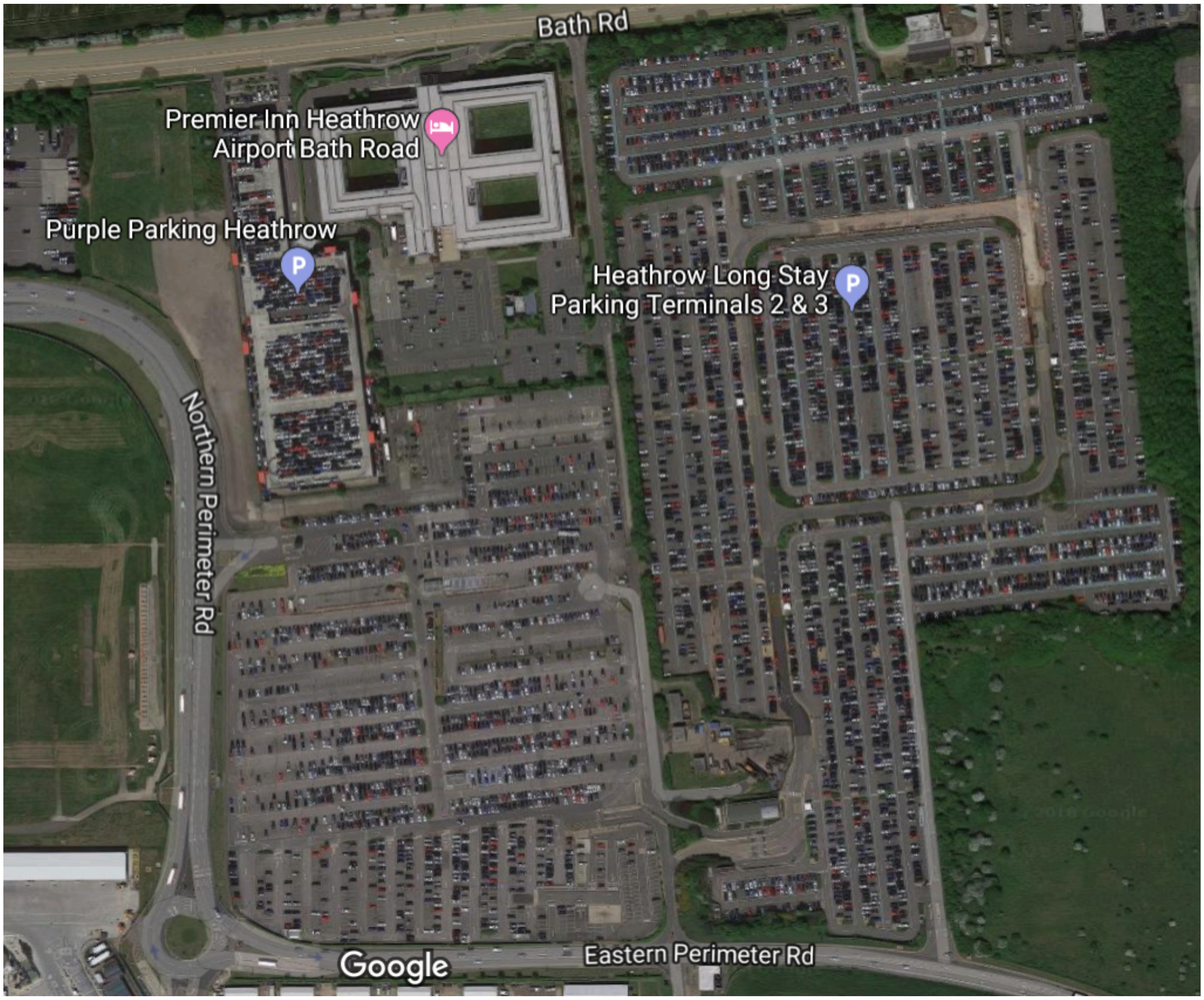


Figure 11: Heathrow Airport Parking Lots

Figure 12: Luxury vehicles in Knightsbridge

Based on hypothesis (1), further analysis has identified industrial areas and large carparks to be significant variables associated with elevated vehicle crime rates. A map of industrial areas and the vehicle crime rates by LSOAs is therefore generated to visualise the relationship between vehicle crime rates and industrial areas (Figure 13). There appears to be a correlation between industrial areas and vehicle crime rates. This may be because these areas tend to be quiet at night thus, the risk of getting caught is lower. Future work to model vehicle crime patterns can therefore consider including distance from industrial areas as one of the variables to be modelled. Distances to the nearest police station can also be considered as a proxy for perceived risk of getting caught.

