

Original Paper

Spatial-Temporal Analysis of Burglary Incidents in Leeds: A Study from 2021 to 2022

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Abstract

In the era of globalization and informatization, urban crime, especially residential burglary, poses a significant threat to societal well-being. This study critically examines the spatial distribution patterns of residential burglaries in Leeds for the years 2021 and 2022, and their temporal variations. Utilizing the global Moran's I and Local Moran's I for assessing spatial autocorrelation, the research identified a consistent and significant spatial association in burglary incidents, displaying persistent and stable patterns throughout the observed period. Additionally, with the aid of Kernel Density Estimation (KDE), the study pinpointed that burglary cases are predominantly concentrated in the central urban region, gradually dissipating towards the suburbs. Finally, employing the Ordinary Least Squares (OLS) model to analyze the determinants of residential burglaries, the results indicated a close association between burglary densities and environmental factors.

Keywords

geographical information system, data analysis, Spatio-Temporal Analysis

1. Introduction

1.1 Research Background

Against the backdrop of globalization and informatization, crimes continuously pose direct threats to people's life and property safety and, concurrently, impart hidden challenges to social stability and economic health (Harries, 2006). With rapid technological advancements and a significant population shift towards larger cities, urban criminal challenges have evolved. Notable shifts in crime characteristics, such as crimes targeting younger individuals (younger age), crimes leveraging advanced technologies (intelligent), organized crimes by experienced criminals (professionalization), and large criminal gangs (groupification), are becoming prevalent (Ackerman and Murray, 2004). On another note, burglaries, a typical urban crime of entering a home or other building by a person with the intent to steal (Nee, 2010),

not only result in direct economic losses for the victims but have a profound impact on the entire societal and economic milieu. Societally, burglaries enhance residents' insecurity towards their living environment, possibly leading to a decrease in community cohesion, thus affecting their overall well-being and stability (Skogan, W. G., 2017). Economically, beyond direct property loss, high crime rates can deter potential investors and business activities in a region. Increased concerns about crime can lead homeowners and business owners to spend more on security measures and insurance, elevating their operational costs (Telep, C. W et al., 2014).

Considering the above, crime research has undeniably become a focal point for numerous institutions and scholars. Beyond traditional criminology and criminal law studies, interdisciplinary researchers, especially geographers, are growing increasingly interested in the relationship between crime and geographical spaces. This has facilitated the rapid progression of the field of crime geography (Wilson, J. Q.).

To delve deeper, the Geographic Information System (GIS) offers an innovative perspective for interdisciplinary research (Brunsdon & Corcoran, 2006). Spatial crime analysis involves studying crime locations, frequencies, and patterns using GIS. Not merely presenting crime distribution, GIS also delineates temporal relations behind crimes. Modern crime geography increasingly values this spatial-temporal analysis, providing valuable insights for crime prediction and strategy formulation (Bernasco & Block, 2009).

Evidence shows intriguing anomalies in crime rates worldwide. Although many cities are striving to reduce their crime rates, specific areas, like Leeds in the UK, depict a contrary trend, especially in areas like house and shop burglaries (Malleon, 2015). Speaking of Leeds, located in northern England, is one of West Yorkshire's major cities. Its history, stretching back to the 5th century AD, has witnessed transformations from a textile-industry-driven city to a modern financial and service hub (Chatterton P and Hollands R. 2003). As posited by Ratcliffe, the history and economic structure of a city often correlate with its crime patterns. Hence, Leeds, with its unique socio-economic background, city layout, and population dynamics, presents a rich tapestry for such research (Ratcliffe, J., 2004).

1.2 Research Aims & Significance

Criminal activities often exhibit distinct spatial and temporal patterns, such as spatial hotspots and high-incidence timeframes (Harries, 1999). To address these security challenges, understanding these patterns is paramount. With the burgeoning growth of GIS, it has become a potent tool for crime analysis, revealing intricate details about crime activities' spatial distributions, time trends, and underlying factors (Chainey et al., 2008). Such detailed analysis is invaluable for law enforcement, facilitating real-time surveillance strategies, resource optimization, and crime prediction and prevention. Spatial crime analysis offers governments and law enforcement a broader view of crime activities, intensifying regulation. Moreover, it promotes inter-departmental collaboration for cohesive crime prevention strategy formulation. Within this realm, GIS plays a pivotal role, not only in crime prevention and evaluation but also in police force planning, inter-departmental information exchange, and empirical

verification of crime theories. This study employs GIS to undertake a comprehensive spatio-temporal analysis of theft cases in Leeds from 2021 to 2022 (GROFF and LA VIGNE, 2001). Through this method, we aim to unveil the spatial distribution and time trends of crimes, delving deep into potential influencing factors. Additionally, this data and analysis will aid policymakers and law enforcement officers in understanding Leeds' crime dynamics more precisely, enabling the formulation of more targeted security strategies.

This research addresses the following questions:

- How have burglary cases in Leeds evolved over time?
- How has the spatial distribution of burglary cases in Leeds changed?
- Are there specific areas or times that emerge as "hotspots" for burglaries?
- Which socio-economic (e.g., unemployment rate, education level, ethnicity) and environmental factors (e.g., transportation accessibility, commercial density) might be related to the spatial distribution of burglary cases?

1.3 Dissertation Structure

This study is structured into the following sections: Introduction, Literature Review, Data Sources and Research Methods, Analysis and Results, and Discussion. Within the Literature Review, theoretical and empirical studies of crime geography are explored, laying the foundation in theory and methodology for the subsequent analysis of burglary cases in Leeds. The Data Sources and Research Methods section elucidates the techniques employed in this research, alongside the data collection and analysis methods adopted. The Analysis section displays the spatiotemporal distribution patterns of burglary incidents and delves into potential influencing factors. Finally, in the Discussion section, the research findings are summarized, recommendations for urban crime management and policy-making are offered, and the limitations of this study are reflected upon.

2. Literature Review

2.1 The Progress and Application of Geography in Criminology

In the early stages, numerous foreign scholars began utilizing geographical concepts to explore the spatial distribution patterns and trends of crime. They proposed a series of criminological theories with distinct geographical characteristics. Through an analysis of relevant geographical theories on crime, this progression can be categorized into six stages (Lowman, 1986)

1. Cartographic School (19th Century):

- The emergence of the earliest phase focused on utilizing geographical concepts to study crime.
 - Exploration of spatial distribution patterns and trends of criminal activities.
- (Friendly, 2007)

2. Chicago School (1920s-1930s):

- The development of the "Chicago school" marked a significant milestone.

- Concentration on understanding the relationship between urban spatial structures and the residential locations of criminals.

- Investigation into the social dynamics contributing to crime hotspots.

(Burgess et al., 1925)

3. **Factor Analysis School (1950s-1960s):**

- Shift towards the "factor analysis school" in this period.

- Emphasis on identifying and studying variables that influence criminal behaviour and crime rates.

- Consideration of socio-economic, demographic, and environmental factors.

(Harries, 1999)

4. **Environmental Criminology and Crime Geography (1970s-1980s):**

- Rise of the "environmental criminology" and "crime geography" schools.

- Investigation into how urban spatial environments impact the distribution and occurrence of criminal activities.

- Examination of physical, social, and economic factors shaping crime patterns within different geographic contexts.

(Lowman, 1986)

5. **Advancement of Computer Hardware and GIS (1990s-2000s):**

- The rapid advancement of computer hardware and Geographic Information Systems (GIS) technology.

- The emergence of sophisticated crime spatial analysis techniques.

- Enhanced ability to process and analyze large volumes of crime data in a spatial context.

- Introduction of innovative mapping and visualization tools to understand crime patterns.

(Chainey et al., 2008)

6. **Integration of Complexity Science (Early 21st Century):**

- Convergence of crime theory with complexity science methodologies.

- The emergence of stages such as virtual crime simulation.

- Focus on utilizing advanced computational techniques to simulate and model complex interactions affecting crime patterns.

- Incorporation of multidisciplinary approaches to gain deeper insights into the dynamics of crime in various geographical settings (Malleon et al., 2010).

2.2 *Research on Spatial Distribution and Time Variation of Criminal Events*

The spatial distribution of urban crime follows certain patterns, which have been extensively studied in various contexts. For instance, through a 20-year study of 21 American cities, Shaw and McKay revealed that the incidence of urban crime is inversely proportional to the distance from the city centre (Shaw and McKay, 1942). A phenomenon also observed by Schmid is that as distance increases, crime rates tend to

decrease. Schmid's research focused on the distribution patterns of different crime types within downtown Seattle. His findings unveiled distinct spatial clusters of urban crime. Analyzing the correlation between crime rates and distance from the city centre, he noted a decreasing trend as distance increased. The highest crime rates were concentrated in the central business district and disadvantaged neighbourhoods. Schmid proposed a model illustrating the varying attractiveness of different areas for criminal activities in Seattle. For instance, financial theft and fraud cases were more common in the Seattle CBD, while robbery and behaviours like female alcohol abuse were more prevalent in lower to middle-class streets (Schmid, 1960). In the UK, Smith's research indicated that areas with higher incidences of robberies were often characterized by public access, including streets, underground rail systems, and parks. Furthermore, these incidents were frequently observed in commercial thoroughfares and transportation intersections. Notably, public transportation users were often targets of robbery (Smith, 2003).

These research findings have piqued the interest of numerous scholars who have attempted to explore and interpret this pattern using diverse methodologies. For example, Erdogan and his team employed the empirical Bayesian smoothing technique to explain crime rates. They also utilized global spatial autocorrelation indices to assess the spatial dependence of crime rate distributions. Through simulated analyses of crime rates and by incorporating key indicators such as unemployment rates and levels of urbanization, they utilized geographic weighted regression to delve into crime patterns. Their research unveiled the uneven spatiotemporal distribution of criminal activities, particularly property crimes, which exhibited evident clustering tendencies in the western and southern regions of Turkey (Erdogan et al., 2012).

Furthermore, the spatial distribution of urban crime is not static but evolves over time. Block and his team employed the Kernel density estimation method to identify areas with high crime densities. They conducted a spatial analysis of crime events within specific time intervals to identify crime hotspots during those periods. Subsequently, by generating a series of time-series crime hotspot maps, the authors were able to visually demonstrate how crime hotspots change over time. To better comprehend the dynamic nature of these hotspots, researchers tracked how certain crime hotspots migrated or disappeared in different time segments. Ultimately, they discovered that while some areas may maintain their status as crime hotspots over extended periods, many hotspots undergo temporal changes or shifts. These findings not only contribute to a better understanding of the trends and dynamics of urban crime but have also led to the application of various techniques to predict future spatial crime distributions (Block and Block, 1995). Chainey and colleagues conducted a comparative analysis of four mapping methods, including point mapping, thematic mapping, spatial ellipses, grid thematic mapping, and kernel density estimation (KDE), to assess their ability to predict the future spatial distribution of four crime types (residential burglary, street crime, car damage, and car theft). The research findings indicated variations in predictive capabilities among different techniques and crime types. KDE consistently demonstrated superior performance, with hotspot maps for street crime showing remarkable proficiency in forecasting future street crime locations compared to other types of crimes (Chainey et al., 2008).

