Mapping the spatial variations in crime in rural Zimbabwe using geographic information systems

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Abstract: Understanding the distribution and densities of crimes is of importance in order to facilitate the development of investigation preference strategies for policing. Within the Zimbabwean context, less attention has been given to the applicability of Geographic Information Systems (GIS) in crime mapping. In this study, we determined crime densities and crime hotspots and clusters in rural Zimbabwe using Geo-spatial technologies. Data were collected using mobile Global Positioning Systems and interviews. Moran’s I was used to determine crime clustering and Gertis~Ord statistic was used to determine crime hotspots in Chivi district. Results show that crime densities of 4.6 were located at Chivi growth point and low crime densities (1.15) were found as distance from the growth point increases. Significant high-high crime clusters were located in wards 11, 15 and 30 (Chivi growth point). Crime hotspots at 99% confidence level were located in ward 11, 12, 15 and 30. The results of the study indicated that crime hotspots and clusters were distributed around Chivi growth point and this will help the law enforcement agents in establishing beat patrols in the problematic areas to curb crime and safeguard life and property.

Keywords: crime; geographic information systems; global positioning systems; hotspot; mapping

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Courage Mafumbabete is a former student from the Zimbabwe Open University and currently employed as a police officer at Chivi Growth point in Southern Zimbabwe. His research interests are in Geographic Information Systems (GIS) and Global Positioning Systems (GPS) and their applications in law enforcement studies. The research presented in this paper is part of the broader study on spatio-temporal variations in crime in rural Zimbabwe such that it contributes towards the use of open source GIS and GPS technologies in the Zimbabwe’s Republic Police for easy mapping of crime and human resource deployment.

PUBLIC INTEREST STATEMENT
Crimes occur on a daily basis and they occur at random positions on the earth’s surface. Traditionally crimes have been manually mapped using charts and pins which are static. However, Geographic Information Systems (GIS) and Global Positioning Systems (GPS) provide dynamic ways to rapidly map the spatial distribution of crime in rural Zimbabwe. The study identified crime hotspots in Chivi district, Zimbabwe and this provides a key input for crime management, prediction and resource evaluation. Information on spatial distribution of crimes in the rural areas will be of importance to the law enforcement agents in resource distribution in the hotspot areas to curb crime and safeguard life and property.
1. Introduction

Crime is a well-known social problem affecting the quality of life and the economic development of any society (Bogomolov et al., 2015) and as such, there is need to identify the location of different types of crimes in space and time. The traditional criminal record system and its maintenance have become very difficult in the existing crime scenario and manual processes neither provide accurate, reliable and comprehensive data round the clock nor does it help in trend analysis, prediction and decision support (Ahmad, Uddin, & Goparaju, 2017). Traditional strategies of intelligence and criminal record maintenance have failed to suffice with the requirements of the present crime scenario. The use of pin maps, crime registers and dockets is manual processes which neither provide accurate, reliable or comprehensive data for crime trend prediction (Herrmann, 2015) and decision support in the Zimbabwe Republic Police and other law enforcement agencies. Therefore, there is need for an accurately identified and clearly visualized crime map which will significantly benefit police practices by aiding threat visualization, police resource allocation and crime prediction (Lin, Chu, Wu, Chang, & Chen, 2011; Tsai, Lin, Chu, & Perng, 2009).

In this regard, crime mapping using Geographic Information Systems (GIS) based spatial analysis and modelling is considered as a powerful tool for the study and control of crime, because crime maps help the police to identify/locate problems at various levels.

Areas in which crime is concentrated represent natural targets for crime prevention effort, as these locations are likely to have the greatest impact (Rosser, Davies, Johnson, & Cheng, 2017). This study is informed by the geometric theory of crime (Brantingham & Brantingham, 1981) which uses model building and quantitative methods of analysis to examine the importance of the environment and place in understanding the geographic distribution of crime. The geometric theory of crime looks at where crime occurs based on geographic distribution of activity patterns and opportunities for crime (LaRue, 2013). The geometric theory of crime also demonstrates that criminal activity is a product of the routine activities of potential offenders and victims and that these routine activities have a geometric component (Ding, Chen, Liu, Cheng, & Wang, 2015). Crime occurs at a specific site and in a specific situation; an offender is influenced by both the site, time and the situation (LaRue, 2013). The geometric theory of crime uses concepts of nodes, paths, and edges to demonstrate that the majority of crime occurs within the offender’s awareness and activity space. Thus, this study intends to determine how crime density, crime hotspots and clusters in Chivi district can be explained by the geometric theory of crime. Chivi district also contains Chivi growth point which is a zone of different socio-economic activities. A growth point is defined as a centre of economic activities which are artificially created or stimulated in disadvantaged regions with the intention that they will eventually become centres of economic growth (Mushuku & Takuva, 2013).

