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A Spatial Approach to Surveying Crime-Problematic Areas at the Street Level

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Abstract

Reaching far beyond the realm of geography and its related disciplines, spatial analysis and visualization tools now actively support the decision-making processes of law enforcement agencies. Interactive mapping of crime outperforms the previously manual and laborious querying of crime databases. Using burglary and robbery events reported in the urban city of Manchester, England, we illustrate the utility of graphical methods for interactive analysis and visualization of event data. These novel surveillance techniques provide insight into offending characteristics and changes in the offending process in ways that cannot be replicated by traditional crime investigative methods. We present a step-wise methodology for computing the intensity of aggregated crime events which can potentially accelerate law enforcers' decision making processes by mapping concentrations of crime in near real time.
Keywords: Crime, spatial visualization, kernel density estimation, decision support.

1 Introduction

Criminal events which accumulate over the geographic space have severe consequences, such as creating fear and general distrust among residents [1]. Burglaries for example are a common occurrence which deteriorates the economic framework of urban cities by discouraging local and international investors. Researchers, planners and law enforces can increase urban safety by predicting criminal events. Identifying common patterns of crime distribution across space enables the strategic placement of order enforcement mechanisms and programs.

2 Literature Review

The potential of dynamic visualization to explore temporal changes in spatial data by manipulating spatial displays is clear. Brundson et al. compare the effectiveness of three visualization techniques; map animation, comaps, and isosurfaces [2]. Later studies have also employed interactive and dynamic visualization tools to map crime patterns within the spatial and temporal contexts [3, 4]. At local, regional and global conferences discussions of the capabilities of various tools to analyze crime within many applications have become commonplace.

To understand how to effectively apply such tools, crime mappers and law enforcers use various interdisciplinary principles that demystify offender behaviour. Three such principles which underlie the methods used in this study, are time geography, routine activity and the offender's rational choice [5, 6]. Time geography explains the rhythmic variations of human activity. Constricted by movement, people converge during specific spatio-temporal windows through the transport system. This forces social interaction and creates audience between criminals and their victims [7]. While recognizing this interaction, routine activity on the other hand explains crime to result from three elements uniting; a motivated offender, an attractive and unguarded victim or property, and the absence of a guardian to prevent the crime. Reducing crime therefore requires removing offenders or increasing safety guardians. Finally rational choice explains the offender as one who weighs the risks and returns associated with each crime. Guided by this principle we compare the occurrences of burglary alongside robbery which has higher associated risk and returns, to identify the variability in spatial and temporal signatures of different offenders.

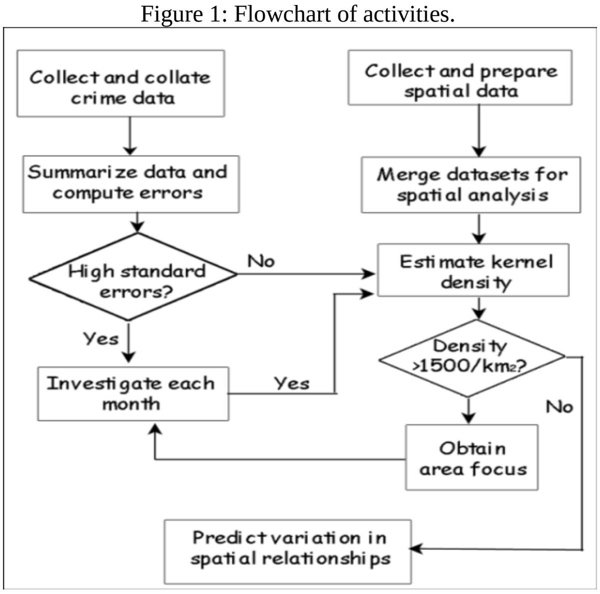
While each single criminal record contains vital and unique information, the collective mapping of multiple events in time and space unearths underlying patterns which inform the decision support processes of order enforcement practitioners. Hotspot mapping of crime events is a common and innovative use of crime mapping. To visualize the spatial and temporal dimensions of crime, several studies [8, 9] recommend computing kernel density for a locale of interest.