2.3 Research on Factors Affecting Crime Distribution

The study of factors influencing crime occurrence is an area of considerable research. Through the analysis of urban crime geographic spatial patterns, many scholars have revealed that crime events are not isolated incidents; rather, they are influenced by the surrounding spatial environment. Brantingham and colleagues combined theories from criminal psychology, environmental psychology, and behavioural geography to discuss the complex mechanisms behind crime generation, general patterns of crime distribution, and decision-making processes at both individual and group levels. They discovered that crime and the environment have intricate relationships, with distinct mechanisms operating at individual and group levels. At the individual level, the choice of crime targets was strongly connected to everyday activity paths and nodes. At the group level, crime distribution was associated with urban activity nodes, pathways, boundary effects, and the characteristics of security domains within communities. Environmental cues created a "crime template" for criminals, shaping their decisions (Brantingham and Brantingham, 2010). Consequently, there is a need for further investigation into the interconnectedness between urban environments and the distribution of crime. These environments can be categorized into two main types based on the nature of factors affecting criminal behaviour: the physical spatial environment and the social environment (Thornberry and Farnworth, 1982).

2.3.1 Relationship between Crime and Physical Environmental Factors

The physical environmental factors primarily encompass the tangible aspects of spatial surroundings, including characteristics related to land use, distribution of roads, spatial arrangement, and building size. Duffala employed chi-square tests to analyze the relationships between various independent variables and the dependent variable. The study tested four variables - the distance between convenience stores and major thoroughfares, traffic volume, surrounding land use types, and the number of adjacent commercial activities - in relation to their impact on susceptibility to armed robbery. The findings indicated that while individual variables showed no significant correlation with the robbery incidence rate, a notable correlation emerged between convenience stores with high robbery rates and a combination of all four variables when their collective influence was considered (Duffala, 1976). Loukaitou-Sideris and her colleagues conducted a study in Los Angeles, USA, to investigate public transit stations and determine the architectural and urban design factors that could potentially influence crime rates in their vicinity. Through the application of multiple regression analysis, the researchers analyzed the relationship between various built environment factors, such as lighting, obstructions, pedestrian flow, and the crime rates at these transit stations. The findings of the study demonstrated distinct associations between specific architectural and urban design factors and the crime rates observed around the public transit stations. Notably, factors such as inadequate lighting and obstructed visibility were identified as potential contributors to increased opportunities for criminal activities (Loukaitou-Sideris et al., 2001).

2.3.2 Relationship between Crime and Social Environmental Factors

On the other hand, the social environmental factors encompass the intangible aspects of the geographical surroundings, such as population, economy, culture, and society. Scholars have recognized for a long

time that these non-material factors also demonstrate correlations with patterns of crime distribution. As early as 1862, Henry Mayhew observed a correlation between population density and crime rates in regions such as Scotland and Wales, noting that areas with a higher industrial concentration in cities exhibited elevated crime rates compared to more rural regions. (Mark R et al., 2013). Shaw and McKay discovered that the occurrence of criminal phenomena is intricately linked to various variables, encompassing shifts in population dynamics, subpar housing conditions, and economic scarcity, as well as African American and foreign-born residents, among others (Shaw and McKay, 1942). Andresen found that crime rates are positively correlated with unemployment rates and population changes, while also showing associations with income inequalities and the presence of diverse racial groups (Andresen, 2006).

2.4 Burglary Research

Regarding the issue of residential burglary, numerous scholars have delved deeply into the matter. Contrary to the common perception of rationality that burglars often act out of opportunism, they are easily influenced by external factors when choosing a target and may readily shift their focus. Some studies suggest that burglars frequently use environmental cues to evaluate the risks associated with potential targets, such as the observability of a location, the presence of occupants, and the difficulty of intrusion (Cromwell et al., 1991). For instance, Cromwell et al. (1991) explicitly pointed out in their research that alarm systems, security measures, vigilant neighbours, and even the presence of a dog in the house can serve as effective deterrents. Additionally, research has unveiled a significant connection between drug use and residential burglary. This connection manifests primarily in the way burglars often resort to theft to finance their drug habits, and they are more prone to commit burglaries under the influence of drugs (Cromwell et al., 1991). On another note, a study by Chiu and Madden (1998) indicates that as income distribution in society becomes increasingly unequal, the number of residential burglary cases also rises. This provides a broader perspective to contemplate the social backdrop of this criminal activity (Chiu and Madden, 1998).

Building upon the insights gained from the literature review, this study will primarily employ methods such as the Standard Deviational Ellipse, spatial autocorrelation tools including the Global Moran's I and local Moran's I, and kernel density estimation to analyze the spatial distribution and temporal variations of burglary incidents in Leeds. Additionally, the research will leverage correlation analysis and Ordinary Least Squares (OLS) regression to investigate the potential influences of physical and socio-environmental factors on burglaries.

3. Data Sources and Research Methods

3.1 Overview of the Study Area

Leeds, located in the northern part of England, stands as a prominent city in West Yorkshire. Geographically speaking, Leeds occupies a central position within England. In terms of population, Leeds holds the distinction of being the second most populous local administrative district in England. As a major city in the UK, Leeds exerts significant influence in various sectors, including economy,

culture, and education (Chatterton P and Hollands R., 2003).

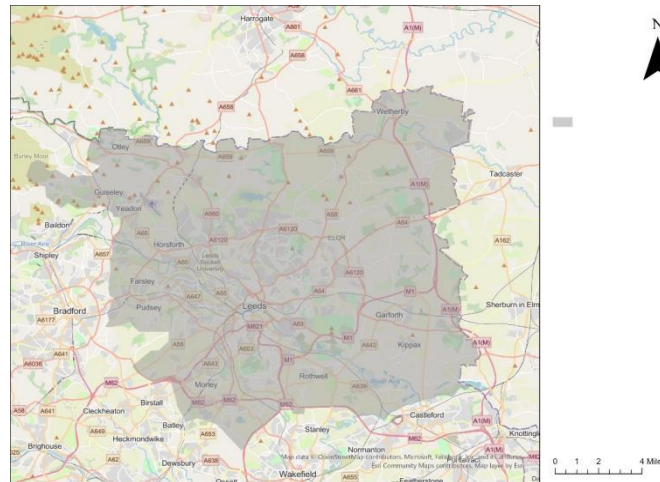


Figure 1. Leeds Location

3.2 Data Sourcing and Preprocessing:

The focus of this research is centred on the city of Leeds, United Kingdom. Leeds City is divided into 488 Lower Layer Super Output Areas (LSOAs). For context, Output Areas (OAs) represent the smallest unit of geographical area used for census statistics. LSOAs, on the other hand, are amalgamations of several OAs—typically four or five. These LSOAs house between 400 and 1,200 households, encompassing a resident population that usually ranges from 1,000 to 3,000 individuals.

Delving into the specifics of data sourcing and preprocessing:

3.2.1 Spatial-Temporal Analysis of Burglaries:

The foundational layer, representing the LSOAs for Leeds in 2021, was retrieved from the Open Geography portal provided by the Office for National Statistics (ONS). For the criminal instances, monthly datasets spanning January 2021 to December 2022 were downloaded from the data. police. UK website, specifically from the "West Yorkshire Police" dataset. These records elucidate various attributes of each crime: the type of crime, and its longitude and latitude. Of particular note for this study, the crimes are categorized monthly based on their occurrence.

To preprocess this dataset, the initial steps involved using Excel to filter out all cases that were marked under the "burglary" crime type. Subsequently, ArcGIS Pro was employed: firstly, the "Add XY point data" tool was utilized to integrate all burglary instances onto the map based on their longitude and latitude. Then, using the "spatial join" tool in ArcGIS Pro (a tool that amalgamates attributes of two spatial datasets based on their spatial relationship), the count of burglaries within each LSOA was aggregated.

3.2.2 Analysis of Factors Influencing Residential Burglaries in Leeds

The comprehensive investigation of factors contributing to burglaries in Leeds necessitates the incorporation of both environmental and social variables. These factors have been further detailed in the subsequent sections:

a. Environmental Factors:

The environmental data draws from two primary sources. The road information was obtained from OpenStreetMap's records for Leeds, while the categorized Points of Interest (POI) were sourced from Ordnance Survey, specifically the 02/2022 version. The POIs were categorized into classifications such as "Transport," "Retail," and "Accommodation_Eating and Drinking."

The specific POI are classified as shown in the figure below:

01 Accommodation, eating and drinking

01 Accommodation	
0003 Bed and breakfast and backpacker accommodation	0007 Self catering
0002 Camping, caravanning, mobile homes, holiday parks and centres	0008 Timeshare
0005 Hostels and refuges for the homeless	0009 Youth accommodation
0006 Hotels, motels, country houses and inns	
02 Eating and drinking	
0012 Banqueting and function rooms	0020 Fish and chip shops
0013 Cafes, snack bars and tea rooms	0025 Internet Cafes
0018 Fast food and takeaway outlets	0034 Pubs, bars and inns
0019 Fast food delivery services	0043 Restaurants

Figure 2. POI Classification

10 Transport

53 Air	
0728 Airports and landing strips	0729 Helipads
54 Road and rail	
0730 Bridges	0737 Petrol and fuel stations
0733 Cattle grids	0740 Signalling facilities
0734 Fords and level crossings	0743 Viaducts
0735 Motorway service stations	0744 Weighbridges
0736 Parking	
55 Walking	
0747 Footbridges	
56 Water	
0751 Aqueducts	0753 Moorings and unloading facilities
0760 Ferries and ferry terminals	0754 Rivers and canal organisations and infrastructure
0752 Locks	0755 Weirs, sluices and dams
57 Public transport, stations and infrastructure	
0731 Bus and coach stations, depots and companies	0758 Taxi ranks
0794 London Underground entrances	0756 Tram, metro and light railway stations and stops
0738 Railway stations, junctions and halts	0761 Underground network stations
59 Bus transport	
0732 Bus stops	0759 Hail and ride zones

Figure 3. POI Classification

09 Retail

46 Clothing and accessories	
0797 Baby and nursery equipment and children's clothes	0659 Jewellery and fashion accessories
0656 Clothing	0660 Lingerie and hosiery
0657 Footwear	
47 Food, drink and multi item retail	
0671 Alcoholic drinks including off-licences and wholesalers	0668 Green and new age goods
0661 Bakeries	0669 Grocers, farm shops and pick your own
0662 Butchers	0670 Herbs and spices
0768 Cash and carry	0703 Livestock markets
0663 Confectioners	0705 Markets
0699 Convenience stores and independent supermarkets	0672 Organic, health, gourmet and kosher foods
0665 Delicatessens	0819 Supermarket chains
0666 Fishmongers	0798 Tea and coffee merchants
0667 Frozen foods	

Figure 4. POI Classification

48 Household, office, leisure and garden	
0824 Adult shops	0683 Garden centres and nurseries
0712 Art and antiques	0684 Garden machinery and furniture
0674 Books and maps	0685 General household goods
0693 Camping and caravanning	0717 Gifts and cards
0675 Carpets, rugs, soft furnishings and needlecraft	0686 Hobby, sports and pastime products
0714 Charity shops	0687 Leather goods, luggage and travel accessories including handbags
0676 China and glassware	0688 Lighting
0827 Comic books	0704 Mail order and catalogue stores
0828 Computer shops	0689 Music and video
0720 Computer supplies	0690 Musical instruments
0677 Cosmetics, toiletries, perfumes and hairdressing supplies	0718 Party goods and novelties
0678 Craft supplies	0691 Pets, supplies and services
0679 Cycles and accessories	0724 Photographic and optical equipment
0700 Department stores	0763 Post offices
0701 Discount stores	0831 Potteries
0680 DIY and home improvement	0719 Second-hand goods
0721 Domestic appliances	0708 Shopping centres and retail parks
0722 Electrical goods and components	0725 Stationery and office supplies
0716 Florists	0710 Surplus goods
0682 Furniture	0726 Telephones and telephone cards
0766 Fuel distributors and suppliers	0694 Travel agencies
0764 Garages, garden and portable buildings	
49 Motoring	
0695 New vehicles	0697 Vehicle auctions
0696 Second-hand vehicles	0698 Vehicle parts and accessories

Figure 5. POI Classification

b. Social Factors

The social factors were gleaned from the 2021 UK census data provided by the UK Data Service. The following is an explanation of the social factors selected for this study:

- **Employment History:** This metric classifies individuals not employed as of Census Day based on their recent work experiences. The categories include:
 - Not in employment, but worked in the past 12 months.
 - Not in employment and haven't worked in the past 12 months.
 - Never been employed.
- **Ethnic Group:** This category captures the ethnicity an individual identifies with during the census. The determination might be based on several criteria, such as cultural practices, family lineage, self-identity, or even physical attributes.

