ESTIMATION OF CRIME CLUSTERING USING A PLACE-BASED VICTIMIZATION SURVEY IN KADUNA METROPOLIS, NIGERIA

BY

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ABSTRACT

The need to study crime trends at smaller spatial units has long been recognized in the literature. Yet, researching patterns of crime at a micro-level of place i.e., individual buildings, addresses or street segments has been very slow in many developing countries such as Nigeria, perhaps due to the paucity of reliable data from the police incident reports. Data for this kind of research is required to be captured digitally and should contain the exact location of where incidents occur. In this paper, an approach is introduced for crime mapping at a micro-level of place, as well as for the estimation of crime clustering. This approach utilizes data that were drawn from a place-based victimization survey and a field mapping exercise. A total of 3,294 households, drawn from a sample of 12,524 residential homes, were interviewed of which 2,932 were included in the analysis. The utility of these data for geospatial and statistical analysis has been demonstrated here using a Nearest Neighbour Analysis method to show whether crime clusters at a micro-level of place, and if so, whether the clustering is more than would be expected on a chance basis. As demonstrated in prior studies, evidence is found to suggest that crime clusters in space more than would be expected in the study site, and the pattern is beyond mere chance. The implication of this finding for crime control and prevention is that strategies developed for elsewhere might also work in the settings of Nigeria. Future research could build on the findings from this study to further advance our understanding regarding the patterns of urban crime.

Key words: Crime analysis, Crime clustering, Crime mapping, Place-based victimization survey

INTRODUCTION

Crime mapping and analysis is not a recent endeavour, it has existed for some time and has served crime analyst remarkably well in the quest to understand spatial patterns of crime. The pin mapping technique, for instance, an old tradition that uses pins on a paper map to indicate the location of crime incidents allows analyst to visualize crime data and to determine how incidents are distributed across space (Chainey and Ratcliffe, 2005). Prior to the advent of computing technology, this approach for visualizing crime incidents' data is being utilized across many police departments around the world. In the last three decades or so, however, crime mapping using Geographic Information Systems (GIS) has been the dominant approach, offering a holistic framework for not only visualizing incidents data, but also for analysing and modelling the spatial patterns of crime (Wilson and Filbert, 2008; Townsley, 2017; Ristea and Leitner, 2020). This approach usually relies on data from police incident report, often stored in a digital form with clear reference to locations of where incidents of crime have occurred.

The police incident report contains the record of all crime incidents that have been reported to the police (in theory). In more advanced settings, the information about location of crime is often recorded as fix addresses or as x and y coordinates, thus, allowing the geocoding of the crime data (Chainey and Ratcliffe, 2005). Understanding the crime problem through mapping is largely dependent on the availability of this incident report that when digitized, can be used in a GIS environment (Wilson and Filbert, 2008; Townsley, 2017; Ristea and Leitner, 2020). Such data are very common in police departments and often available for research in countries that have embraced the use of GIS technologies in addressing the question of "where?". In many developing countries such as Nigeria, however, the utilization of GIS as a crime analysis tool has been very slow, perhaps due to the paucity of reliable incidents report datasets from police departments and elsewhere.

Generally, Nigerian police do not often publish crime statistics for the country. Although police incident report is the official record of every crime (in theory) that has been reported to the police, official crime statistics/data in Nigeria should be treated with caution as it only represents a fraction of the actual rates of crime in the country. An annual national crime victimization survey conducted by the Centre for Law Enforcement Education in Nigeria (also known as CLEEN Foundation), for instance, has consistently revealed a high rate of underreporting and the trend has gradually increased over the years (Alemika, 2013). However, it is worth noting that this issue is not unique to Nigeria – the situation is similar in many other countries across sub-Saharan Africa e.g. Malawi (Sidebottom, 2013).

The police incident report would typically contain information about reported incidents and their attributes (for example, the type of crime, location, time etc.). In the developed world, these data are usually stored in digital format and are available for research purposes. However, this is not the case in Nigeria and in many others across the developing world. Every police station in Nigeria maintains a single police crime diary (usually a notebook) where all reported crimes are manually recorded (i.e. not in digital format). Typically, each entry would have the date, time and type of crime reported as well as the details of both the victim and any potential suspects.

