UNIVERSITY OF CAPE COAST

SPATIAL ANALYSIS OF CRIME IN THE SEKONDI-TAKORADI METROPOLIS

ISAAC OBENG EBU

2020

UNIVERSITY OF CAPE COAST

SPATIAL ANALYSIS OF CRIME IN SEKONDI-TAKORADI METROPOLIS

BY

ISAAC OBENG EBU

Thesis submitted to the Department of Geography and Regional Planning of the Faculty of Social Sciences, College of Humanities and Legal studies, University of Cape Coast, in partial fulfilment of the requirements for the award of Master of Philosophy degree in Geography

MAY 2020

DECLARATION

Candidate's declaration

I hereby declare that this thesis is the result of my own original research and that not part of it has been presented for another degree in this university or elsewhere.

Candidate's Signature ……………… Date ………………

Isaac Obeng Ebu

Supervisors' declaration

We hereby declare that the preparation and presentation of the thesis were supervised in accordance with the guidelines on supervision of thesis laid down by the University of Cape Coast

Principal Supervisor's Signature: …………. Date: …………….

Comfort Ogunleye Adetona (PhD)

Co-Supervisor's Signature: ………….. Date: ………………

Emmanuel Abeashie Mensah

ABSTRACT

In the Sekondi-Takoradi metropolis, the crime rate has been on the ascendency, and the rate of ascendency of crime has increased since the discovery of oil in commercial quantities. One issue that has been absent from the Police Service in the metropolis and which has contributed to this rise is the lack of use of technology by the Police in fighting crime in the Sekondi-Takoradi Metropolis. The research therefore employs various technological techniques to investigate the problem. As such the main objective of this research is to analyse the spatial patterns of crime in the metropolis. In order to achieve this objective, various methodologies were employed.

A one-way repeated measure ANOVA test was performed to see if there were any statistical significant difference between the differences between the study years. A clustering map was created to show the hotspots of the various crimes in the metropolis over the study period. A routine activity space map was also created through the routine activity space theory. Lastly, a regression analysis was also performed to examine the relationship between the crime data, routine activity map and the hotspot map. The research wanted to examine if there was a relationship between these three variables employed in the study.

The study findings were found to be generally consistent with the Routine Activity theory by conclusively demonstrating that place, in this instance, suburbs and their location influence the distribution of crime.

The Ghana Police Service should set up GIS departments in all police stations to provide spatial analysis resource in fighting crime in Ghana.

KEY WORDS

Crime

Geographic Information System

Hotspot

Routine Activity

Sekondi-Takoradi metropolis

Spatial Analysis

ACKNOWLEDGMENTS

I would like to thank God for sustaining me throughout this programme. My special thanks and foremost appreciation goes to my supervisor Comfort Adetona (PhD) whose encouragement and valuable contributions motivated and sustained me. Further thanks goes to my co-supervisor Mr. Emmanuel Abeashie Mensah for his support and his unwavering availability to my cause and guidance throughout the research project.

I am also grateful to my two mothers Mrs. Charlotte Nanka-Bruce and Miss Regina Hackman, without them this Mphil education would have been impossible. I am also thankful to Mr. Osman Adams and Mr Richard Adade for their wonderful support especially with the GIS aspects of this work.

I owe a great deal of appreciation to the Ghana Police Service especially the Western Regional Police command for giving me access to their crime records which formed the backbone for this work, I am also grateful to the Town and Country planning department of the Sekondi-Takoradi metropolitan assembly and Ghana Statistical Service for the valuable data that they gave me.

Finally, I enjoyed the cordiality of the Department of Geography and Regional Planning during my studies. I am really proud of you for your support.

DEDICATION

To mothers Mrs. Charlotte Nanka-Bruce and Miss Regina Hackman.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER ONE

INTRODUCTION

Background to the study

Criminal activities have become more frightening in the world today and it is a major source of social concern. Once a marginal debate among scholars in the global North, the age-old question of why an individual conducts criminal behaviour has recently attracted universal interest and passion with no end in sight (Aning, 2006; Ceccato, 2012). Lives and properties no longer seem safe anywhere in the world, and this is not peculiar to a particular socio-economic or cultural group; both rich and the poor suffer the same fate and the whole society appears helpless in the face of crime (Badiora & Afon, 2013; Aning, 2006). Since 2000, this realisation has been chronicled in several seminal reports: for example, in 2005, the UN Secretary General's report, "In Larger Freedom", which examined some of the challenges mitigating against the attainment of the Millennium Development Goals (MDGs), pencilled crime as a potential threat to global peace and security. A more recent publication, "Keeping the Promise", quotes the UN Secretary-General reiterating that to achieve the SGDs, the world needs to build the capacity to explicitly respond to crime.

The ongoing problem of crime has been recognised and addressed in many different ways by different societies and researchers over time. To some, crime is the act of breaking rule(s) or regulation(s) for which a governing authority (via mechanisms such as legal system) can ultimately prescribe a conviction (Fafa, 2010). Crime is seen as a deviant behaviour that violates prevailing norms–cultural standards (Chang & Janeksela, 1996). Crime is a universal phenomenon and differs only in degree among the various societies of the world, as such the various definitions of crime differ from one society based on location, time of the crime incidence and intent (Havi, 2014).