- **Religion:** Reflects the religious affiliation an individual aligns with. It's imperative to note that this doesn't necessarily mean active practice but merely identification or connection to a specific religion.
- **Highest Level of Qualification:** This categorizes residents aged 16 years and above in England and Wales based on their peak academic achievements.

Table 1. Highest Level of Qualification

0	No qualifications
1	Level 1 and entry level qualifications: 1 to 4 GCSEs grade A* to C, Any GCSEs at other grades, O levels or CSEs (any grades), 1 AS level, NVQ level 1, Foundation GNVQ, Basic or Essential Skills
2	Level 2 qualifications: 5 or more GCSEs (A* to C or 9 to 4), O levels (passes), CSEs (grade 1), School Certification, 1 A level, 2 to 3 AS levels, VCEs, Intermediate or Higher Diploma, Welsh Baccalaureate Intermediate Diploma, NVQ level 2, Intermediate GNVQ, City and Guilds Craft, BTEC First or General Diploma, RSA Diploma
3	Apprenticeship
4	Level 3 qualifications: 2 or more A levels or VCEs, 4 or more AS levels, Higher School Certificate, Progression or Advanced Diploma, Welsh Baccalaureate Advance Diploma, NVQ level 3; Advanced GNVQ, City and Guilds Advanced Craft, ONC, OND, BTEC National, RSA Advanced Diploma
5	Level 4 qualifications or above degree (BA, BSc), higher degree (MA, PhD, PGCE), NVQ level 4 to 5, HNC, HND, RSA Higher Diploma, BTEC Higher level, professional qualifications (for example, teaching, nursing, accountancy)
6	Other: vocational or work-related qualifications, other qualifications achieved in England or Wales, qualifications achieved outside England or Wales (equivalent not stated or unknown)
7	Does not apply

- **Population Density:** This represents the number of residents per square kilometre in England and Wales.
- **Car or Van Availability:** Enumerates the number of cars or vans accessible to household members. For clarity:
 - Included vehicles: pick-ups, camper vans, motor homes, vehicles temporarily out of order, vehicles that failed their MOT, vehicles belonging to or used by a lodger, and company vehicles available for personal use.
 - Excluded vehicles: motorbikes, trikes, quad bikes, mobility scooters, vehicles with a Statutory Off Road Notification (SORN), vehicles solely used by visitors, and vehicles stored at a different address or not easily accessible.
- **Length of Residence:** This metric classifies usual residents based on the duration they've lived

in the UK, deduced from their most recent arrival date. However, it doesn't consider short-term stays or holidays outside the UK.

- **Accommodation Type:** A metric to categorize households in terms of their living arrangements:
 - Entire houses or bungalows.
 - Flats, with apartments being synonymous with flats and maisonettes being defined as two-storied flats.
 - Temporary or mobile structures, including caravans.

The datasets mentioned above are tailored for England and Wales. Therefore, Excel was utilized to filter out and focus on the LSOA data pertinent to Leeds.

3.3 Research Methods

3.3.1 A General Description of the Research Methodology Used

This study employs multiple analytical methods to delve deeply into the dynamics and relationships underlying burglary cases in Leeds. In terms of the spatiotemporal distribution of burglary cases, initially, Excel's chart analysis tools were utilized to comprehensively review data from January 2021 to December 2022. This analysis depicted variations in crime distribution across different months, quarters, and years, aiding in discerning significant fluctuations in criminal incidents over distinct time periods. The next task is to create thematic maps illustrating the burglary density (per thousand people) across each LSOA over specified time periods, such as monthly or quarterly. Thematic maps are primarily designed to represent one or several natural or economic phenomena. They encompass a wide range of representation forms, conveying thematic information effectively, with the aid of GIS technologies, to make it more comprehensible. These maps vividly accentuate spatial distribution patterns and temporal trends (Baykal and topal, 2022).

Subsequently, the standard deviation ellipse method was adopted to explore the spatial distribution trends of these cases, revealing the concentration and dispersion degrees of criminal data in space and capturing the evolution of criminal incidents through the annual variations of ellipses. To further elucidate the spatial distribution characteristics of criminal incidents, spatial autocorrelation analysis, particularly the Global Moran's Index, was introduced, facilitating the assessment of spatial clustering of criminal events. Afterwards, the Local Moran's I method is employed to explore the clustering patterns of home burglary incidents. Moreover, the kernel density estimation method was applied in hotspot analysis, offering an effective tool for identifying and analyzing crime concentrations in Leeds. Crime hotspot maps allow for an intuitive understanding of the spatial distribution of criminal incidents in the city and the temporal shifts in crime hotspots from year to year (Chainey et al., 2008).

Finally, to comprehend the various factors related to criminal incidents, correlation analysis and Ordinary Least Squares regression (OLS) were employed. Correlation analysis focused on the linear relationship between criminal incidents and various societal and environmental factors. Through this analysis, preliminary insights into which factors might strongly associate with Leeds' burglary cases were obtained, guiding the selection of appropriate explanatory variables for subsequent regression analysis. Then, a

deep dive was undertaken with OLS regression, providing not only a quantitative estimate of the relationship between each explanatory variable and the response variable but also their statistical significance (Erdogan et al., 2012).

The following is a detailed explanation of some methods:

3.3.2 Standard Deviation Ellipse

Crimes inherently possess spatial attributes, and the location, timing, and nature of criminal events can be represented spatially using point coordinates. Utilizing the standard deviation ellipse method enables the analysis of the spatial distribution trends of residential burglary cases on a two-dimensional plane. This method evaluates their spatial dispersion and the primary direction of data variability. The generated ellipse visually illustrates the dispersion degree and predominant shift direction of the data, providing valuable insights for spatial data analysis. By plotting standard deviation ellipses of multiple datasets, one can compare their distribution trends and levels of dispersion. Such comparisons facilitate the identification of spatial pattern variations between different datasets. (Chainey et al., 2008).

The formula for calculating the standard deviation ellipse is as follows:

1. Mean Location of Events:

Given a set of point events with coordinates x_i and y_i for $i=1, \dots, n$, where n denotes the total number of events, the mean locations for x and y coordinates can be articulated as:

$$\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$$

$$\bar{y} = \frac{1}{n} \sum_{i=1}^n y_i$$

2. Variance and Covariance Computations:

The variances for the x and y coordinates, as well as the covariance between them, are pivotal in defining the orientation and shape of the ellipse. These can be derived as:

$$S_{xx} = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2$$

$$S_{yy} = \frac{1}{n} \sum_{i=1}^n (y_i - \bar{y})^2$$

$$S_{xy} = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})$$

Orientation of the Ellipse

The tilt angle of the Ellipse relative to the x-axis is determined by:

$$\theta = \frac{1}{2} \arctan \left(\frac{2S_{xy}}{S_{xx} - S_{yy}} \right)$$

Principal and Minor Axis Lengths

The lengths of the major and minor axes, denoted by σ_{major} and σ_{minor} respectively

$$\sigma_{major} = \sqrt{2 \left(S_{xx} + S_{yy} + \sqrt{(S_{xx} - S_{yy})^2 + 4S_{xy}^2} \right)}$$

$$\sigma_{minor} = \sqrt{2 \left(S_{xx} + S_{yy} - \sqrt{(S_{xx} - S_{yy})^2 + 4S_{xy}^2} \right)}$$

3.3.3 Global Moran's I

Global Moran's I is a spatial statistical metric employed to gauge the presence of spatial autocorrelation within a spatial dataset. Spatial autocorrelation refers to whether the value at a given spatial location is similar to values at its neighboring locations, thus indicating a tendency for them to cluster together or disperse (Erdogan et al., 2012).

To compute Global Moran's I, the following formula is utilized:

$$I = \frac{N \sum_i \sum_j w_{ij} z_i z_j}{\sum_i z_i^2}$$

Where:

I represents the Global Moran's Index.

N denotes the total number of spatial units in the map.

z_i is the deviation of the attribute value at location I from the global mean.

w_{ij} signifies the spatial weight between location i and location j.

The value range for Global Moran's I spans from -1 to 1. A positive I suggests positive spatial autocorrelation, indicating a propensity for similar values to cluster. Conversely, a negative I signifies negative spatial autocorrelation, suggesting a propensity for similar values to disperse. When Global Moran's I is close to 0, it indicates that the data is approximately randomly distributed with no discernible spatial autocorrelation.

3.3.4 Local Moran's I

Local Moran's I is a statistical measure employed to identify spatial clusters or outliers within a dataset. It can identify statistically significant hot spots, cold spots, and spatial outliers. Diverging from the global Moran's I, which evaluates spatial autocorrelation across an entire dataset, the Local Moran's I assesses spatial autocorrelation for individual locations, offering insight into specific areas of clustering or dispersion. Mathematically, the measure can be defined as:

$$I_i = \frac{n \cdot z_i \sum_j w_{ij} z_j}{\sum_i z_i^2}$$

Where:

(I_i) represents the local Moran's I value for location(i).

(n) is the total number of locations.

(z_i) is the deviation of the attribute for location(i) from its mean.

(w_{ij}) is a spatial weight that quantifies the spatial relationship between location(i) and (j)

A positive I_i value indicates that a location is surrounded by neighbors with similar values, suggesting

a spatial cluster, while a negative value indicates potential spatial outliers. Interpretation of the significance of these values requires comparison to a reference distribution, typically derived from Monte Carlo simulations. Local Moran's I has been extensively employed in spatial epidemiology, criminology, and environmental studies, among other fields, to uncover patterns obscured in global measures.

3.3.5 Kernel Density Estimation for Hot Spot Analysis

Kernel Density Estimation (KDE) serves as an effective technique for gauging spatial local density variations and identifying spatial hotspots. It offers a smoothed estimation, delineating the distribution shape of data. At the heart of KDE lies the principle of positioning a 'kernel' function around each data point. Subsequently, these 'kernels' are aggregated and the entirety is normalized, culminating in an estimated probability density function. The mathematical representation can be articulated as:

$$\hat{f}(x) = \frac{1}{nh} \sum_{i=1}^n K\left(\frac{x-x_i}{h}\right)$$

n stands for the count of data points.

x_i signifies the i -th observation within the dataset.