However, it is important to note that not all entries into the police crime diary are as detailed as indicated above – for instance, many would be entered using the name of a nearby landmark such as a market or place of worship or local neighbourhood name rather than the specific address of where the incident occurred (Umar, 2017). This is symptomatic of the lack of a comprehensive addressing system. As such, this presents a major challenge for the geocoding of police crime data. Even if the geocoding were to be straightforward, in Nigeria, the official police incident report data is not readily available for public or research use (Alemika, 2004; Musah et al., 2020; Umar, Johnson, and Cheshire, 2020). Moreover, police incident report in Nigeria has been a subject of controversy, including allegations of egregious acts of record alteration (Alemika and Chukwu, 2005). Besides these caveats regarding police crime records, it is practically unwieldy to rely on data drawn from any police crime diary in the conduct of a micro-level crime mapping and analysis task. This paper presents an alternative approach to gathering crime incident data that uses a place-based victimization survey and a field mapping exercise. This approach would allow the geocoding of every reported crime to a specific location, a prime requirement for conducting any micro-level crime mapping and analysis.

A crime incident location is key to understanding whether or not spatial patterns exist, and the finer the resolution of data the better for the analysis of crime. The need to study crime trends at smaller spatial units has long been recognized about two centuries ago (Glyde, 1856), and the bulk of research in this regard is now known in the literature as 'crime at place'. The term 'crime at place' was coined by Eck and Weisburd (1995) to refer to the growing literature concerned with the study of crime at the micro level of place. A micro place in this context refers to a very small area such as individual buildings, addresses, or street segments. Over the years, crime at place research has presented some astonishing revelations that advanced our understanding of the spatiality of crime one of which is the law of crime concentration (Weisburd, 2015). David Weisburd postulated that not all places will experience crime in a city and very few places will account for higher proportion of incidents. In other words, crime tends to concentrate spatially. As policing resources tend to be scarce in many countries, including Nigeria, this law has significant implication for crime control and prevention strategies.

As research consistently demonstrates that crime incredibly concentrates at micro–places (Sherman, Gartin and Buerger, 1989; Eck, Gersh and Taylor, 2000; Weisburd, Bushway, Lum and Yang, 2004; Johnson, 2010; Johnson and Bowers, 2010; Andresen and Malleson, 2011; Braga et al., 2011; Weisburd et al., 2012; Bowers, 2014; Weisburd and Amram, 2014), understanding its patterns has implication for crime prevention practices. Consider the example of police patrols where resources are limited, the knowledge of where crime concentrates – typically few places – helps in the rational deployment of personnel to mainly high crime locations, a strategy known as 'hotspots' policing. The evaluation of this strategy has been the focus of many prior studies and a systemic review of them reveals that hotspot policing is effective in reducing the rate of crime (Braga, Papachristos and Hureau, 2014). Hotspot policing is when policing activities are concentrated in places where crimes are more likely to occur. The advantage of this policing strategy is to ensure that limited resources are deployed to the most needed places.

It is important to note that research concerned with the geographies of crime largely relies on geographically-referenced datasets often drawn from the police incident report. In Nigeria and many other countries in the developing world, this type of data rarely exists. This presents a huge challenge and thwarts the progress of research concerned with the geographies of crime.

THE STUDY AREA

The site for this study is located in Kaduna, the capital city of Kaduna state. The city is located in the northern Guinea savannah zone of Nigeria along River Kaduna, which is a major tributary of River Niger, and lies between Latitudes 10°26'-10°38'N, and Longitudes 7°22'-7°32'E at an altitude of 645m above sea level (Bununu, Ludin and Hosni, 2015). Kaduna was founded around 1913 by Sir Fredrick Lugard, the first Governor-General of the colony and protectorate of Nigeria to serve as the capital of the country (Agboola, 1986). It is strategically located at the centre of Northern Nigeria – about 210km north of Abuja. The city serves as an important regional transportation hub and is considered to be the symbolic political capital of Northern Nigeria. Unlike the typical pre-colonial cities in the country that are characterized by conservative traditional urban settings, Kaduna exhibits influences of western town planning. The map of the city is shown in Figure 1.