Crime has an inherent geographical quality, that is, when a crime is committed, it happens at a place with a geographical location. For someone to have committed a crime they must have also come from a place (such as their home, work or school). This place could be the same location where the crime was committed or is often close to where the crime was perpetrated (Rossmo, 2000; Wiles & Costello, 2000). Location, therefore, plays a vital role in understanding crime and how crime can be tackled.

The distribution of the incidents across the landscape is not geographically random since incidents are human phenomena. For incidents to occur, offenders and their targets - the victims and or property are required to exist at the same location for some time. Several factors, including the lure of potential targets and simple geographic convenience for an offender, influence where people choose to break the law (Akpinar & Usul, 2003).

In Ghana, for example, all daily newspapers devote a significant proportion of pages to reports of murder, robbery, theft, and various crimes. The announcement concerning murder, rape, burglary and stolen vehicles among others are daily features on the news and national dailies. Many societies in Africa, have had to contend with the consequences of criminal activities, which affects lives and properties, thereby making people live in fear of the unknown, political instability, victimisation by conventional criminals, amongst others (Fayeye, 2010).

According to Numbeo (2015), crime levels in Ghana are rising steadily on yearly bases. In the last three years, the crime index for Ghana rose from 50 per cent to 63.33 per cent which is a percentage change of about 13.33 per cent. Again, the crime index (52.90) is 5.8 per cent higher than the safety index (47.10 per cent). Due to the increasing crime rates in Ghana coupled with the relatively small size in the number of the police service, there is the need for faster adoption of GIS in crime analysis by the various police departments. There are numerous advantages of GIS in crime analysis, in Ghana, many car thieves have been nabbed due to the presence of global positioning systems (GPS) on-board the vehicles.

Statement of the problem

There has been a considerable increase in the crime rate in Ghana over the years (Akpinar, 2005). Which is why Osei-Tutu, Badu and Owusu-Manu (2010) stipulate that Ghana has not been up to the standard in combating the activities of criminals in the country. The policies and the measures are ineffective because of their inability to meet up with the sophisticated methods used by the perpetrators (Costanzo & Gerrity, 2009). They further argued that the increase in criminal activities could be attributed to the fact that punishments assigned for these offences have not been effective in combating the crimes. The problem becomes serious as the criminal justice agencies in Ghana do not have reliable and comprehensive crime statistics (Appiahene-Gyamfi, 2009).

Sekondi-Takoradi, a sprawling city of about 662,809 people, has undergone a rapid socioeconomic and physical transformation since the 1960s (Ghana Statistical Service, 2014 and 2015). These changes have affected the pace and tempo of people's routine activities and lifestyles increased wealth and accessibility to portable goods and electronic devices such as laptops, television sets, cellular phones, and luxury cars, and created opportunities for criminal offences (Appiahene-Gyamfi, 2009). Sekondi-Takoradi, a once-sleepy coastal town, has now become the hub for the new industry, or the oil city as it is known locally, the first city in Ghana to host the oil industry. Most of the oil companies have premises there and it provides a base to move workers to and from the drilling platform, thus making it one of the fastest urbanising cities in Ghana (Walker, 2011).

By way of detail, according to records from the Ghana Police, of about 1,172 armed robbery cases recorded in the country in 2010, 25 of the cases in Sekondi-Takoradi. Of the 225 murder cases recorded, 42 were in Sekondi-Takoradi. Recent crime rates recorded in Sekondi - Takoradi suggests that recent social changes and economic transformation will have a significant impact on routine activities and opportunities for crime, all of which has implications for neighbourhood security, social cohesion and crime patterns. It is no longer a hidden fact that the metropolis is a conducive setting for criminal activities since it provides the anonymity required for the individual crime, and space for a specialised and organised underworld. Robbery, burglary, fraud, defrauding by false pretence, assault, and armed robbery have been at its highest rates in recent times and are still occurring at an increasing rate (Oteng-Ababio, Owusu & Wrigley-Asante, 2016).

Data from the Ghana Police Service revealed many areas within Sekondi-Takoradi Metropolis are areas notoriously known for serious crimes such as armed robberies. The increasing social sophistication and modernisation of the metropolis, the growing inequality, and the continuous rise in unemployment (especially among young school leavers and university graduates) have greatly accentuated urban crimes in recent times. Although there have been recent increases in the spate of criminal activities, it has not gained the same attention as the oil discovery and its related issues have gained (Van Gyampo, 2011).

Unfortunately, at present, little or no application of even the inadequate pin-on-maps in some police stations in Ghana especially Sekondi-Takoradi metropolis, let alone the use of GIS (Brookman-Amissah, Wemegah, & Okyere, 2014). The non-application of GIS and geodatabase in the fight against crime in this technological age is costly and counter-productive.

United Nations recommends a minimum police strength of 1 per 500 people (United Nation Office on Drugs and Crime, 2013). According to the Ghana Statistical Service (2012), the population of Ghana is estimated at 25,370,000; the implication is that even if the current estimate of 30,635 police officers is used against an estimated population of 27, 036, 809 assuming a growth rate of 2.19 per cent over 2012 census data it would result in a ratio of approximately 1 police personnel per 784 people at the time of this work. This ratio is well below the UN recommended ratio and hence there is a need to devise ways of mitigating the impact of the shortfall and to generally improve efficiency.