K denotes the kernel function.

h symbolizes the bandwidth parameter, dictating the width of the kernel. The judicious selection of bandwidth is paramount as it influences the smoothness of the estimation.

3.3.6 Correlation and Ordinary Least Squares

Correlation is a statistical concept employed to measure the strength of the relationship between two variables. It facilitates our understanding of whether, to a certain extent, two variables vary in conjunction with each other. The value of correlation lies between -1 and 1, where -1 indicates a perfect negative correlation, 1 implies a perfect positive correlation, and 0 denotes no correlation at all. The method of Ordinary Least Squares (OLS) is a statistical technique commonly used in linear regression analysis to estimate the relationship between independent and dependent variables. The model can be expressed as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k + \varepsilon$$

Where:

y represents the dependent variable vector.

$\beta_0, \beta_1, \beta_2, \dots, \beta_k$ are regression coefficients, denoting the coefficients corresponding to each feature in the model.

$x_1, x_2, \dots, x_k$ are the individual features of the independent variable vector.

ε is the error term, representing the random error that the model cannot fully account for.

The method aims to find a line (or a more generalized linear model) that minimizes the sum of vertical distances from all data points to this line, thereby obtaining the best-fit line. Both regression and correlation analysis study the relationships between variables, but their objectives and methods slightly differ. Correlation analysis primarily focuses on the strength and direction of the relationship between variables, whereas regression analysis seeks to establish a predictive model. If the correlation strength between two variables isn't significant, the fitted regression model might lack robust predictive power. Additionally, it's paramount to be cautious about multicollinearity in regression models, which arises

when two or more independent variables are highly correlated. Therefore, regression analysis should ideally be conducted subsequent to correlation analysis (Erdogan et al., 2012).

4. Analysis and Results

4.1 Temporal Distribution Characteristics of Residential Burglary Incidents in Leeds

In this section, an analysis is conducted on the temporal distribution patterns of residential burglary incidents in Leeds for the years 2021 and 2022. The data is aggregated to provide insights into the frequency of these incidents on an annual, monthly, and quarterly basis. The subsequent subsections present the findings through line graphs that illustrate the variations observed in both monthly and quarterly trends.

4.1.1 Annual Trends

Year	Reported Burglary Cases
2021	5,107
2022	5,948

The analysis of the annual residential burglary data in Leeds reveals a pronounced escalation of such incidents in the year 2022. More specifically, there was a substantial increase of 841 cases in 2022 compared to the previous year.

4.1.2 Monthly Variations

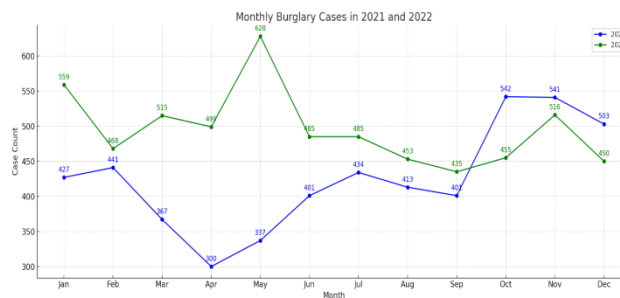


Figure 6. Comparison of Monthly Burglary Incidents in Leeds

When considering the data every month for both years, certain fluctuations are apparent. In 2021, the beginning of the year saw a higher number of cases, particularly in January and February. However, this heightened activity diminished in the months of March and April. Notably, a resurgence in incidents was observed towards the end of the year, with significant spikes occurring in October and November. In contrast, the year 2022 exhibited its peak in May. Although a subsequent decrease in incidents was witnessed in June and July, a noteworthy increase was once again noted in November. A more detailed comparison between the two years underscores that the months of March, April, and May in 2022

experienced a pronounced surge in comparison to the same period in 2021. Conversely, the latter part of 2022, specifically October, November, and December, saw a relative decline in burglary occurrences.

4.1.3 Quarterly Variations

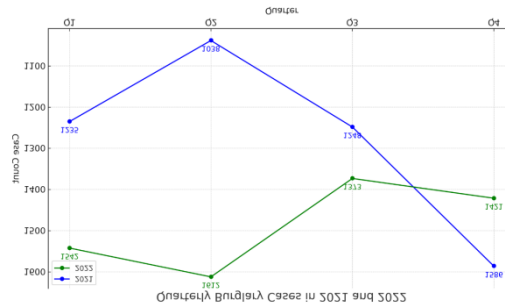


Figure 7. Comparison of Quarterly Burglary Incidents in Leeds

When examining quarterly trends, discernible disparities emerge between the years 2021 and 2022. In 2021, the fourth quarter recorded the highest number of incidents, totalling 1,586. In contrast, during 2022, the second quarter displayed the peak count, with a total of 1,612 cases reported. However, a more detailed analysis of the first two quarters highlights substantial differences between the two years. The initial quarter of 2022 witnessed a significant increase in incidents when compared to the corresponding period in 2021. This upward trajectory persisted into the second quarter, as 2022 continued to report a higher number of incidents than its preceding year.

In summary, despite the month-to-month fluctuations, a prevailing trend becomes evident. The city of Leeds experienced a discernible escalation in burglary incidents during the year 2022.

4.2 Analysis of Burglary Rates within Each LSOA

Given the variations in population density and area across different regions, solely assessing a region's criminal situation based on the number of robberies in census tracts might not provide a comprehensive picture (Andresen, 2006). Consequently, this study adopts the residential burglary crime rate (number of burglaries per thousand residents) as an indicator to evaluate the criminal situation in a region. By preprocessing the data, the number of burglaries within each LSOA is divided by the permanent population of the LSOA and then multiplied by 1000, yielding the number of burglaries per thousand residents. This research utilizes the natural breakpoint method to categorize the burglary crime rate (per thousand) in census tracts into five levels, with the distribution across different years in Leeds presented in the following graphs:

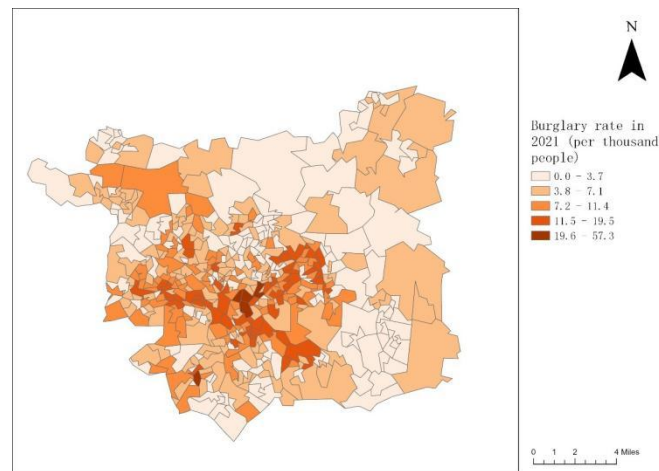


Figure 8. The Burglary Rate in 2021 (per thousand people)

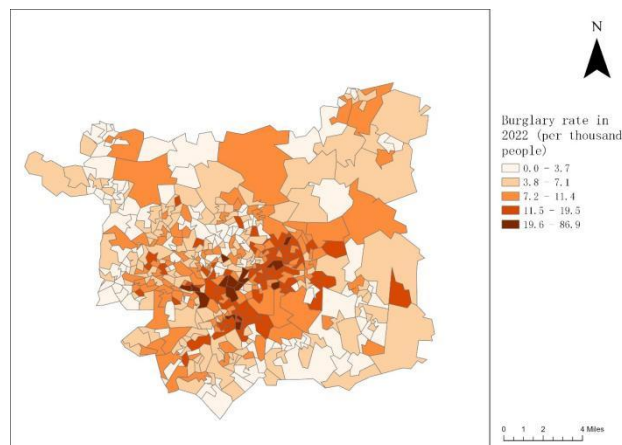


Figure 9. The Burglary Rate in 2022 (per thousand people)

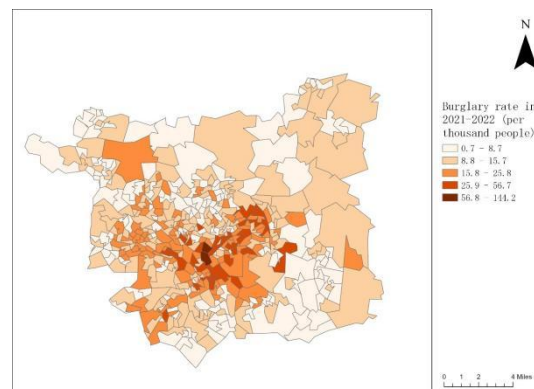


Figure 10. The Burglary Rate in 2021-2022 (per thousand people)

From these three diagrams, several shared characteristics emerge. Broadly speaking, these patterns consistently highlight higher rates in the city's central districts, which gradually taper off as one moves

away from the core urban areas. It's noteworthy that the highest burglary occurrences are predominantly concentrated inwards situated in the city's epicenter. These regions exhibit a conspicuously lower count and encompass a reduced geographical expanse compared to wards in the lower-level tiers. Transitioning to the second most pronounced tier, wards manifesting elevated burglary rates are densely clustered around the city nucleus, typically positioned at an intermediate distance from the central district. Utilizing ArcGIS Pro, the difference obtained by subtracting the 2022 residential burglary crime rates from those of 2021 provides the annual change in burglary crime rates for each LSOA. The natural breakpoint method is employed for its distribution:

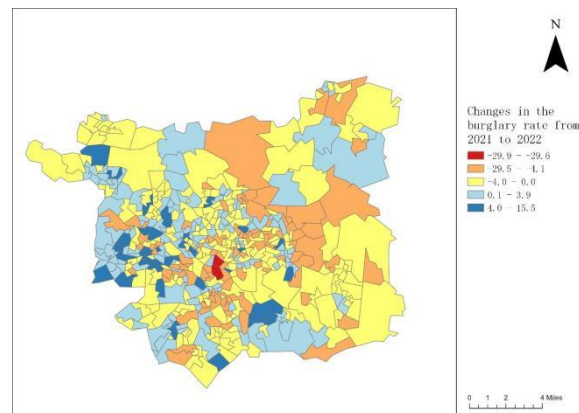


Figure 11. Changes in the Burglary Rate from 2021 to 2022 (per thousand people)

By scrutinizing the crime rate fluctuations between 2021 and 2022, it's feasible to delve deeper into the intricacies of the 2021-2022 timeframe. In this context, negative values suggest an escalation in crime rates, while positive ones denote a downturn. From a spatial distribution perspective, territories observing an upswing in crime rates marginally surpass those marking a decline. Particularly salient is the finding that wards showcasing the most pronounced increment in residential burglary crime rates are chiefly aggregated in Leeds' central heartland. This could potentially indicate an increased seriousness of burglary incidents in the central urban area of the city.