Due to the resources available, it was not practical to study the entire city of Kaduna, and so the present study is limited to two urban districts of Kaduna-Badarawa-Malali and part of Kawo, which are highlighted in Figure 1. The estimated population of this study area is about 137,540 (Max–Lock Consultancy Nigeria [MLCN], 2010), which represents 12% of the total population of Kaduna city. The average household size is about 9.91 persons per household, which is similar to the city's average of 9.88 (MLCN, 2010). There is considerable variation in terms of both the physical and social settings of residential neighbourhoods within Badarawa-Malali, making the setting ideal for studying spatial patterns of urban crime.

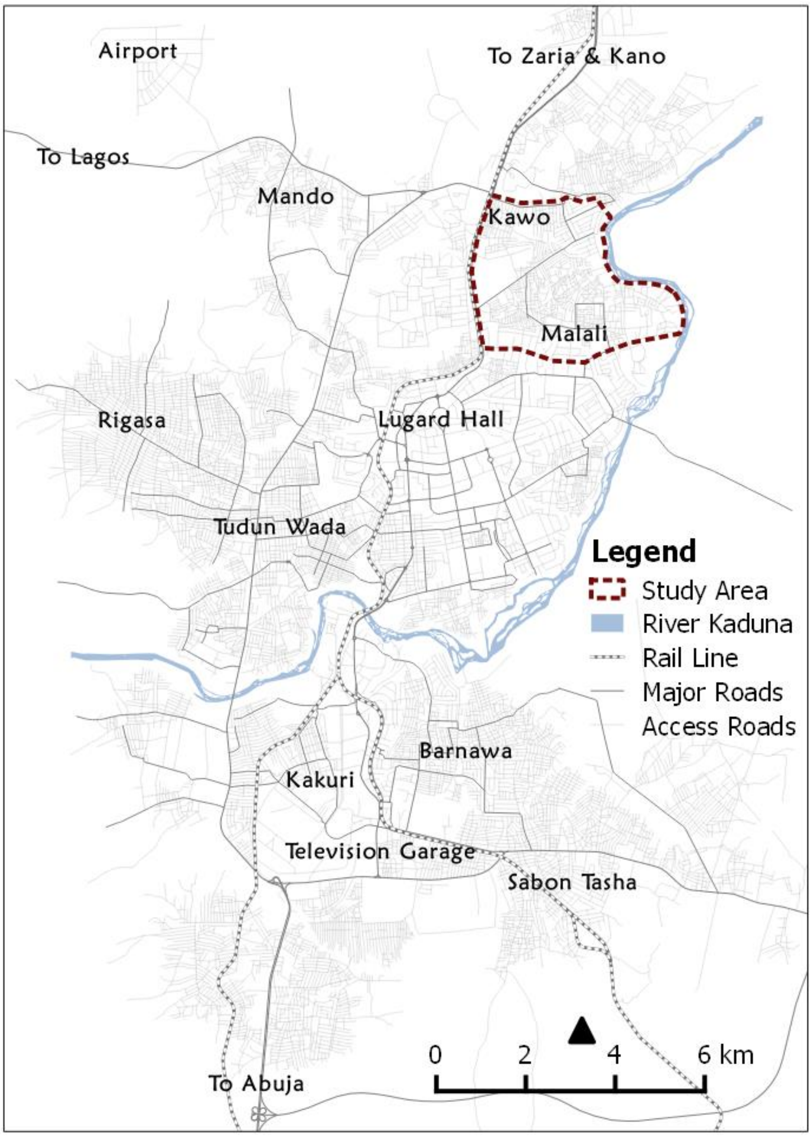

Figure 1: Kaduna metropolis
Source: Adapted and Modified from Administrative Map of Kaduna

Broadly, there are three distinct types of residential neighbourhoods within the study area, these being high, medium and low–density residential neighbourhoods. The high density residential areas, which MLCN (2010) refer to as urban villages, account for almost 50% of the total residential land use. These areas have no formal physical planning. They are characterized by irregular plot layouts with narrow streets that are mostly unpaved. Despite being the most deprived communities, these areas have the strongest traditional community identity, which encourages neighbours to care for each other. In contrast, the low and the medium density residential areas exhibit western influences of physical planning. The streets are wide and mostly paved with regular sized plots aligned and well-arranged on large street blocks. The most affluent groups in the population live in these areas – however, traditional community identity is weaker in these areas than in others (MLCN, 2010).