The various police stations in the Sekondi-Takoradi metropolis have the responsibility of handling the various crime incidences in the boundary under their jurisdiction, but at the moment have problems with their recording system and aggregation of crimes incidents in all police stations. There are not systems for crime mapping, incident time, and place; to inform the targeting of resources for crime prevention, to evaluate the effectiveness of crime prevention initiatives, and to assist in the prevention and rapid response to crime.

Although there have been countless researches on crime trends and statistics in Ghana (Owusu, Wrigley-Asante, Oteng-Ababio, & Adobea, 2015; Owusu, 2016; Oteng-Ababio, Owusu, Owusu, & Wrigley-Asante, 2016) very few studies have been done on the spatial patterns of crime in Ghana. There has been an enormous number of studies of spatial analysis of crime particularly in Europe and North America, recently there have been some studies in Nigeria and South Africa. After an extensive search on the topic of spatial analysis of crime in Ghana, the work of Brookman-Amissah, Wemegah, and Okyere (2014) was the only work that was discovered. Even with this work, the scope was limited to a small area within Dansoman Police subdivision in Accra. Therefore, this work seeks to complement the literature on the spatial analysis of crime in Ghana.

Purpose of the study

The purpose of this study was to analyse the spatial patterns of crimes in the Sekondi-Takoradi Metropolis.

Objectives of the Study

1. To conduct a statistical analysis of crime from 2007-2015.
2. To identify crime hotspots in the metropolis.
3. To map the locations of routine activity spaces of the metropolis.
4. To examine the influence of routine activity spaces on crime hotspots.

Research questions

1. What is the statistical trend of the selected crimes in the metropolis?
2. Where are the crime hotspots in the metropolis?
3. Where are the locations of routine activity spaces within the metropolis?
4. Are there any relationships between the routine activity spaces, location of police stations and the location of crime hotspots?

Significance of the study

The problem of crime is a national issue. Considering the simultaneous loss of innocent lives, cost in the medication of victims, loss of productive hours, destruction and loss of properties, fear and panic, security threats, budget constraints and many more, it requires renewed commitment from the government, non- governmental organisations, the police service and all and sundry to help fight for complete reduction in crime in the country.

Much of crime mapping is devoted to detecting high-crime density areas known as hot spots. Hot spot analysis helps police identify high-crime areas, types of crime being committed and the best way to respond to criminal activities. An assessment on the spatial analysis of crime hotspot policing will certainly contribute to the reconstruction of history as a whole.

Unlike many innovations in policing, spatial crime analysis was primarily developed by academics responding to theoretical innovations and empirical data. As such, the proposed review will also include a literature review that sets the theoretical context for the development of spatial crime analysis approach to crime prevention. This research work shall act as a basis for further investigation on crime prevention and some tactical ways which crimes can be dealt with.

The study would seek to present a visual display of how various crimes are distributed spatially. In addition, the crime hot spots mapped in this study using GIS technology can communicate crime patterns and crime prevention policies to decision makers such as the Police service commanders in making informed and intelligent policy decisions with regard to the management and reduction of crime rates especially in the Sekondi-Takoradi metropolitan Assembly that would spearhead the developmental agenda in terms of peace and total tranquillity. The Ghana Police is hoped to benefit greatly from accurate forecasts of crime within the small geographic area such as in the metropolis.

Limitations

Problems associated with data collection relate to the recording and collection of crime data. First, when recording crime information, the police made sure that manual recording was done. This greatly affected the work as it took a lot of time before all the information was collected. Secondly, as a result of poor record keeping, some crime data for some particular months were missing, this greatly affected the overall data.

The range and type of data gathered demonstrates the positivist, quantitative approach to analysing the crime situation in the metropolis. It should also be recognised that the range of analyses is dictated by the data available from the official police data. It is true that this information changes according to location or over time, so an exact comparison with other studies of this nature will always remain problematic.

Organisation of study

The first chapter of the thesis provides the introduction which include the background to the problem, the problem statement, the research objectives, research questions, significance of the study, limitation of the study and organisation of the study.

Chapter Two will also be concerned with the review of theoretical literatures and empirical work relevant to the study. Chapter Three will focus on the research methodology and a description of the study area, the Sekondi-Takoradi metropolis while Chapters Four will also focus on the analysis and discussion of the findings. The last chapter, Chapter Five will focus on the summary, conclusion and recommendation of the study.

CHAPTER TWO

REVIEW OF RELATED LITERATURE

Introduction

The essence of the literature review is to provide background information about the current study with the aim to primarily set the research in the context of available knowledge. The first part deals with the concept of crime and the various types of crime. The second part explains the various concepts that dwell on ideas from both theoretical and empirical literature to guide the study.

Concept of Crime

Crime is a complex phenomenon that occurs when an offender, a victim and a law intersect in time and space. Crimes, whether they be property crime, violent crime, white-collar crime or nuisance crime, are prevalent in most societies with huge cost (Andresen, 2006).

Morrison (2013) further argues that even the meaning of the concept of a crime depends on those who have the power to make their claims as to what crime is. Adebayo (2013) also believes that crime is like other concepts in Social Sciences which has no generally accepted definition. To him, the definition of crime centres on moral and legal factors. Bruce, Hick and Cooper (2004) also argue that not only do inconsistency and disagreement exist among the definitions of crime but also divergent views exist among scholars on the various types of crime. Consistently, Morrison (2013) argues that crime is a social construction and this poses a difficulty for creating a general definition because it varies across cultures.