4.3 Analysis of Spatial Distribution Trends in Residential Burglary Incidents

Utilizing the "Directional Distribution (Standard Deviation Ellipse)" tool from ArcGIS, standard deviational ellipses for various years in Leeds city were derived. By closely examining these ellipses, insights regarding the spatial distribution trends and the degree of clustering for residential burglaries in Leeds can be discerned. To capture a holistic view of data distribution, the ellipse size was set to one standard deviation. The results are as follows:

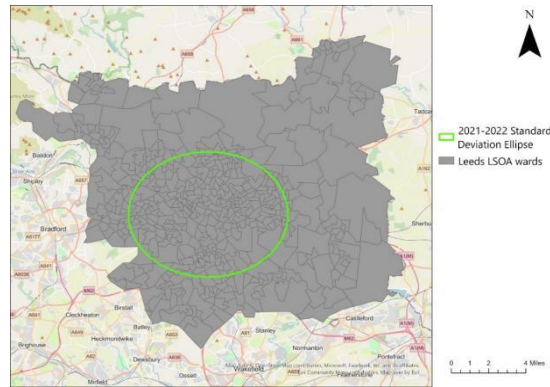


Figure 12. 2021-2022 Standard Deviation Ellipse

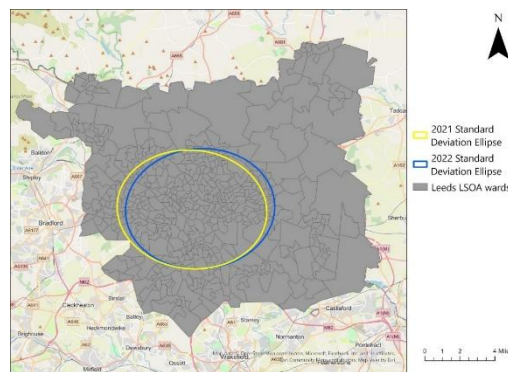


Figure 13. 2021 and 2022 Standard Deviation Ellipse

Overall, the standard deviation ellipses from these two diagrams are situated around the city centre of Leeds, with the major axis oriented east-west and the minor axis oriented north-south. This indicates that criminal activities seem to exhibit a dispersed trend in the east-west direction, with data points being more scattered in this direction. Conversely, in the north-south direction, criminal activities appear to be concentrated, with data points clustering more closely.

Regarding shifts in spatial centres, the eastward movement observed in the transition from the yellow to the blue ellipse suggests a notable change in the spatial centre of criminal activities in 2022 compared to 2021. This eastward shift implies a dynamic repositioning of criminal activities towards the eastern direction. As for the stability of spatial dispersion, despite the changes in spatial centres, there is no significant alteration in the size and shape of the standard deviation ellipses between 2021 and 2022. This stability indicates that the spatial dispersion of criminal activities remained relatively consistent during this period. This stability could imply that although the central locations of criminal activities shifted, the overall range and concentration did not undergo significant alterations, potentially reflecting a certain equilibrium within the city.

4.4 Spatial Clustering Examination of Burglary Cases

This study employs the Global Moran's I tool within ArcGIS to assess whether robbery crimes exhibit spatial clustering. The "Contiguity edges corners" option was chosen for the "conceptualization of spatial

relationships", which considers polygon features that share a boundary, share a node, or overlap to influence computations for the target polygon feature. The generated reports for each year are as follows.

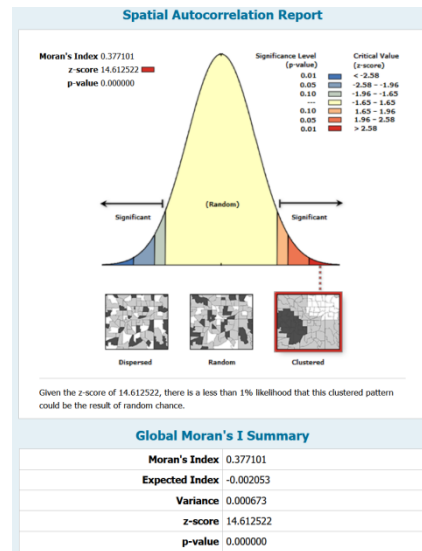


Figure 14. 2021-2022 Spatial Autocorrelation Report

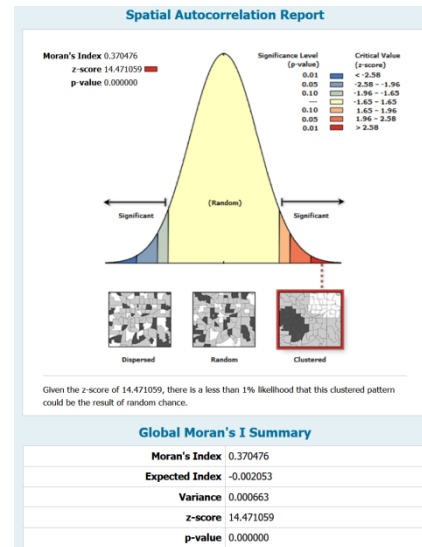
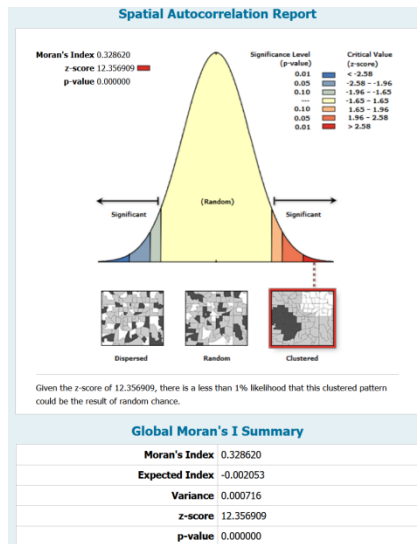


Figure 15. 2021 Spatial Autocorrelation Report Figure 16. 2022 Spatial Autocorrelation Report

In the examination of the spatial autocorrelation of crime densities using Global Moran's I statistic for different periods, significant clustering patterns in crime densities were identified over the periods of 2021, 2022, and the combined years of 2021-2022. Specifically, a positive Moran's I value indicates a spatial autocorrelation where areas of similar values cluster together. For all three time frames, the values were notably positive, suggesting that areas with high crime density tend to be adjacent to areas of similar density. The combined period of 2021-2022 displayed significant clustering with a Moran's I value of

0.370476. The high z-scores for all periods underlined the statistical significance of these clustering patterns, as evidenced further by the p-values of 0.0, indicating an extremely high level of statistical significance. While the year 2021 demonstrated a clustering with a Moran's I value of 0.377101, 2022 showed a slightly reduced clustering intensity, reflected by its Moran's I value of 0.328620. This suggests potential temporal variations in the spatial distributions of crime density between these years.

4.5 Analysis of Burglary Clustering Patterns

The Local Moran's I can assist in identifying which geographical units are clustered, meaning their values are similar to those of neighbouring units. This aids in detecting hotspot areas and concentrated geographical patterns. The Cluster and Outlier Analysis (Anselin Local Moran's I) tool in ArcGIS was utilized. Additionally, given the large sample size and understanding that more random permutations enhance the precision of statistical tests, the number of random permutations was set to 999. The resulting map is presented below:

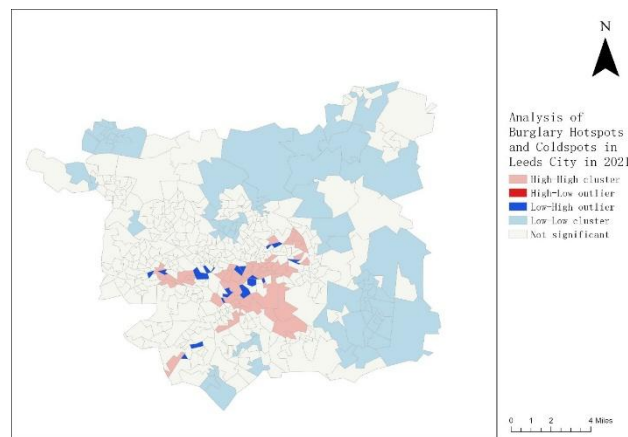


Figure 17. Analysis of Burglary Hotspots and Coldspots in Leeds City in 2021

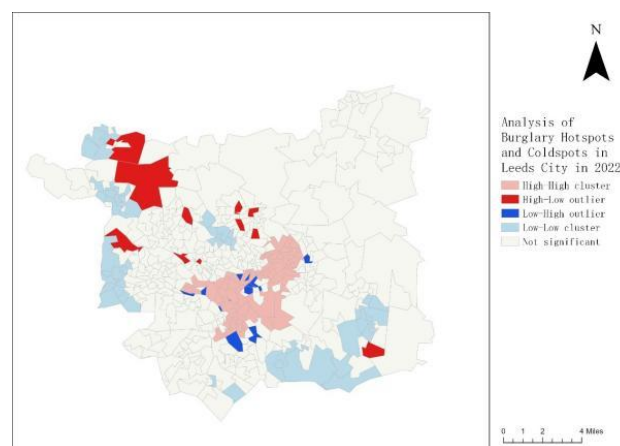


Figure 18. Analysis of Burglary Hotspots and Coldspots in Leeds City in 2022

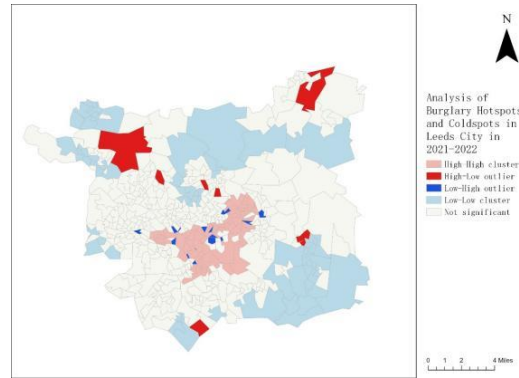


Figure 19. Analysis of Burglary Hotspots and Coldspots in Leeds City in 2021-2022

Based on the Local Moran's I spatial analysis of burglary cases in Leeds for the years 2021, 2022, and the cumulative data from 2021-2022, several key findings have emerged: In terms of spatial patterns, 51 areas exhibited a high-high crime pattern in 2021, and this number increased to 64 areas in 2022. Conversely, the low-low pattern was prevalent in 71 areas in 2021, but this decreased to 52 areas in 2022. However, when considering the cumulative data across the two years, the number of areas with high-high and low-low patterns stabilized at 63 and 64 respectively.

Geographically, the high-high pattern predominantly manifested in central Leeds, likely influenced by the high foot traffic and concentrated commercial activities there. On the other hand, in 2021, the low-low pattern was concentrated in the eastern part of Leeds, but by 2022, it shifted to the western region. However, over the two years, these low-low patterns largely migrated to the northern and southern parts of Leeds. Additionally, 2022 witnessed the emergence of a high-low pattern, suggesting a potential crime spillover into new areas.

Further observation of significant regions revealed that areas with high-high and low-low patterns consistently dominated in both years, showcasing a significant spatial association. This significance suggests that burglary cases in Leeds exhibit a distinct spatial clustering, as opposed to a random distribution. In summary, burglary cases in Leeds demonstrate a consistent and significant spatial association. This association has been on an upward trajectory between 2021 and 2022. While some areas have experienced fluctuations in patterns on a year-to-year basis, the overall trend showcases persistence and stability.