GIS technologies and methods constitute a powerful toolset for analysing spatial data, and have been pivotal in identifying the links between crime and features of social and physical environments (Walker, Schuurman, & Hameed, 2014). GIS methods were adopted as a fundamental crime analysis tool by many law enforcement agencies due to an interest in the geography of crime and environmental criminology (Mao et al., 2018). The understanding of crime patterns within the police’s area of jurisdiction enhances the department’s ability to identify areas in need of police resources (LaRue, 2013). Knowledge of crime patterns will imply that resources will be deployed judiciously and that intelligence-led policing strategies will be more likely to have beneficial results (Paulsen, 2004; van Sleeuwen, Ruiter, & Menting, 2018). Thus, the integration of crime data with GIS in crime mapping facilitates in the visualisation and analysis of crime hot spots along with other trends and patterns. GIS allows police personnel to plan effectively for emergency response, determine mitigation priorities, analyse the historical and predict future crime events on crime sites by displaying them on a graphical, layered, spatial interface or map (Cohn & Breetzke, 2017; Tang, Zhu, Guo, Duan, & Wu, 2018). GIS encourages an effective utilisation of manpower through an understanding of the spatial and temporal crime distribution. Thus, the analysis of the spatial and temporal patterns of crime and police station location through the GIS can assist the police force in the effective implementation of crime prevention strategies.
Much of crime mapping is devoted to detecting high-crime-density areas known as hot spots and hot spot analysis helps police identify high-crime areas, types of crime being committed, and the best way to respond (Sibanda et al., 2015). Hotspot mapping is used as a basic form of crime prediction, relying on retrospective data to identify the areas of high concentrations of crime and where policing and other crime reduction resources should be deployed (Chainey, Tompson, & Uhlig, 2008). The assumption of this place-based policing strategy is that crime concentrates in relatively small geographic areas (Zhang, Zhao, Ren, & Hoover, 2015). Police use this understanding every day for decisions about how to allocate scarce resources based partially on where the demands for police are highest and where they are lowest (Eck, Chainey, Cameron, Leitner, & Wilson, 2005). Community policing is particularly attentive to high-crime neighbourhoods, where residents have great difficulty exerting social controls (Rosser et al., 2017). Problem-oriented policing pushes police officials to identify concentrations of crime or criminal activity, determine what causes these concentrations, and then implement responses to reduce these concentrations (Eck et al., 2005). To the best of the authors’ knowledge, there has been limited or no study that has mapped crimes in Zimbabwe using geospatial technologies. It is with the benefits of crime mapping using GIS that the researchers intend to map the spatial distribution of crimes in rural Zimbabwe and specifically wards in Chivi district, analyse the crime densities, hotspots and clusters.

2. Materials and methods

2.1. Study area

The decision to choose Chivi district as the study area is based on the researchers’ familiarity with the area, the relatively high level of crime and the availability of geospatial crime data. The study area was undertaken in Chivi District of Masvingo Province in Zimbabwe as shown in Figure 1. The District covers an area of 3534 square kilometres and has a population of 166 049 (ZimStat, 2013). Chivi District falls into agro-ecological regions 4 and 5. Region four receives a total annual rainfall of 650–800 mm, whilst region five receives a total annual rainfall of 450–650 mm. Chivi also experiences hot summers of 30 to 40 degrees Celsius and warm mild winters (6–25 degrees Celsius) with mean temperatures of 22 degrees Celsius. Granitic sands are the most common
type of soils in Chivi. Some doleritic blackish soils are found in Ngundu and Chasiyatende. Mandamabwe is dominated by granite to give the landscape a fersiallitic type of soil which requires 500 mm of rainfall. Sandy soils, however, have susceptibility to erosion and are infertile. It is estimated that 2.6 tonnes of soil are lost every year in Chivi, causing serious river siltation and lowering the capacity of irrigation. The vegetation in the district is typically savannah, dominated by Miombo woodlands and the grasses are dominated by Hyparrhernia and Heteropogon species.