However, in an attempt to define crime, some scholars Morrison (2013), Hale, Hayward, Wahidin, and Wincup (2014) share the view that crime can be defined in four frameworks: (1) Crime as a social construction; (2) crime as a product of religious authority/doctrine; (3) crime as a reflection of nation-state legality; and (4) crime derived from social and political theory. These authors are of the view that crime can be seen from the social construction perspective as created through social interaction. When created, it has both symbolic and practical reality. In this situation, crime and punishment are created to enable us to identify and distinguish different events (Morrison, 2013). In explaining crime as a social construction, Christie (2004) argues that crime does not exist, only acts exist. These acts often given different meanings within various social frameworks.

Hale, Hayward, Wahidin, and Wincup (2014) argue that modern societies have mainly explained crime in the conditions laid down by the nation-state concerning crime derived from social and political theory. To them, a crime is defined as an act or omission that leads to strict sanction per the constitutionally legal procedures of that nation-state.

Douglas, Burgess, Burgess and Ressler (2013) argue that there are common characteristics attributed to all crimes. They further explained that “crime disturbs those feelings that are to be found in all normal individuals in the society considered; these feelings are intense; they are definite”. Prades (2013) also posits that Durkheim defines crime as an act which offends intense and well-defined states of collective conscience. The collective conscience is a set of shared beliefs and sentiments which operate as a unifying force within society (Burkhardt &

Connor, 2015). From a different point of view, Schwendinger & Schwendinger (2001) define crime as an act that harms a person. They further explained that ‘anything’ could be considered a crime if actions or attitudes by any person, social system, or social relationship deprive or abrogate someone’s basic rights.

By legal standard, crime is an intentional act or omission in violation of criminal law; statutory or case law committed without defence or justification, and sanctioned by the state as a misdemeanour or a felony (Barak, 2009; Hagan, 2010). By definition, a crime involves social harm and requires vindication through a public process (Barak, 2009; Hagan, 2010). Carson and Felthous (2003) also state that a person cannot usually be found guilty of a criminal offence unless two key elements are present: an “*actus reus*,” (Latin for the guilty act); and “mens rea,” (Latin for guilty mind). To be convicted of a crime, it is the responsibility of the state to prove the existence of both the *actus reus* and *mens rea* and also has the burden of proving the guilt beyond a reasonable doubt (Milovanovic, 2006). One must have “intended” to commit a crime, and one must have committed some act to be found guilty of a crime (Schmalleger, 2009; Boylan-Kemp, 2013). Thus a person may intend to commit a crime (guilty thoughts) but may not do the act this is not a crime. However, where a person plans to do an act, and takes one step in furtherance of the crime, although short of accomplishment, she/he can be prosecuted for the crime.

On the other hand, one may have harmed another, but did not have “intent” (Milovanovic, 2006). “This either diminish responsibility for the act, or evaporates it, as in cases of insanity, duress and accident”. However, the author further stated that in some cases, such as "possession of burglary tools, may be tantamount to the act itself or as a crime".

The *actus reus*, is the physical/external feature of the crime; the defendant must have committed the proscribed act and he or she must have committed the act in the right state of mind. It is a voluntary act that causes social harm and it may include all the elements of the offence other than the state of mind of the defendant (Simons, 2003).

In another attempt to define crime, Ahmadi (2003), postulated that crime is a multifaceted concept that can be defined in a legal and non-legal sense. From a legal point of view, it refers to breaches of the criminal laws that govern particular geographic areas (jurisdictions) and are aimed at protecting the lives, property and rights of citizens within those jurisdictions. Most of the crimes with which the criminal justice system is concerned to involve breaches of state/territory legislation that cover offences relating to persons (such as, murder and sexual assault), property (including theft and property damage) and regulation (such as, traffic violations).

Theoretical framework

While the majority of criminological theories currently used by researchers focus on individual offenders, a considerable number of theorists have advocated some variation of the ecological approach to crime studies (Cohen & Felson, 1979; Miethe & Meier, 1994; Wilcox, Land, & Hunt, 2004; Eck & Weisburd, 2015). The basic thrust of this modern stream of research is the pervasive belief that crime cannot be understood without having accurate knowledge of the full demographic, economic, geographic, and social context in which it occurs. The most immediate geographic contexts are the neighborhoods in which people live and the places where their lifestyles frequently situate them. Wider geographic contexts, reflecting variation in both individual-level resources and society-wide norms, are determined by the different activities, both routine and non-routine, in which these people engage.

For most of the last two decades, ecological studies of crime have been informed by two different perspectives: social disorganisation theory and routine activities theory. Although the two schools of thought are closely related, an important distinction can be made. Social disorganisation theory focuses on the ability (or lack thereof) of residents of some geographic unit (e.g. a neighborhood) to come together to achieve a common goal, like reducing predatory crime.

Alternatively, routine activities theory focuses on the presence of opportunities for crime in an area, as shaped by residents' daily activities. In addition, the two theories suggest different levels of analysis: social disorganisation theory considers community explanations for crime, while routine activities theory is often interpreted as focusing on the individual. However, the difference between the two perspectives can be reconciled, and an integration of the two theories provides the most robust theoretical explanation for ecological studies of crime. Wilcox, Land, and Hunt's (2004) recent articulation of the integration of social control-disorganization and routine activities theories into a criminal opportunity perspective provides the most successful attempt.