With the blossoming of spatial analysis and GIS availability, empirical geography of crime is now embedded within the justice system of England and Wales [10]. This paper contributes to the existing body of literature by providing a systematic approach to analyze and visualize patterns of crime disturbance in the urban city of Manchester, England.

3 Methodology

We introduce a step-wise statistical analysis and visualization process to identify general areas affected by high criminal activity and to focus on these areas. This involves the simultaneous computation and display of descriptive summaries to pinpoint problem areas, and the subsequent spatial analysis and display of spatial output (Figure 1). We primarily used two packages of the R language; the SPAtial Relative Risk (sparr, [11]) and ggplot2 [12] to analyze and visualize the concentration of crime respectively. The flexibility of R allows the reuse of code functions among datasets, graphical displays and devices.

Figure 1: Flowchart of activities.



We estimated relative clustering of crime with kernel density estimation (KDE). This exploratory technique estimates the density of aggregated point events which lie within a defined boundary. An intensity variable (z – value) estimates density for all parts of an area. Resultant measures are displayed as surface maps. Such maps provide a certain level of abstraction at which areas in need of security prioritization can be clearly identified while the private details of individual crime events remain hidden.

We summarized crime information to obtain means and standard errors. To generate risk surfaces we used an adaptive bandwidth where the kernel width is varied in different regions of the sampling space. For each observation with positional information in two columns, data[i, 1:2], i = 1,2,..n), the bandwidth, h[i] is derived by:

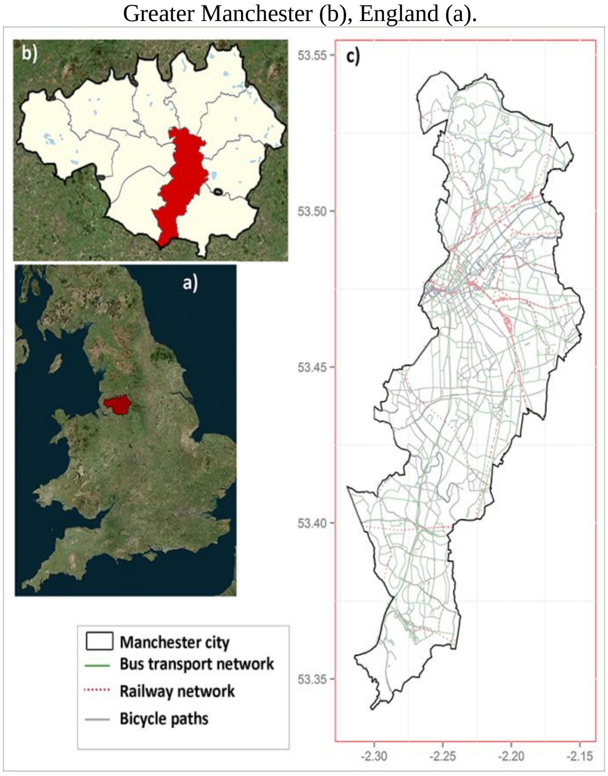
$$h[i] = globalH/(w(data[i, 1:2]; pilotH)^\wedge(1/2) * gamma)$$

Here w denotes the fixed bandwidth pilot density that is constructed with bandwidth *pilotH* (a positive smoothing parameter), and the scaling parameter gamma is the geometric mean of the *w^(-1/2)* values. We then identified an appropriate extent for the search of clusters.

4 Study area and Data

The city of Manchester comprises 33 wards and has a well developed road network infrastructure. Primary generators of crime are the city's nodes of transportation (Figure 2). To visualize the influence of transport nodes on offending behaviour we obtained shape files of public bus routes, the railway network, bicycle paths and the waterways within the city of Manchester. This spatial data are provided by the Great Britain's national mapping authority through the OS Openspace application programming interface (API) under the UK's Open Government License (OGL).

Figure 2: Transport network of the city of Manchester (c) in Greater Manchester (b), England (a).