MATERIALS AND METHOD

Place-based victimization survey and data processing

It is important to begin with the note that, there is limited guidance in the geographies of crime literature on how to address the practical realities concerned with research in settings of the developing world, particularly sub-Saharan Africa – for instance, issues regarding access to crime data (Sidebottom, 2013). Consequently, the task of gathering appropriate datasets would perhaps be the first challenge to resolve at the onset of most research that is concerned with geographies of crime in such settings. The data required to study the spatial patterns of crime must include information about crime and its attributes e.g. crime type, the location of incident and period that the incident occur. These datasets rarely exist in most resource limited countries such as Nigeria, and where they do, access is a major challenge. Consequently, in this study, two fieldwork-based protocols were developed to produce a geographically-referenced datasets.

- A field mapping exercise to create a base map of the study area and to provide unique reference number (URN) for every identified property
- A place-based household and crime victimization survey to obtain crime victimization that could be geographically-referenced

Prior to the commencement of the field mapping, enumerators were recruited, trained and paired to work as teams of two persons each throughout the exercise. Paper maps extracted from Google earth satellite images were utilized for the mapping exercise. Enumerators conducted site visits and used pencils to trace out the boundaries (and also indicated the entrance point) of all properties on the paper maps so as to best reflect the actual boundaries (and entrance point) of a property as observed in the field. A unique reference number (URN) was assigned to each property to allow the integration of all datasets in a Geographical Information System (GIS) environment. The boundaries produced (and associated URNs) were subsequently digitized in QGIS 2.0 with the aid of the Google Satellite OpenLayers plugin.

For the household and crime victimization survey, A 44-item structured questionnaire interview was developed to collect data regarding household characteristics and crime victimization. Among these questions, respondents were asked whether they have been victims of two crime types – breaking-and-entering (B&E) and domestic theft – in the last one year prior to the survey. The analysis that follows consider the data for these two crime types. The total population from which the sample for this survey was drawn is 12,524 residential homes. Those were the properties identified as residential or mixed–residential land uses (being occupied, not vacant or abandoned) during the field mapping exercise described earlier. The survey targeted a sample size of 3,131 households – 25% of the total population, as an ideal sample size for the current study (Fraley and Vazire, 2014).

To achieve the target sample size, houses were selected from within the population using systematic random sampling, whereby one adult of every 4th household (within a street segment) was approached to participate in the survey. The starting point on any street segment was randomly selected from within the first four houses to ensure that every household has equal chance of being selected. In some cases, selected samples were replaced with the household next to such sample. The reason for this was largely because nobody was at home during the survey period.

A total of 3,294 households were interviewed (163 households more than the target sample) but only those data from 2,932 of the survey were included in this study – 105 responses were rejected either because no URN was recorded, or because the URN duplicated an existing record. The remaining surveys (257) were rejected because respondents declined to respond to most (or all) questions during the interview. This means that there was a non–response rate of 7.8%. With such limited attrition, the data analysed here are representative of the local population from which the sample was drawn.

Analytical approach

The first analytical approach taken was to visualize the distribution of crime in the study area by plotting the xy-coordinates of all incidents in a R-Studio environment. Next is to determine whether the distribution of these crimes is purely random or was generated by something other than chance. One approach to do this is to compute the expected frequency distribution assuming a simple Poisson process (Sherman et al., 1989; Sagovsky and Johnson, 2007; Sidebottom, 2012). The Poisson distribution assumes that the probability of a household being victimized is the same for all places, and that the probability does not depend on the number of previous events (Nelson, 1980). A Chi-test is then performed to confirm whether the difference between the observed and expected distribution was statistically significant.

Estimation of Spatial Clustering

There are various approaches to examining spatial clustering in a point pattern, but the one employed here is the Nearest Neighbour test (Getis, 1964). This quantifies spatial clustering by comparing the observed mean nearest neighbour distance for a sample of incidents to that expected; assuming the spatial distribution of incidents is random. For each reported crime incident, the first-order nearest neighbour distance is determined by simply calculating the Euclidean distance between that incident and the one closest to it. The second–order nearest neighbour distance is the distance between the incident and its second closest, and so on. The mean nearest neighbour distance for a particular order is then calculated by taking the average distance across all reported incidents.