2.2 Methods
The research data collection in this investigation was done through interviews which were conducted with police officers from various segments of the police force at Ngundu, Chivi and Mashava police establishments. Interviews were done to collect data on the type of crime, distance from station to where the offence was committed, time and place of occurrence. The researcher developed a data sheet based on the type of crime, time of crime occurrence, place, altitude, distance from the station and the geographic position of the place using the mobile Global Positioning System (GPS)- Polaris Navigation GPS. Crime data collected were from the period commencing July 2018 to September 2018. Crime data were integrated with QGIS Version 2.18.4 (Las Palmas) and Geo Da for data analysis and presentation. The coordinate system used in the study were the Universal Transverse Mercator (UTM zone 36S, WGS 84 datum). The researcher also recruited and trained some members of the Zimbabwe Republic Police force on how to capture spatial data on crime location within the district. For every crime location, the following data were collected: x and y coordinates, crime type and category, altitude, land cover and approximate distance from the police station. The collected data were entered into Microsoft Excel 2010 spreadsheet. The researcher managed to collect data on 100 crime cases from July 2018 to September 2018.

2.3 Statistical analysis
In order to determine the crime hotspots and crime clusters in the study area, Local Indicators of Spatial Association (LISA) were implemented in QGIS (www.qgis.org) and GeoDa V 1.12 (http://geodacenter.asu.edu/). In this case, the experimental Hotspot analysis plugin in QGIS was used. In order to implement the Hotspot analysis plugin in QGIS, PySAL and related dependencies such as NumPy and SciPy(Oxoli, Prestifilippo, Bertocchi, & Zurbaran, 2017) were installed from the source code obtained from GitHub (https://github.com/danioxoli/HotSpotAnalysis_Plugin). Specifically, the LISA statistics which were implemented in QGIS were Gertis-Ord and Local Moran's I which were calculated based on the spatial weights matrix of crime counts of any location in the Chivi dataset. In order to map the spatial distribution of crime incidences, Gertis-Ord G*hotspot analysis was conducted in QGIS 2.18.4. From the Gertis-Ord G*analysis there was production of two vital statistics namely p-Value ($\alpha = 0.05$) and the Z score. From the results of the Gertis-Ord G*, if value is greater that the p-value it signifies a significant hot spot, a Z score lower than the p-Value represents a significant cold spot and a Z score closer to zero illustrates lack of spatial clustering (Sibanda et al., 2015). Gertis-Ord G* was calculated as follows

$$G_i^* = \sum_{j=1}^{n} w_{ij} x_j - \bar{x} \sum_{j=1}^{n} w_{ij}$$

where $x_j$ is the number of crimes in ward $j$, $w_{ij}$ is a spatial weight that defines neighbouring wards $j$ to $i$; $n$ is the total number of wards. Spatial weights were defined by contiguity where neighbours are identified according to boundary relationships, in which 1 = adjacent and 0 = non-adjacent. Specifically, in this study, adjacency is defined using a first-order queen polygon continuity weight file which was constructed based on wards which shared common boundaries and vertices. Non-neighbouring wards are given a weight of zero and the neighbours of wards are defined as those with which the ward shares a boundary. A simple 0/1 matrix is formed, where 1 indicates that the wards have a common border or vertex; 0 otherwise (Tsai et al., 2009).
The Local Moran's I is also calculated as follows

$$I_i = \frac{z_i - \bar{z}}{\sigma^2} \sum_{j \neq i} W_{ij} (z_j - \bar{z})$$  (2)

where $\bar{z}$ is the mean value of $z$ with the sample number of $n$, $z_i$ is the value of the variable at location $i$, and $z_j$ is the value at other locations (where $j \neq i$). $\sigma^2$ is the variance of $z$. $W_{ij}$ is a distance weighting between $z_i$ and $z_j$, which can be defined as the inverse of the distance. $W_{ij}$ can also be determined using a distance band: samples within a distance band are given the same weight, while those outside the distance band are given the weight of 0. Moran's I varies between $-1$ and $+1$. Values greater or less than the expected Moran's I value ($E(I) = -1/(n - 1)$) indicate a positive or negative self-correlation, respectively. A positive spatial self-correlation indicates that neighbouring areas present values similar to those of the analysed area, and a negative spatial self-correlation indicates that neighbouring areas present values different from those of the analysed area (Fontes et al., 2018). A Moran's I value of 0 (zero) represents the hypothesis of spatial independence.

3. Results

3.1. Spatial distribution of crimes in Chivi district

We determined the spatial distribution of different crimes in Chivi District as shown by the results in Figure 2. The crimes were grouped into four categories conforming to Zimbabwe’s Criminal Law (Codification and Reform Act) Chapter 9.23 namely crime against persons, crime against property, crime against public order and crime related to drugs. Specifically, crimes against persons were in the form of rape, crime against property like unlawful entry and theft, crime against public order and those related to drugs. Crimes related to property comprised of unlawful entry and theft, theft, stock theft murder and attempted murder. Results show that the crimes against a person are randomly distributed across the district, followed by crimes against property and the least are crimes against drugs and public disorder. Places holding liquor, public transit areas like bus stops, vacant and abandoned residential and other
commercial areas seemed to influence crime's spatial distribution. Thus, the results show clustering of different types of crimes around the growth point. From Figure 2, randomness can be observed for the other different types of crimes.