We obtained from the UK Government police API 28,340 burglary and robbery events reported between 1 January, 2011 and 31 December, 2013 by the Greater Manchester police agency. Table 1 shows a summary of the observation data. These figures provide an overview of the offending patterns in Manchester. As described by the work flow, high standard errors with monthly crime aggregates necessitated investigating crime data for each month. An additional observation is the sparse distribution of crime across the temporal space (e.g. 1.3 per square m), which suggests unequal distribution of criminal activities. This observation calls for the visualization of the crime events together with their associated spatial information to observe if certain areas experience increased offending rates.

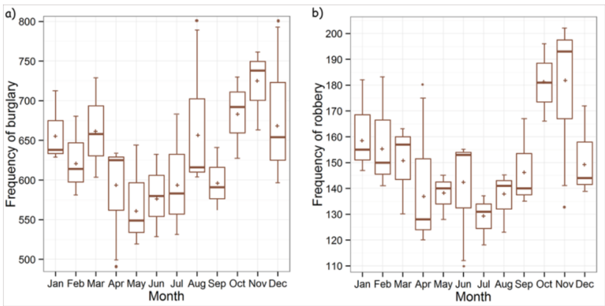
Table 1: Burglary and Robbery frequencies in the city of Manchester

Crimes	Count	Mean Annual Crime	Mean Monthly Crime	Annual crime/km2	Monthly crime/km2
Robbery	5435	1811.67 (min=1691, max=1929, σ= 119)	150.97 (min=112, max=202, σ= 23)	47	1.31
Burglary	22905	7635(min=7165, max=7946, σ=344.3)	636.25 (min=499, max=792, σ=73.6)	198	5.50
Total	28340	393.61	393.61	245	3.40

5 Results and Discussion

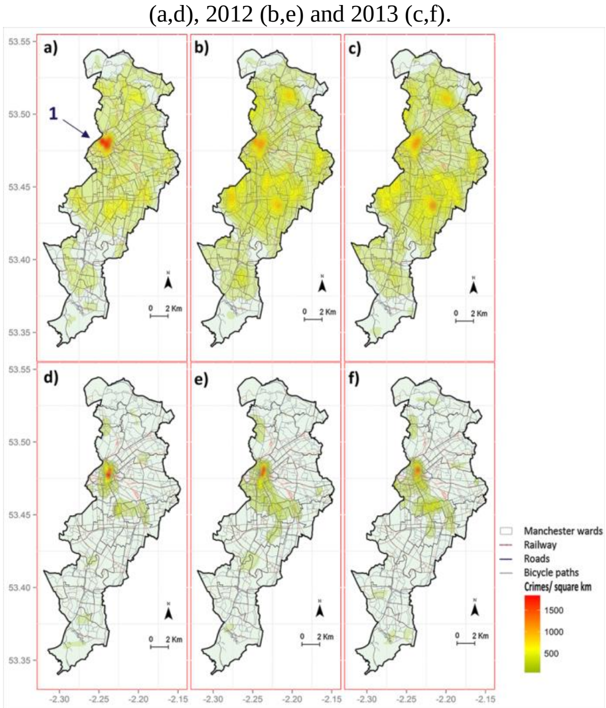
Figure 3 provides a summary of monthly crime data. Visualizing crimes in this way allows the comparison of the crime distribution. More burglaries than robberies are, for example, observed during the study period, and this can be explained by the theory of rational choice discussed above. While robberies often provide higher returns than burglaries, the risk of apprehension during robberies is often higher, as is the penalty to the apprehended robber. Both categories of crime have reduced activity between April and September, and increased activity in October and November.

Figure 3: Burglaries (a) and robberies (b) in the months of 2011 to 2013.