4.6 Hotspots in Burglary Cases

"Criminal hotspots," as the term suggests, refer to areas with high frequencies of crime. The study of these hotspots represents a more detailed and microscopic analysis of the spatial distribution of crime. In this research, the kernel density estimation (KDE) method was employed, utilizing the Kernel Density tool from the Spatial Analyst suite in ArcGIS. This section presents a monthly analysis of burglary hotspots in the city of Leeds to observe monthly variations in criminal patterns because KDE can produce a smoother density map, making hotspots more intuitive and easier to identify when compared to other methods.

An initial analysis revealed the burglary hotspots in Leeds for the years 2021, 2022, and 2021-2022. An

output cell size of 100 units was chosen, as it provided ample spatial resolution to capture the intricacies of crime hotspots. Simultaneously, a search radius of 3000 units was determined based on preliminary observations of crime data from Leeds, ensuring that the identified hotspots were meaningful. The resulting map is as follows:

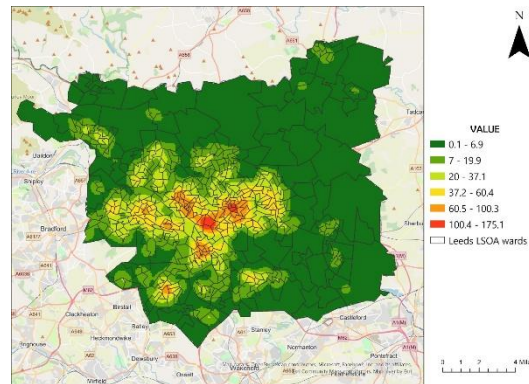


Figure 20. Kernel Density of Burglary Cases in 2021

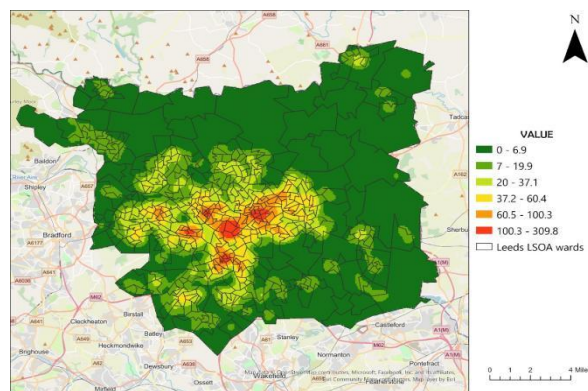


Figure 21. Kernel Density of Burglary Cases in 2022

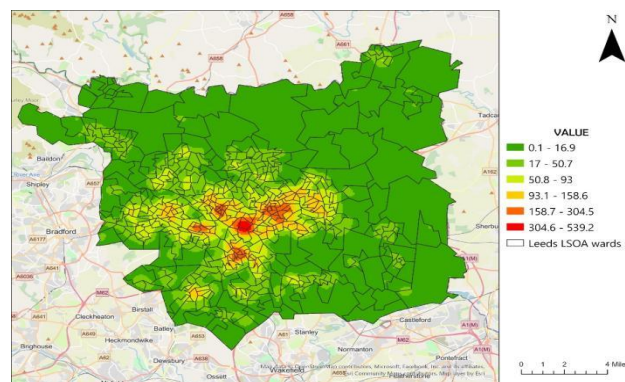


Figure 22. Kernel Density of Burglary Cases from 2021 to 2022

It can be seen from the figure that burglary cases are prominently clustered in the central urban area and gradually extend towards the suburbs. The number of cases in this region is significantly higher than in

other places, marking it as a primary hotspot. Notably, as the distance from the city centre increases, the hotspot density progressively diminishes, suggesting that areas farther from the centre have a relatively lower risk of burglaries. This pattern reveals an association between the city centre and higher crime rates. Utilizing the raster calculation feature within ArcGIS, perform a subtraction operation by deducting the kernel density values of 2022 from those of 2021. This process will yield alterations in kernel density spanning the period from 2021 to 2022.

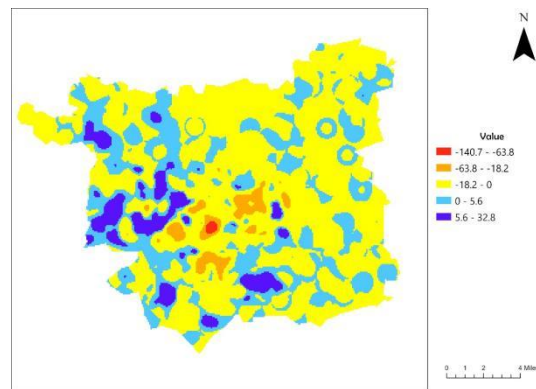


Figure 23. Changes in the Kernel Density of Burglary Cases from 2021 to 2022

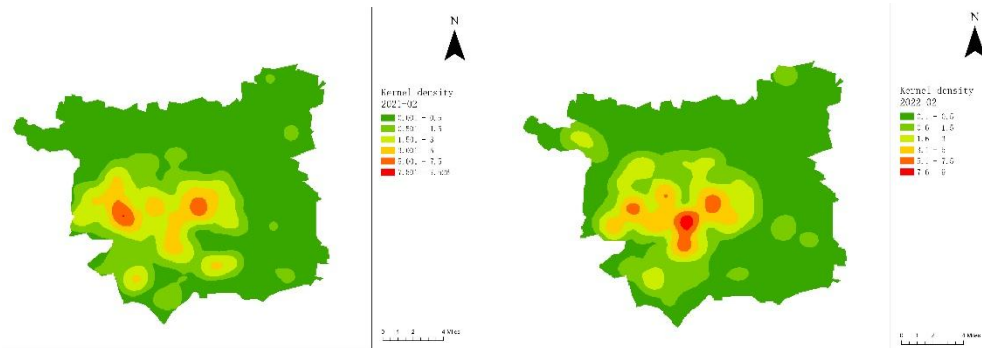
In the "Changes in the kernel density" chart, negative values indicate an increase in crime point density near that location, while positive values signify a decrease in crime point density. From the chart, it's evident that the crime point density in Leeds city centre has increased, and the majority of the areas are experiencing a rise in crime data point density. The spatial distribution of crimes has become more concentrated.

A subsequent monthly analysis was conducted. Given the reduced density of crime points on a monthly scale compared to annual data, the search radius was adjusted to 1000 units. This yielded monthly maps of burglary hotspots in Leeds. Values in each plot are grouped with the same colour.

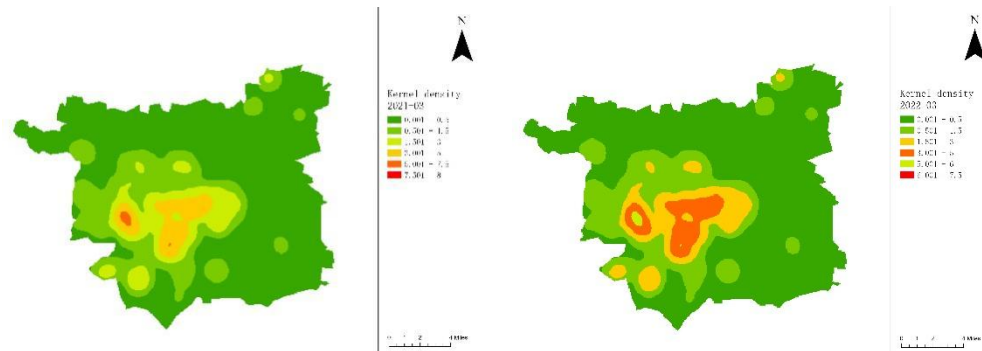
Table 2. Monthly Maps of Burglary Hotspots in Leeds