As recently as a decade ago, most researchers took an exclusive focus on either the individual or on the aggregate level (Kubrin & Weitzer, 2003). Concurrent with a revival in the use of social disorganisation theory, however, recent development has seen a number of researchers advocating the development and use of multilevel models of crime, considering individual, situation, and social context together.

Routine activities theory

In 1979, Lawrence E. Cohen and Marcus Felson published in the American Sociological Review an article, 'Social Change and Crime Rate Trends: A Routine Activity Approach'. Their focus was on predatory crimes, which were defined as illegal acts that involved the direct damaging or taking of a person or property of another (Cohen & Felson, 1979). To Cohen and Felson, there are three necessary ingredients for crime: a motivated offender, a suitable target, and absence of a capable guardianship. All these elements influence and interact with each other in an urbanised environmental setting, which are also influenced by other forces in the external environment. The external environmental forces which are pertinent to crime prevention strategies are either situations that are inherent or beyond the control of the individual, such as weather, time, season, terrain, etc. or situations which can be influenced by man such as poverty, ignorance, injustices, fear, etc. both situations influences everyday life. Thus, for a predatory crime to occur, a willing, motivated offender must come into contact with a target that can be overtaken in a time and space context. In other words, the theory examines how work, recreation, spending patterns and everyday involvement in routine activities contribute to the likelihood of a motivated offender to commit crime (Lersch, 2007).

The theory was criticised for taking offenders as given (Hirschi's 1969), and in response Felson's later works in 1986 took into account informal social control of offenders. This resulted in a two-step version of the control theory: First, society establishes social bonds and thus attaches a 'handle' to each individual; and the second, being the task of identifying exactly who is breaking the rules. As the ecology of everyday life changes, it becomes easier to evade social controls by breaking rules in places where one is not recognised. In a nutshell, just as a guardian supervises the suitable target in the routine activity theory by Cohen and Felson, a handler supervises the likely offender in this new routine activity approach by Felson. In both cases, direct physical contact serves to discourage crime from occurring. Thus, social control in society requires keeping suitable targets near capable guardians and likely offenders near intimate handlers (Felson, 1989).

Spatial Analysis Theory

The development of different crime theories to explain crime patterns has been complemented with the recent development of different spatial analysis techniques to represent and visualise crime patterns (Hiropoulos & Porter, 2014). Spatial analysis is defined by Haining (1994), as "the analytical technique of geographical data based on the spatial distribution of geographical objects."

Crime research conducted in the early 20th century recognised the value of spatial analysis in finding spatial patterns in data. Since this time, highlighting location, distance, direction and patterns are considered to be the most important considerations when mapping data (Wikström, Oberwittler, Treiber & Hardie, 2012). These factors have been categorised by Chainey & Ratcliffe (2005), as spatial heterogeneity, spatial dependency and centrographic statistics. Spatial heterogeneity is displayed as variation in crime patterns from place to place, spatial dependency relates to the influence of one (e.g. assault) on another variable (e.g. bar) and centrographic statistics illustrate the spatial tendencies of data.

This section reviews different spatial analysis theories commonly applied in crime research, displaying variation in crime patterns and also, the spatial tendencies of crime. First, density based theories including vector and raster density theories are examined as measures of spatial heterogeneity in illustrating the different types of crimes in the study. Secondly, distance based theories and clustering theories are explored. Finally, centrographic theories are explored that highlight the spatial disposition of data.

Raster Based Density Theories

In contrast to line based vector techniques, raster based techniques "offer(s) a practical method for storing land characteristics with digital values of a parameter on grid square elements" (Julien, Saghafian & Ogden 1995). Different raster based methods have been applied in crime research, including kernel and point density analysis. These techniques have been applied in a range of different settings in crime research, including crime prediction, (Groff & LaVigne 2001; Bowers, Johnson & Pease, 2004) crime perception (Ratcliffe & McCullagh, 2001) and hot-spot analysis (Fitzgerald, Wisener & Savoie, 2004; Savoie, Bedard &

Collins 2006; and Charron 2009). The studies of Fitzgerald et al., (2004); Eck et al. (1995); Savoie et al. (2006); Charron (2009), all employed the kernel density technique to visualise data patterns.

The study by Groff & LaVigne (2001), used raster based methods to conduct spatial analysis on data to identify locations that provide increased opportunities for burglary in Charlotte, North Carolina. The study utilised a binary coding system to highlight places and locations at and adjacent to those places at greater risk of burglary. The research concluded that burglary rates were higher where there were more opportunities for crime. Furthermore, the model used in the research was more accurately able to analyse areas of less crime than those where there was more crime. A similar methodology to that used in the Groff and LaVigne study could possibly be used to highlight those areas where the opportunity for assault are greater than others. Other research by Ratcliffe and McCullagh (2001), used raster based methods to highlight police officers perception of crime areas compared with actual hotspots of crime. The study highlighted that there was significant variation in results on perceived versus actual crime from place to place.