The expected distribution is usually computed assuming complete spatial randomness (Getis, 1964). However, this assumption is unrealistic for crime events since opportunities are not evenly distributed across space. For instance, B&E or domestic theft crimes can only occur at residential households. For this reason, an alternative approach which uses a Monte Carlo (MC) simulation (Hepenstal and Johnson, 2010; Johnson, 2010; Davis and Johnson, 2015) was used here to calculate the expected distribution. Not only does this method compute the nearest neighbor distances between points of interest, but it takes account of the distribution of crime opportunities, and allows for significance testing for nearest neighbour orders other than the first nearest neighbour (which the standard test does not).

To do this, one computes the observed nearest neighbour statistics for every order of interest in the usual way. To compute the expected distribution, N households from the list of all residential properties are selected using a uniform random number generator (with replacement), where N is the number of observed crimes. Having done so, expected nearest neighbour statistics can be computed and compared to those for the observed distribution. This process is repeated many times, and the (pseudo) probability of observing the values obtained, assuming the null hypothesis is calculated using the formula specified by North et al. (2002):

$$p=(n - r+1)/(n+1) \qquad \text{Eq.(1)}$$

where n is the number of iterations of the MC simulation (in this case 999), and r is the number of realizations for which the value of the test statistic for the expected distribution is equal to or larger than the observed value.

RESULTS AND DISCUSSION

Distribution of Crime

It is important to first visualize the crime incident data to have a general overview of the distribution of incidents. Figure 2 is a plot of the dataset for the B&E and domestic theft using RStudio. In this plot, the xy-coordinates of all samples (locations of 2,932 households) are shown as blue dots and the places where B&E (left panel) and domestic theft (right panel) incidents occurred are shown as red dots.

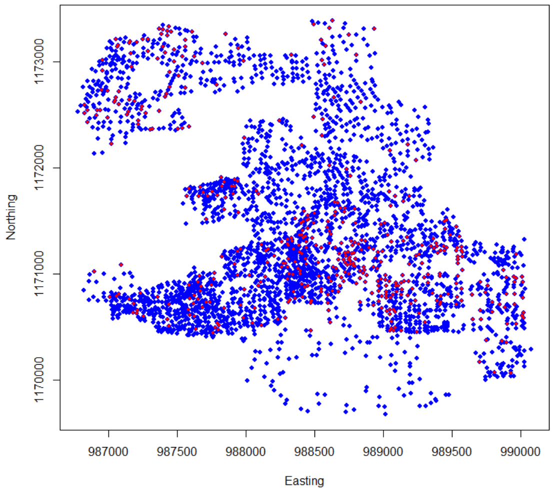

Figure 2a: Spatial distribution of B&S

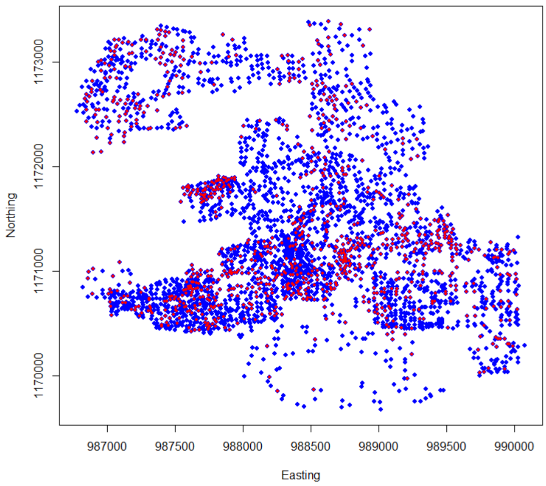

Figure 2b: Spatial distribution of domestic theft

The observed and the expected frequency distribution for both B&E and domestic theft, calculated assuming a simple Poisson process, are presented in Table 1 along with the actual observed frequencies.