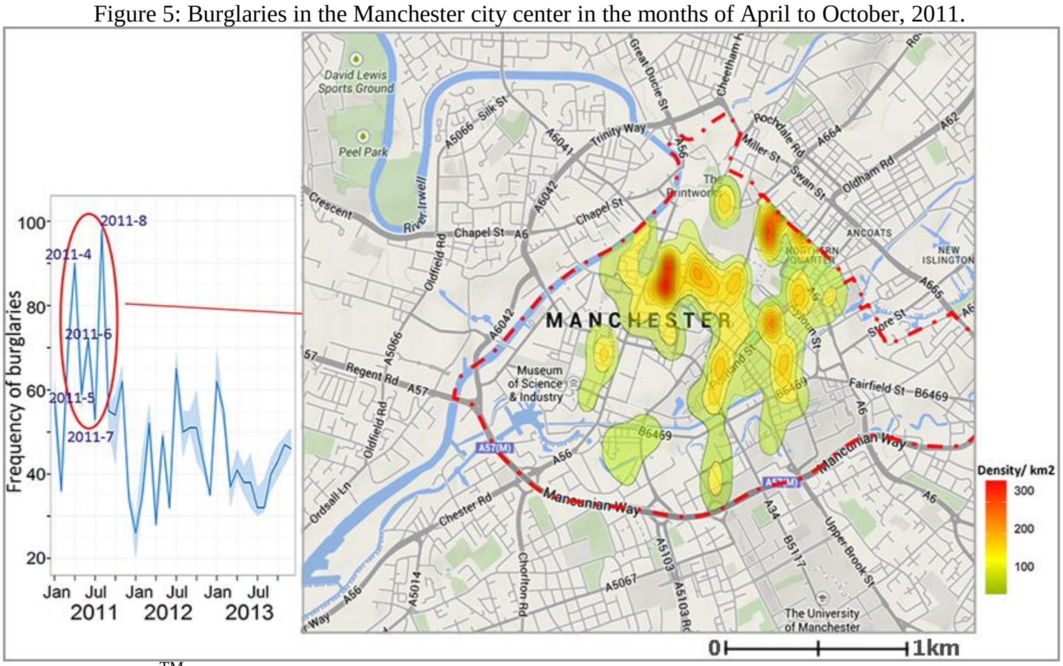
To observe the geographic distribution of crime we visualized density estimates side by side (Figure 4). The most frequent burglaries were observed in 2013 (Figure 4c). The highest concentration of burglaries in space, labeled "1", was however observed at the city center in 2011. Robbery hotspots were also consistently observed near the city center, with the widest distribution observed in 2013. The city center has the busiest network of railway, roads and bicycle paths. This results in constant human traffic, and, as explained by the theory of crime geography, it creates an opportunity for offenders and their victims to converge.

Figure 4: Concentrations of burglary and robbery in 2011 (a,d), 2012 (b,e) and 2013 (c,f).



We obtained a detailed focus of the city centre to visualize crime incidents at the street level with Google map using ggmap's [13] function, get_map() (Figure 5). The output explains the same variability in offense distribution as had been observed previously, especially with burglaries. The month of August, 2011 in which the highest number of burglaries are visualized, witnessed one of the most intense riots and random looting of property in the city centre of Manchester [14]. Such an illustration makes obvious the potential that spatial analytical and visualization tools have for measuring historical events and pinpointing patterns that inform the prediction of crime.

Figure 5: Burglaries in the Manchester city center in the months of April to October, 2011.



Source: Google Maps™.

6 Conclusions

Surveying concentrations of crime in time and space guides the police on how and when to prioritize the enforcement of law and order. The simplicity of the techniques used in this study enhances their usefulness. The tools employed are reusable, which allows for easy and quick analysis and display of crime data in different formats. These techniques are not limited to the area of study but are widely applicable for identifying crime patterns at a local scale, such as within cities, as well as at a global scale.

Our analysis is however limited by the exclusion of crime-influential factors such as weather and demographics. Future research should consider such factors for more precise observation and prediction. This limitation notwithstanding, the potential of crime mapping techniques to guide security-related decisions cannot be understated. Based on the results of our observation, we recommend the use of spatial mapping and visualization of crime when making predictions of future crime events.

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