In comparison to the choropleth analysis techniques which are used at a variety of scales, the raster based density analysis methods are most widely used at the city wide scale. This is evidenced in the studies of Fitzgerald, et al. (2004); Charron (2009), where the emphasis is on highlighting crime “hot-spots” in different city suburbs. Using a density analysis method at a region wide level could effectively illustrate any spatial variation (such as an urban-rural dichotomy) crime distribution. However, it would be difficult to represent the detail of any localised hot-spot activity at a region wide level through this technique. It is therefore appropriate that raster based hotspot activity is best represented at a city or at the neighbourhood level.

It is considered that application of raster as opposed to vector-based analyses are dictated by the purpose of the research and by the ability through the functionality that the respective vector or raster based technique has in meeting the research objectives. In formulating a GIS framework to measure urban sprawl, Harris and Longley (2000) applies raster over vector data techniques to find the total land area of newly developed areas. Even though the amount of urban sprawl is often modelled using vector techniques, these methods use proximity and neighbour analyses which are only available using raster based techniques. The benefits of applying this raster based method are that it accounts for the characteristics of neighbouring areas and the influence that these areas may have on the subject area. For this reason, raster based techniques such as kernel and point density have been employed in this study as they serve to illustrate "hot-spots" in assault patterns.

Hotspot Analysis Theory

As the name suggests, data clustering, according to Jacquez (2008), is "an excess of events in geographic space". Clustering analysis may either take place at locations that are composed of discrete features throughout a region, or summarized at the local level at a census tract unit (Mitchell 2005). Many clustering tests, such as Moran's I statistic (Moran 1948) and the "nearest neighbour" test (Clark & Evans 1954) have evolved by comparing the results of an observed set of distances with an expected set of distances to calculate the degree to which data clusters (Chainey & Ratcliffe 2005). The practical application of clustering analysis is commonly conducted by testing a null hypothesis of complete spatial randomness versus an alternative hypothesis that describes the spatial pattern that the test is trying to detect (Jacquez, 2008). Jacquez (2008) has argued that using a null hypothesis of "Complete Random Sampling" is not appropriate for the complex systems that are encountered in the physical and social world.

The measure to which clustering indices are statistically significant (assuming the data is normally distributed) is determined by evaluating Moran's I statistic, Moran's Z score and p value. Moran's I statistic is a measure of clustering. Moran's I statistic typically range between -1 and +1, results that range towards -1 are dispersed, 0, random, and +1 being clustered (Goodchild 1986).
Moran's Z score and associated p values are measures to which any assault clustering pattern "is simply not due to chance" (Mitchell, 2005). Areas that are not randomly distributed will typically have high p values, Z scores with standard deviations greater than 1.95 from the mean and p values of less than 0.01. (Mitchell, 2005). Arc software uses 2.5 standard deviations as a critical score (ESRI 2010). Hence, a large negative or positive Z score of greater than 2.5 standard deviations and low p values of <0.001 illustrates that there is significant randomness or clustering found in the data respectively. Results in this research

are presented as standard deviations of Moran's Z score as Moran's I statistics for assault clustering exceed the value of 1.

A variety of test statistics used to test for data "clustering "includes the Nearest Neighbour statistic (Clark & Evans, 1954); Getis- Ord's "G" statistic (Ord & Getis, 1995), Ripley's K statistic (Ripley, 1977); and Moran's I statistic (Moran, 1948). A complete explanation of cluster tests is presented by Jacquez (1996). Moran's I coefficient that is used as a measure of clustering and Geary's C coefficient are also commonly used tests for spatial autocorrelation between similar neighbours. The various test statistics exhibit different characteristics even though they are used to illustrate the spatial dependence of data on each other. The nearest neighbour statistic is calculated using the following formula:

Mean (d) min = $\Sigma^{n}_{(i=1)} d_{Ij} / n$

Where d_{min} = minimum mean distance

D_{ij}= distance between i and j

n = total number of events in data set

i = event number

Expected values for the mean nearest distance are:

$F_{(e)} = 0.5/ \text{sqrt} (A/n)$

A = area of study region

n = number of points

And suggested that the ratio R or nearest neighbour statistic for calculating clustering is calculated by:

R (NNI) = r_o / r_e

Where r_o = total mean observed distances

R_e = total mean expected distances

Results from this test statistic suggest that zero indicate a clustering pattern, while values tending towards 2.1491 shows a lack of clustering. The Getis-Ord statistic (Ord & Getis 1995), or G statistic is indicated by:

$G_i (d) = \Sigma_j w_{ij} (d) x_i x_j / \Sigma_{ij} x_i x_j$, $j <> i$ (Getis & Ord, 1992)

W_{ij} (d) is a spatial weighting matrix

$\Sigma_{ij} x_i x_j$ = sum of observations calculating distance between i and j

i = data point i

j=data point j

d = distance from point i to j

The nearest neighbour statistic (Clark & Evans, 1954) is a distance based statistic for point data that compares the closest point to another point in the study area. The average statistics are compared with expected statistics that is based on the number of events and the size of the study area. The Getis-Ord (G) statistic (Getis Ord, 1995) is used to "measure the degree of local association for each observation in a data set" (Anselin, 1996). The G statistic "is useful in the detection of like (high or low) values in an area of interest" (Anselin, 1996).