The data suggest that fewer households are victimized than would be expected but those that are, are victimized more often than would be expected, assuming a Poisson process. That is, the risk of victimization appears to be more concentrated than would be expected. This is true for both B&E and domestic theft incidents. A Chi-square test confirmed that the difference between the observed and expected distribution was statistically significant (B&E: $\chi^2 = 440$, df = 10, P–value = 0.0001, n = 2932 and domestic theft: $\chi^2 = 1368$, df = 20, P–value = 0.0001, n = 2932). Therefore, evidence exists to suggest that mere chance generated the distribution of crime in the study area.

Table 1: Observed and expected distribution of crimes by households (assuming a Poisson distribution)

No. of Crimes	B&E		Domestic Theft	
	Observed	Expected	Observed	Expected
0	2,475	2,172	1,970	1,253
1	253	652	348	1,065
2	109	98	250	453
3	49	10	177	128
4	21	1	100	27
5	6	0	34	5
6	9	0	17	1
7	5	0	12	0
8	1	0	2	0
9	0	0	1	0
10	4	0	8	0
11	0	0	1	0
12	0	0	1	0
15	0	0	1	0
18	0	0	1	0
20 ≥	0	0	9	0
Total	**2,932**	**2,932**	**2,932**	**2,932**

The analysis presented above demonstrates that the concentration of crime at the household level can be explained by a simple Poisson process. What is unclear is whether victimized places, considering the distribution of opportunities (households), are spatially clustered in some particular areas. It is important, however, to note that the occurrence of clustering, when the distribution of opportunities is considered, could be insignificant (i.e. a pattern generated by mere chance).

Nearest Neighbour Analysis

It is worth noting that prior studies of this kind do not use survey data (Johnson, 2010). One issue with a survey sample is that this will not, by definition, provide complete coverage of a study area. As such, the sample taken could itself exhibit spatial clustering, which could lead to errors of inference regarding the distribution of crime. This issue is addressed here by using the distribution of surveyed households to estimate the expected distribution of crime. Plots of the observed and the mean expected nearest neighbour distances (for orders 1 – 10) for B&E and domestic theft are shown in Figure 3. In each graph, the solid black line shows the mean nearest neighbour distances for the observed distribution, while the mean expected values are represented by black dotted lines, and the 95% confidence intervals are shown as grey dotted lines.

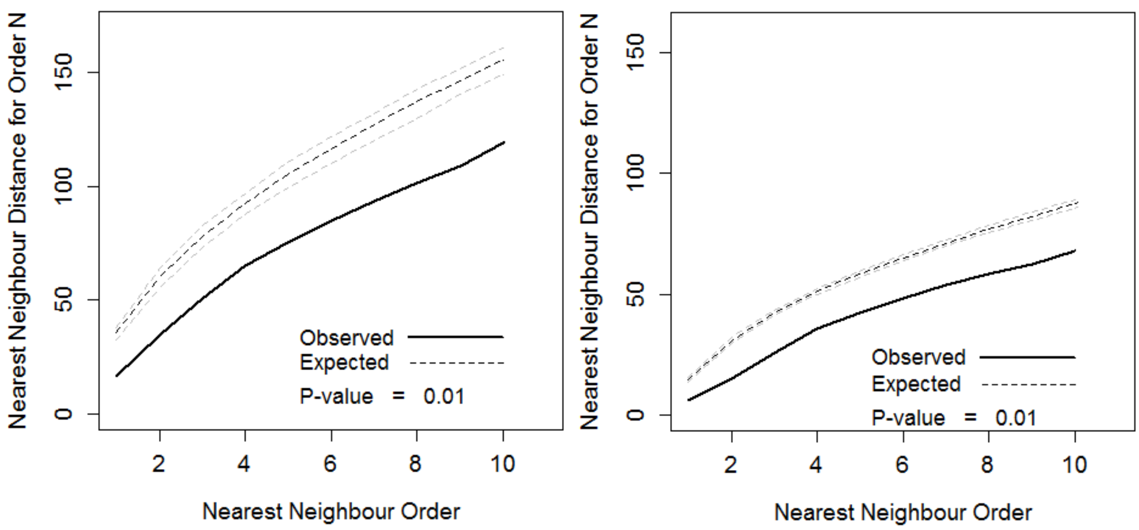

Figure 3: Plot of the observed and the mean expected nearest neighbour distances (for orders 1 – 10) for B&E (left panel) and domestic theft (right panel)