Month	2021	2022
1		

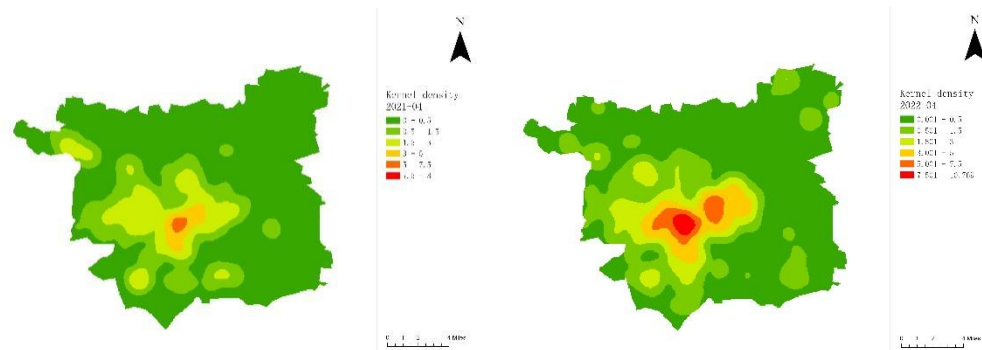
2



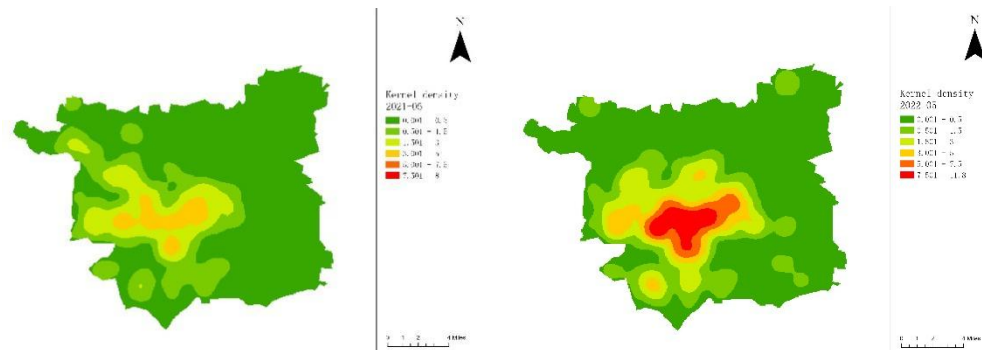
3



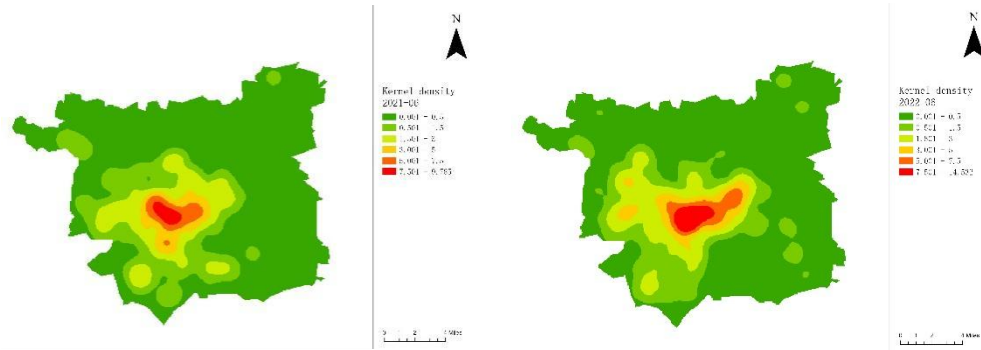
4



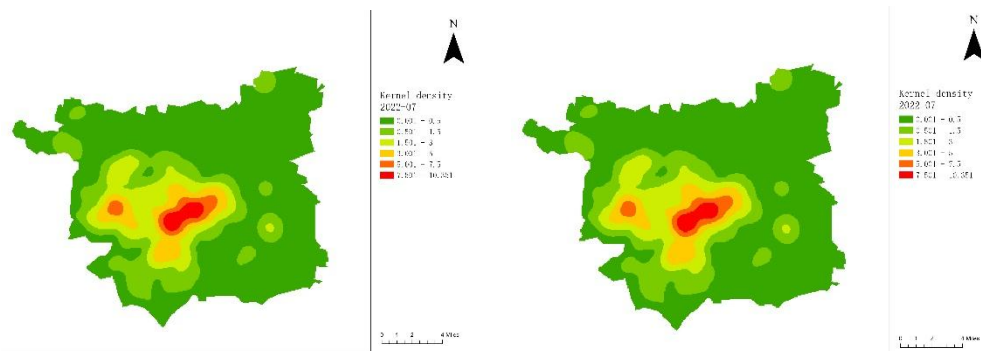
5



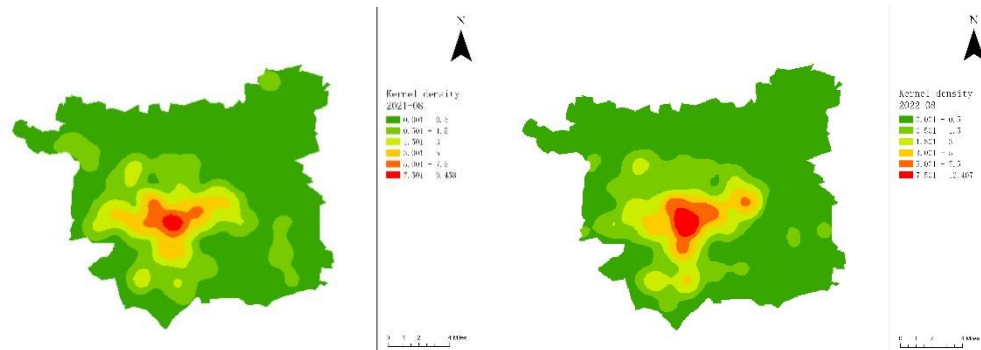
6



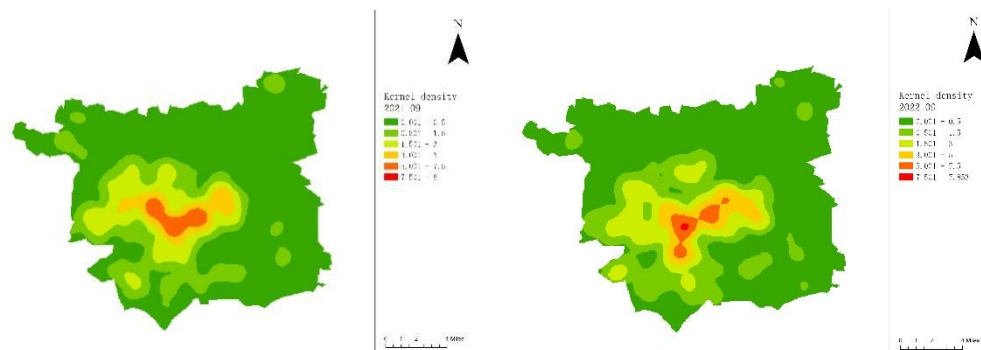
7



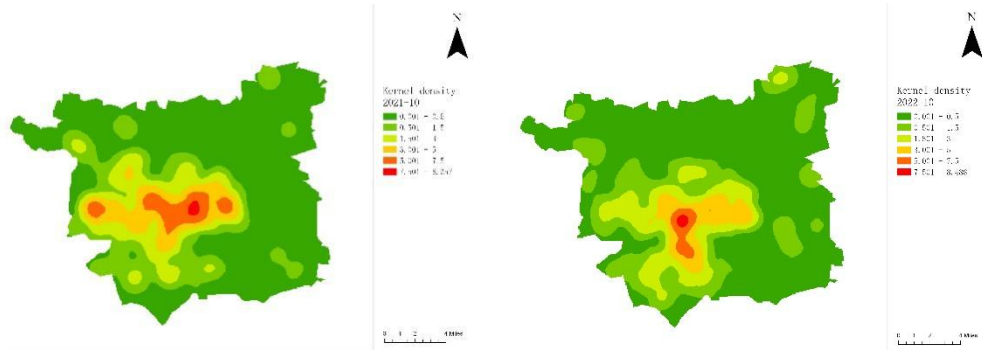
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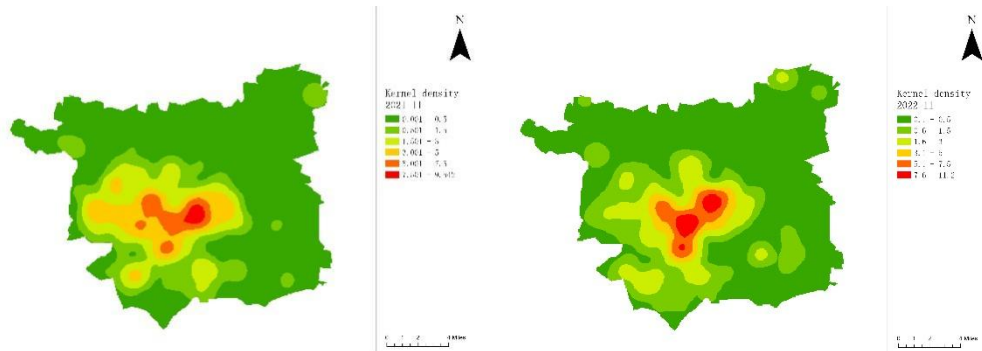
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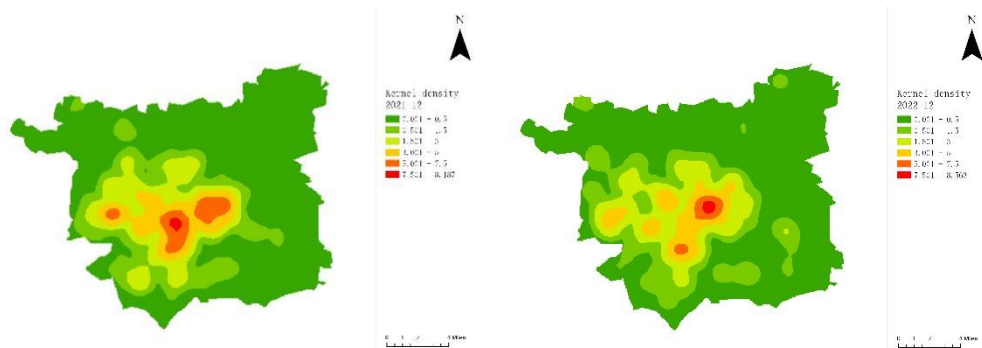
10



11



12



From these maps, it is evident that monthly burglary hotspots consistently concentrate around the city centre, with no other areas exhibiting particularly high densities of crime. Between March and May of 2022, burglaries appeared more clustered than in the same period of 2021. From February to June of 2021, a notable crime hotspot located slightly to the west of the city centre gradually diminished. However, from February to May of 2022, the density of burglary hotspots in the city centre progressively increased.

4.7 Statistical Analysis of Burglary Cases in Relation to Environmental Factors

Given that criminal activities inherently possess spatial characteristics, it implies that the occurrence of criminal events is often not arbitrary but influenced by various factors (Andresen, 2006). To delve deeper into the spatial distribution patterns of robbery crimes influenced by these factors, spatial modelling becomes essential. Initially, Pearson's correlation coefficient was employed to analyze the linear relationship between the density of burglary cases and both Physical Environmental Factors and Social

Environmental Factors. The purpose of this correlation study is to ascertain whether the observed relationships are statistically significant, whether certain features strongly correlate, and to identify which variables exhibit high inter-correlation. It's crucial to understand that correlation does not directly indicate causation, necessitating further research to validate these factors. The table below presents variables that show an insignificant correlation with the density of burglary cases:

Table 3. Insignificant Variables

	Boundary_Length	Geographical_Area	Nonreligious_Population_Percentage
Pearson Correlation	-0.086	-0.075	-0.083
P-value	0.059	0.100	0.066

Furthermore, the following table displays pairs of variables that have a high correlation:

Table 4. High Correlation

Variable 1	Variable 2	Correlation Value
retail_density	AccEatDrinkDensity	0.865
Boundary_Length	Geographical_Area	0.856

Subsequently, an Ordinary Least Squares (OLS) analysis was conducted. Upon ensuring that all p-values within the model were less than 0.05 and that there wasn't high multicollinearity among the independent variables, the following model was generated:

Table 5. Model Abstract

Model	R	R ²	Adjusted R ²	Standard Error of the Estimate
1	0.719	0.517	0.511	7.083

Table 6. OLS Model

Predictors	s		Standardized Coefficients	t	Sig.
	B	Std. Error			
AccEatDrinkDensity	0.123	0.009	0.474	13.491	0.000
RoadDensity	0.044	0.014	0.116	3.194	0.001
NoCarProp	0.706	0.071	0.498	9.905	0.000
BritBornProp	-0.117	0.037	-0.142	-3.169	0.002
FlatTypeProp	-0.078	0.026	-0.139	-3.010	0.003
resident_density	-0.001	0.000	-0.333	-8.207	0.000

The model's diagnostic metrics highlight its robustness. The R square value stands at 0.517, elucidating that the selected predictors account for approximately 51.7% of the variance in burglary density. Further, the adjusted R square of 0.511 reinforces the model's reliability, even after factoring in the number of predictors. The statistical significance of each predictor is underscored by their respective p-values, all of which fall below the conventional 0.05 threshold. It's noteworthy that while RoadDensity, BritBornProp and FlatTypeProp have p-values greater than zero, indicating relatively weaker relationships, they remain highly significant in the model.

For a structured understanding, the influential factors are categorized into environmental and social dimensions:

4.7.1 Physical Environmental Factors:

Accommodation, Eating and Drinking Density (AccEatDrinkDensity):

An increase in AccEatDrinkDensity is associated with an increase in "burglary_density" (coefficient: 0.123). This suggests that areas with a higher concentration of accommodation, eating, and drinking facilities tend to experience a higher burglary density. The presence of more accommodations and eateries might lead to increased foot traffic, making it difficult to identify illicit activities among the large crowd.

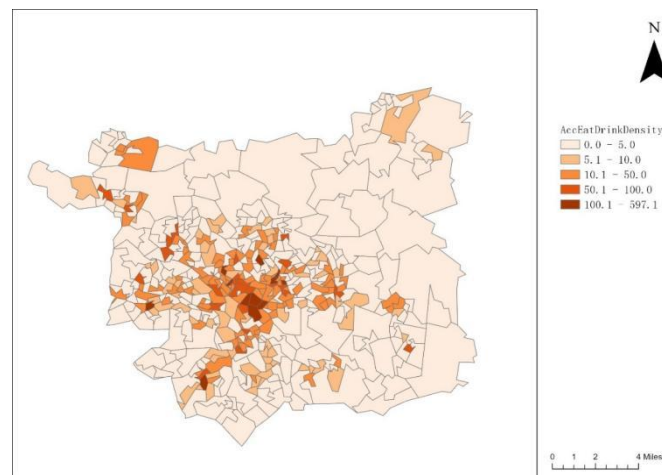


Figure 24. Accommodation, Eating and Drinking Density

Road Density (RoadDensity):

An increase in RoadDensity leads to an increase in "burglary_density" (coefficient: 0.044). More roads might signify better accessibility, potentially offering criminals more routes and avenues to target and escape from locations, thereby elevating potential risks.