The measure of clusters using the G statistic is applied by weighting data within a certain distance of each other. Variations on the G statistic include the F statistic that measures the distance between a random point (i) in the study region to a data point (j) rather than measuring the distance between two data points (Bailey & Gattrell, 1995). Ripley's K statistic differs somewhat from other clustering patterns as the technique allows for clustering patterns based on the distance from all points in a data set. To date, the use of various test statistics has been used to test for spatial dependence in a variety of disciplines, including forest ecology (Dale & Fortin, 2014); crime (Anselin, Griffiths & Tita, 2008; Ratcliffe & McCullagh, 2001; Ceccato et al., (2002)) and employment patterns (Ceccato & Persson, 2002).

The value of significance tests is highlighted in a study by Anselin (1996); who uses various parameters (I statistic, p-value and standardised Z score) to highlight spatial variations in conflict levels for countries in Africa. The test assumes data is normally distributed (Anselin, 1996). The study reveals that there are significant (at 95 percent level of confidence) levels of conflict in countries around the horn of Africa (East Africa), with less levels of conflict recorded around West Africa.

It appears as though alternative clustering statistics are useful in different situations. The scale of the study area, the type of data and the purpose of study dictate what tests are appropriate for a certain situation. For example, global statistics (e.g. Moran's I statistic) are useful in measuring how patterns cluster at the regional level but local statistics (Local Moran's I statistic) can account for local variations in data that is not possible using global statistics. Likewise, visualising high or low clusters of data is perhaps more appropriate using the Getis-Ord statistic rather than Moran's I statistic. To date there is no evidence in research that density based spatial statistics has been used to explore measures of spatial association between bars and assault, whether at an individual or aggregate level. However, visualising and quantifying the spatial patterns through clustering techniques at a relevant enumeration level, such as “basomrade” as has previously been conducted in research through studies by Ceccato and Persson (2002) may highlight an association between crime event (i.e. assault) and land use.

Geographically Weighted Regression Theory

It has been argued that some regression techniques such as “Ordinary Least Squares Regression” do not adequately explain local variations occurring in space (Fotheringham, Brunsdon & Charlton, 2003). “Ordinary Least Squares” regression methods assume independence among observations which violates assumptions of spatial dependence inherent in all spatial data.

Geographically weighted regression (Brundson, Fotheringham & Charlton, 1998) has been proposed as an improvement on previous regression techniques, to “examine spatial variation in associations between dependent and explanatory variables” (Hay, Whigham, Kypri & Langley, 2007).

Geographically weighted regression accounts for spatial variation from place to place and the process produces a separate model at regression points representing each assault observation or, in the case of areal data, the regression point is a polygon centroid and “the distance between points is calculated as the distance between polygon centroids” (Mennis, 2006). The geographically weighted regression technique to date has been applied in research using socioeconomic data that is commonly aggregated to enumeration units such as mesh blocks (Mennis 2006). The local model created at each observation point (in this case, the meshblock centroid) provides estimates of β_k (ui,vi) for each variable k (e.g. bar) , by considering data around each assault point i (Brunsdon et al., 1998).

Conceptual Framework for Spatial Analysis of Crime in STMA

So far, many related theories have been discussed that espouse the spatial patterns of crime. In order to develop a conceptual framework for understanding spatial analysis of crime, this study adopts the routine activities theory and the social disorganisation theory as the primary theories underpinning this analysis. As already discussed, the routine activities theory first developed by Cohen & Felson (1979) hinges on illegal activities and stipulates three important elements that ought to converge in space and time for crime to occur: a motivated offender: a suitable target; and in the absence of a capable guardian which can be law enforcement officer or an adult in the neighbourhood, in this set-up, a crime is likely to occur. The latter, as earlier noted, are people who are likely to keep an eye out for the safety of other neighbours and their property.

Shaw and Mckay's social disorganisation primarily focus on the relationship between neighbourhood structure, social control and crime. Kubrin and Weitzer (2003) are of the opinion that social disorganisation signifies the inability of a community to address social problems due to the breakdown of institutions that ensues that community values are upheld. Thus, a strong social bonding is likely to occur within communities that are successful in believing and sharing in the same set of norms and values and more importantly, are able to socialise children to do same. The above explains that, neighbourhoods with a strong sense of communal identity and this feeling breeds a crop of individuals who are likely to intervene when people are seen perpetrating evil and who will monitor the behaviour of children thereby reducing crime and fear of crime.