3.2. Crime density in Chivi district from July to September 2018

Results of the study show that there are high crime densities in Chivi growth point. The crime density value was influenced by crime incidents found within the search radius (Figure 3). It is apparent that high crime density areas in the district are accorded a value of 4.6 and low crime values were found near the growth point. Thus, there is an emergence of a repeat places where most of the crimes are carried out and mostly in and around the growth point.

3.3. Crime clustering in Chivi district from July to September 2018

Spatial clusters were categorised according to the patterns and characteristics of the adjacent districts. High–high (HH) clusters are a set of districts with high rates that are surrounded by other districts with high reporting rates. Low–low (LL) clusters are groups of districts with low rates surrounded by low rate districts. The global and local spatial autocorrelation coefficients were considered significant when P < 0.05. Spatial Autocorrelation by Moran's I was employed to determine whether a pattern is clustered, dispersed or random. The results of the crime statistics show that there are High clusters in Chivi district. It is observed that High-high cluster areas in the district are identified as the high-crime areas in the Chivi which are mainly located in wards 30 (Chivi growth point), 11 and 15 (Figure 4). From the study, it can be noted that all the other wards had insignificant ant clusters at 95% significance level. For instance assault and unlawful entry and theft cases usually cluster at business centres holding liquor and built up areas whilst rape cases seemed to scatter in the villages where environmental conditions seemed to be conducive.

Figure 3. Crime densities in Chivi district.
3.4. Crime hotspots in Chivi district from July to September 2018

Using Gertis–Ord G* statistics for determining hotspots, Chivi district was characterised by cold and hot crime spots as indicated in Figure 5. Results indicated that significant crime hotspots at 99% confidence level were found in wards 11, 12, 13 and 30. Results further showed that the rest of the wards had insignificant hotspots and coldspots.
4. Discussion
Crime is often concentrated at a few places, even in high-crime areas (Eck et al., 2005). Although crime hotspot places are often concentrated within certain areas, they are separated by other places with few or no crimes. Results of this study recorded crime densities which were in the range of 0–4.6 (when all the crimes are lumped together) which is lower than crimes densities reported by Ahmad et al. (2017) in India where crime densities ranged from 0 to 50. The variability in densities of crime can be attributed to the differences in populations between the study areas and also the length of period for data collection. The findings indicated that crime densities were high located at Chivi growth point which is a business centre and the findings are supported by studies in Australia where it was found that the density of thefts was highest near major commercial and entertainment centres (for example, the business district, retail and recreational areas) (Lama & Rathore, 2017; LaRue, 2013). However, our findings are surprising in that we expected that the crimes should have clustered away from the growth point where the police station is located and police patrols are regularly conducted. Security measures should be increased at these crime hot spots which are located in wards 11, 12, 13 and 30. The hotspots and clusters of crime in this study were located in the shortest distance from the police station in Chivi district and the same was observed in India by Lama and Rathore (2017) where many hot spots were located very near to the police stations and the authors attributed it to the police being complacent during patrolling in those areas. The results of the study indicate that crimes of different types are located mostly around Chivi growth point and they scatter as distance from the growth point increases and these findings are in line with the findings by LaRue (2013) who found out crime is highest in the city centre and decreases as you move away from the city centre.

The results of the study tend to conform to the geometric theory of crime which emphasises the importance of the environment and place in explaining the geographic distribution of crime. Thus, the study demonstrated the spatial variations of the crime in Chivi district as per the demands of the geometric theory of crime. More so the study conformed to the theory in the sense that we showed where crime occurs based on geographic distribution of activity patterns and opportunities for crime (LaRue, 2013). The study managed to indicate that crime occurs at a specific site and in a specific situation; an offender is influenced by both the site, time and the situation (LaRue, 2013).

5. Conclusions
Based on the results it can be concluded that there are crime hotspots and crime clusters which have been identified in this study. Open source software (QGIS, GeoDa and Polaris Navigation GPS (mobile application)) can be successfully used for crime mapping in Chivi district and Zimbabwe in general. Hotspot mapping using open source software can be used by practitioners for policing and crime reduction through identifying spatial patterns of crime. The results of the study can be used for the deployment of police resources based on the identified crime distribution patterns, crime hotspots and clusters. Future studies should include long-term data sets which enable meaningful analysis. Other studies in future can also use standard deviation ellipse (SDE) to map the distribution and occurrence of crime and the kernel density estimation (KDE) in estimating crime densities in rural Zimbabwe. There is need for other studies to look at the temporal variations in crime.
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