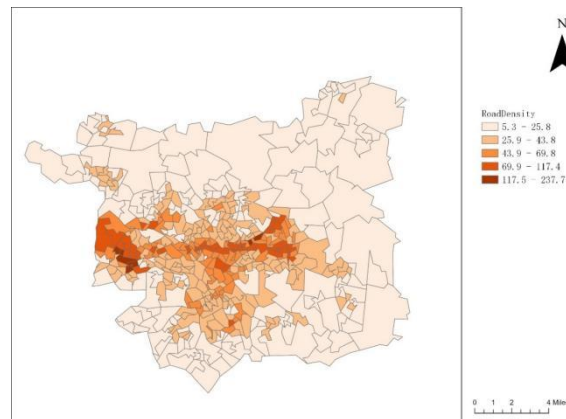


Figure 25. Road Density

4.7.2 Socia Environmental Factors:

No Car Proportion (NoCarProp):

An increase in the proportion of individuals without a car leads to an increase in "burglary_density" (coefficient: 0.706). Areas with more residents without cars might indicate socio-economic challenges, which in turn might lead to increased vulnerabilities and opportunities for burglars.

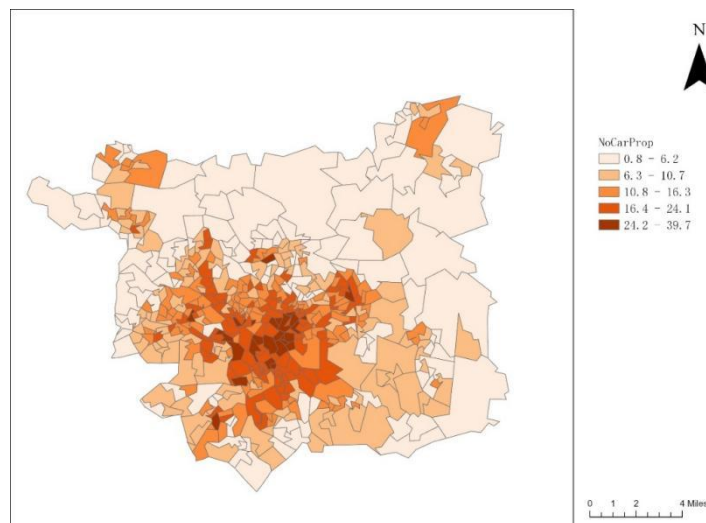


Figure 26. No Car Proportion

Proportion of British-born Residents (BritBornProp):

An increase in the proportion of British-born residents results in a decrease in "burglary_density" (coefficient: -0.117). This may be due to cultural and socio-economic dynamics associated with longer-term residents, potentially fostering stronger community bonds and vigilance against criminal activities.

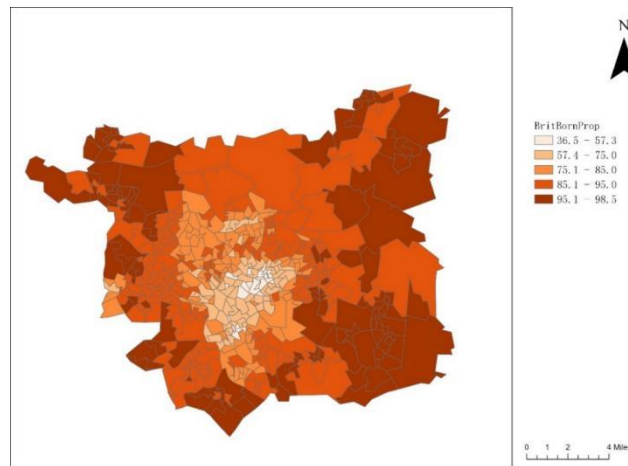


Figure 27. The proportion of British-born Residents

Flat Housing Type Proportion (FlatTypeProp):

A higher proportion of residents living in flats is associated with an increase in "burglary_density" (coefficient: -0.078). Flats, due to their design and concentration, might present certain vulnerabilities making them attractive targets for burglars. Additionally, the shared spaces in such housing types might obscure the perpetrators and facilitate illicit activities.

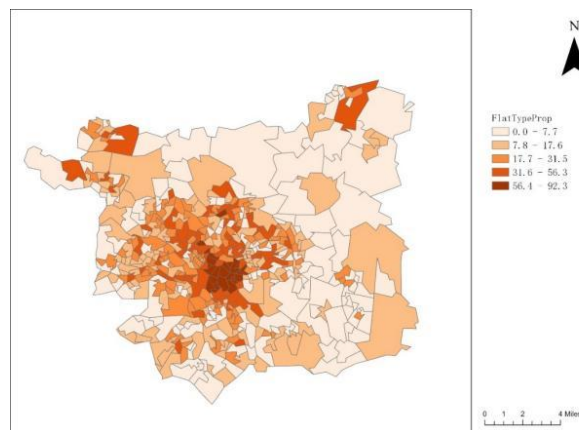


Figure 28. Flat Housing Type Proportion

Population Density (PopulationDens):

An increase in PopulationDens corresponds to a decrease in "burglary_density" (coefficient: -0.001). Densely populated areas might have more vigilant communities, with residents more likely to notice and report suspicious activities, thereby potentially reducing the chances of burglaries.

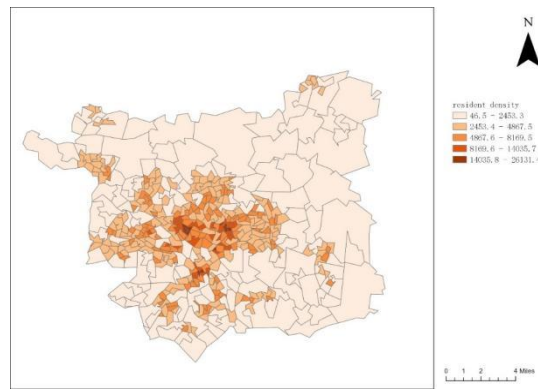


Figure 29. Population Density

Upon the completion of the model, residuals were also derived, representing the differences between the actual observed values and the predictions made by the regression model. By examining the distribution and pattern of the residuals, certain assumptions of the model can be validated. The residual plot reveals that in certain areas of central Leeds, the model fails to adequately explain the observed data. To further refine the model, it may be necessary to consider incorporating additional explanatory variables or using the new method.

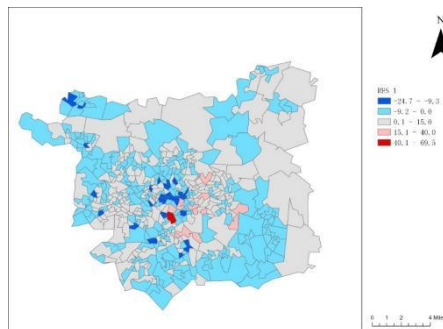


Figure 30. Map of Residuals

5. Discussion

The objective of this research is to undertake a spatiotemporal analysis of burglary incidents in Leeds from 2022 to 2023. Initially, a comprehensive review of data from January 2022 to December 2023 was conducted using Excel's chart analysis tools, revealing crime distribution variations across different months and quarters. To provide a more intuitive representation of the burglary density for each LSOA, thematic maps were generated, distinctly highlighting a higher crime rate in central Leeds. In terms of spatial distribution, the standard deviation ellipse method was employed, indicating that between 2022 and 2023, the concentration and dispersion of burglary incidents remained relatively stable but showcased an overall eastward movement. A spatial autocorrelation analysis, utilizing the Global Moran's Index, revealed a clustering tendency for burglary incidents. Conversely, the Local Moran's I identified specific neighbourhoods or areas with significant crime aggregation. To pinpoint areas of

concentrated crime, the kernel density estimation technique was adopted, determining the hotspot zones for burglary incidents in Leeds and exploring the changing trends of these hotspots across different time intervals. In conclusion, through correlation and OLS techniques, a model was formulated that can elucidate burglary incidents in Leeds. Lastly, through correlation and OLS methodologies, a model was devised to elucidate burglary incidents in Leeds. The density of burglaries may be associated with physical environmental factors such as Accommodation, Eating and Drinking Density, and Road Density, as well as socioeconomic factors like No Car Proportion, Proportion of British-born Residents, Flat Housing Type Proportion, and Population Density. This amalgamation of methods allows for a comprehensive insight into the spatiotemporal trends and underlying drivers of burglary incidents in Leeds.

This study presents several limitations. Firstly, there is a discernible deficiency in the in-depth understanding and exploration of criminological theories. Such theories offer a framework for understanding and interpreting criminal behaviours. The lack of familiarity with these theories might lead to potential blind spots in identifying patterns, interpreting trends, and discerning the underlying mechanisms. More critically, while the research links observed criminal phenomena with tangible environmental elements and socio-environmental factors, it lacks an in-depth interpretation and exploration. This implies that even though certain phenomena and patterns can be observed, the true underlying reasons and motivations might still be elusive. For instance, an increase in crime rates in a certain area might be linked to its economic conditions, community structure, or education levels. However, without adequate support from criminological theories and thorough analysis, these correlations might remain ambiguous (Brantingham and Brantingham, 2010).

In the detailed analysis of environmental factors, significant oversights are evident. Firstly, while examining the impact of Points of Interest (POIs) and roads on crime, the study failed to delve deeply into the specific roles of different types of POIs and roads. Taking transportation as an example, main transport nodes like roads and railways have significantly different impact radii and modes compared to bus stops. Such transport nodes often correlate with specific community functions, human flow, and activity patterns, potentially influencing nearby crime patterns. Moreover, roads vary in type, size, and function. For instance, arterial roads and secondary roads differ in traffic flow, pedestrian movement, and their interactions with the surrounding environment, features that might correlate differently with specific types of criminal behaviour. Regrettably, the paper did not sufficiently distinguish and explore these details when analyzing the potential impacts of roads on crime.

Most crucially, although the study's theme revolves around Spatial-Temporal Analysis, it does not fully integrate the temporal factor into the analysis of influencing factors. Theoretically, both time and space jointly determine criminal patterns and overlooking either can skew the analytical outcomes. Factoring in the temporal aspect not only facilitates a better understanding of the seasonality, cyclicity, and trends of crime but also provides a more accurate basis for future predictions and policy formulation.

Technical limitations are also noteworthy. Firstly, while spatial-temporal hotspot analysis is widely

recognized as an effective method to identify and interpret changes in crime or other social phenomena in space and time, it was not employed in this study. Utilizing spatial-temporal hotspot analysis could offer deeper insights, aiding in more accurately pinpointing specific periods and locations of high crime incidence, thereby formulating more targeted strategies and measures (Butt et al., 2020). Secondly, Geographic Weighted Regression (GWR) analysis was not used in this study. Traditional global regression models often rest on the assumption that relationships between variables remain consistent throughout the study area. However, often, these relationships can vary spatially. GWR is a local statistical technique that accounts for this spatial non-stationarity, offering more precise model estimates. Neglecting GWR might overlook crucial information at the local level, diverging from global trends (Oshan et al., 2020).

Future research should delve deeper into criminological theories, conduct detailed analyses of tangible and social environmental factors, consider temporal elements, and employ advanced technical methodologies to enhance the depth and breadth of the study.

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