Ideally, the relationship between large car parks (as a proxy for the number of parked vehicles) and vehicle crime rates will also be visualised. However, the readily available datasets for carparks are not fully complete - for instance, the data on OpenStreetMap mainly limited to in central London. Moreover, the dataset provides information on general parking spaces (which could be anywhere), and not the locatio of large carparks. Hence, future work can consider examining the relationship between large car parks and vehicle crime rates.

Based on hypothesis (2), future work can consider incorporating income data in residential areas as a variable contributing to vehicle crime rates.

That said, high crime rates in central London and other residential (but not particularly affluent) parts of West London such as Hammersmith cannot be explained based on the above hypotheses. Further studies can therefore look towards understanding criminal behaviour in these areas.

In addition, analysis of the vehicle crime dataset is conducted in the form of areal analysis at the LSOAs level. Different levels of analysis may produce different results, and a higher level of aggregation (e.g. at the borough level) may produce different trends. Whilst the observations at the broader areal level between LSOAs suggests that a relationship between industrial areas, car parks with vehicle crime, as well as a relationship between affluent areas and high-value vehicle crime exists, more detailed point analyses at a local level may suggest otherwise. Thus, further work can be conducted at within the LSOAs level, to examine the interactions between these variables at a local level.

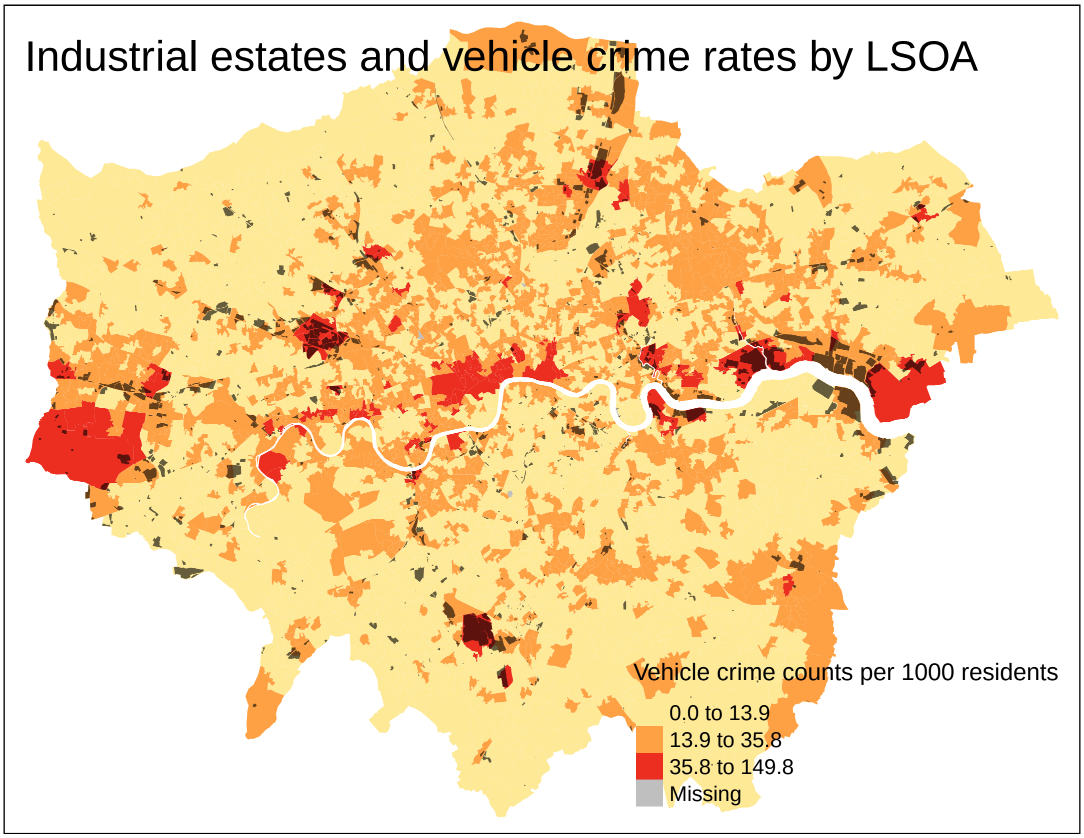


Figure 13: Location of carparks and industrial areas on top of vehicle crime rates

5 Discussion

- limitations and future work

6 Conclusion

In conclusion, analysis of ...

Areal analysis of vehicle crime rates at the LSOAs level indicates cluters of high vehicle crime in parts of West London, East London, Central London and Southwest London. Several hypotheses for these cluster have been formulated. Specifically, these clusters may be attributed to 1) large numbers of parked vehicles, or 2) a concentration of high-end vehicles. Future work can looking into quantifying the effect of variables such as the distance from industrial areas, carparks, and the nearest police station. Analysis at the LSOA level is subject to the modifiable areal unit problem, and further investigation of the individual points can be considered to better understand the dynamics at the local level.

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