Where the observed mean nearest neighbour distance is less than that expected, this provides evidence of spatial clustering. For all nearest neighbour orders, the observed mean nearest neighbour distances were less than those expected. For example, in the case of B&E, the observed mean nearest neighbour distance of 16.4 meters (m) was less than half that expected (35.9m). For domestic theft, a similar pattern emerged and the results for all nearest neighbour orders (1 – 10) were statistically significant ($p<0.001$) for both types of crime. Simply put, at the point level, crimes tended to cluster spatially and do so much more than would be expected, assuming a random data generating process. That this was observed for all of the nearest neighbour orders tested suggests that this clustering produced clumps or hotpots of crime.

Reflection on Crime Data in Nigeria

Considering the issues associated with secondary data, with respect to the crime data, in studies conducted in the developed world, official police records are commonly used to estimate rates of crime. Such data are rarely available for the purposes of research conducted in the developing world, ruling out the analysis of such secondary data sources. Even if such data were readily available, the scale of the under–reporting of crime to the police in Nigeria is substantial. As a result, it is likely that police data would represent a biased sample of offenses (Sherman et al., 1989), the analysis of which would likely lead to errors of statistical inference. Although under–reporting is a concern in most countries around the world (Shaw et al., 2003; Sidebottom 2015), a study of criminal victimization across the industrialized world suggests that almost all burglary incidents are reported to the police (Van Dijk and Mayhew, 1993).

Additionally, unlike in the developed world, Nigerian police data are not available in digital form. While problematic for this research, the development of systems to capture such data in the future may provide opportunities to collect data, particularly spatial data, which are actually more accurate than that recorded in other countries. For example, in the UK and the US, crimes reported to the police are (typically) initially recorded in a text format, and subsequently geocoded using GIS. However, with the proliferation of GPS technology, which is now embedded into most mobile devices, it seems plausible to suggest that spatial data could be more directly captured either by the police or victims of crime.

A field mapping exercise was conducted in this study to address the paucity of spatial data. While this method seemed feasible and reliable, huge resources would be required to apply such in a study that is concerned with larger geographical area. As new and improved web–based mapping platforms continue to emerge, some of which are freely available anywhere around the world, Volunteered Geographic Information (VGI) could be a viable source of spatial data. The use of this data source for research, however, has been limited owing to concerns regarding quality (Haklay, 2010). An organized (controlled and monitored) VGI project could reduce such concerns.

The second contribution of this paper is to demonstrate how an area–based survey data could be utilized to estimate spatial clustering of urban crime. In this regards, a near-neighbour analysis was conducted to estimate whether the two crime types considered here cluster spatially, and do so more than would be expected on a chance basis. As demonstrated in prior studies concerned with the geographies of crime, both B&E and domestic theft appeared to cluster spatially, and the pattern observed is not random. This supports the findings of prior studies despite here a place-based survey data were used instead of data drawn from the police incident report. The implication of this finding for crime control and prevention is that strategies developed for elsewhere might also work in the settings of Nigeria.

CONCLUSION

The contribution of this paper to the geographies of crime literature is in two folds – first, to highlight the challenges associated with access to geographically–referenced data for crime analysis and to introduce a fieldwork protocol for generating an alternative primary data, and second to demonstrate how an area-based survey data could be utilized to estimate spatial clustering of urban crime. Regarding the issue of data, there are two dimensions to collecting these data (i.e., geographically–referenced crime data) for research purpose conducted in settings of Nigeria. On the one hand, as highlighted in this paper, secondary data typically drawn from police incident reports are mostly incomplete, unreliable, or inaccessible. On the other, primary data collection like the one introduced in this paper is not always a straightforward undertaking – it presents a unique set of challenges. It is important to make future research aware of these issues and suggest possible ways in which the known challenges could be addressed.

This study has supported the findings of many prior studies that urban crime clusters spatially. Moreover, it is important to note that development of alternative data source as the one introduced in this paper can help to extend our understanding of the spatial patterns of crime in the settings of Nigeria. This is important for theoretical development more generally, and ultimately it could allow more enquiries about the patterns of urban crime. Future research could build on the findings from this study, using similar approach to address the paucity of appropriate datasets, to further advance our understanding regarding the patterns of urban crime.

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