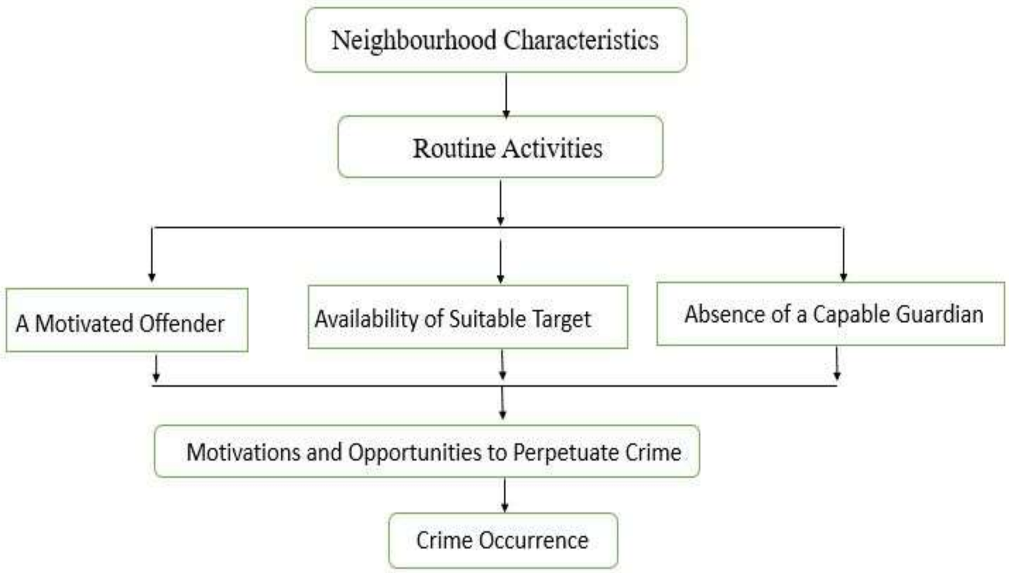


Figure 1: Conceptual Framework Based on Routine Activities and Social Disorganisation Theories, 2017

Source: Author's own construct

Figure 1 is a conceptual framework for the study. It summarises and illustrates the linkages among key concepts and theoretical postulates espoused earlier in this study. First the study conceptualises neighbourhood characteristics as an important determinant of any criminogenic outcome. Neighbourhood characteristics may include the social, economic and physical characteristics of a place that gives it a peculiar identity or ecological feature. In this regard neighbourhood structure also plays a significant role in determining residential differentiation. So for instance the presence or absence of proper planning and layout, income group of the population within a neighbourhood, absence or presence of employment opportunity, housing characteristics, street availability or absence etc. are important features of neighbourhoods and thus constitute neighbourhood feature.

Neighbourhood structure therefore facilitates or inhibits routine activities. For instance, a neighbourhood without lightening facilities, particularly during the night, and if there happens to be no guardian, it is likely that any potential person can be a target of crime. However, if these security infrastructures are available, then crime may not take place. In the context of a search for an appropriate crime prevention strategy, we assume that neighbourhood structure may facilitate crime because it provides a conducive environment for crime to take place. And so, for instance, inadequate security infrastructure such as police personnel, occurring in the context of an urbanising fringe town with brisk business taking place (e.g. the study area) can provide an environment for people to commit crime.

Logically the increase in crime and reported cases of crime will lead to police reaction and some measures being taken to address crime. However, these crime prevention strategies will not be somewhat different from the normative crime prevention strategies which are based on the standard mode of operation. Such crime prevention strategies mostly situational in nature and meant to disrupt the situational dynamics then allows crime to fester may not be adequate in terms of addressing the crime situation and enhancing public safety, particularly within the context of the study area which is experiencing rapid urbanization. More so, with its focus on increasing police size, and expecting to react to complaints, such strategies may not adequately address the security needs of an urbanizing fringe settlement, increasing demographically and expanding spatially. In this context, the researcher, and being her main argument, advocate for appropriate police strategy that incorporate the community in the crime prevention effort.

The increase in crime and reported cases of crime will lead to police reaction and some measures taken to address it, however, these crime fighting strategies will not be somewhat different from the normative crime fighting strategies which are based on the standard mode of operation that is police pushing criminal elements away from the suburbs to other suburbs. Such crime fighting strategies mostly situational in nature and meant to disrupt the situational dynamics then allows crime to fester elsewhere may not be adequate in terms of addressing the crime situation and enhancing public safety, particularly within the context of the study area which is experiencing rapid urbanisation. More so, with its focus on increasing police size, and expecting to react to complaints, such strategies may not adequately address the security needs of an urban area. In this context, the researcher, and being his main argument, advocate for appropriate police strategy that incorporate the application of geographic information systems in the crime fighting effort. This will be beneficial to the police since it will direct the scarce resources the police might have to devote in crime prevention (human and monetary) towards areas which are more prone to crime.

Chapter Summary

A review of different spatial theories has established the variation, versatility and limitation of each technique. Notwithstanding these limitations, it can be argued that using a variety of vector based, raster based, distance-based and clustering analysis can together effectively explain the spatial variation evident from area to area throughout the metropolis.

In the context of this research, it is important to first, utilise the different techniques to assess the relationship between the various crimes under study, and second, to consider how relevant the different crime and spatial analysis theories can assist in explaining the distribution of the various crimes in the metropolis.

In conclusion, it is considered that a number of spatial analytical and crime techniques are relevant and should be used to explore and explain the levels of the various crimes in the Sekondi-Takoradi metropolis. Clustering analysis using distance-based relationships is also relevant and has been used as an additional "locational" technique. Distance based techniques are also relevant to this study, notably the Euclidian-straight line technique that seeks to establish relationships between assault and bar distributions. Centrographic analysis techniques are also considered to be accurate for analysing the spatial patterns of the various crimes under study and accordingly have been applied in this study.

CHAPTER THREE

RESEARCH METHODS

Introduction

The previous chapter interrogated some of the theoretical underpinnings of this study. The endeavour did not only provide the theoretical background to the study, but also helped identify some of the existing gaps in literature. The current chapter explores the methods and techniques employed in data gathering and its analysis. The section had two main divisions. The first division detailed the methods and methodology used in the study. This included research design, data collection procedure and data analysis techniques. The second section presented the profile of the study area.

Study area – Sekondi–Takoradi Metropolis

This section details the features of Sekondi-Takoradi Metropolis where the study was conducted.

Background of the study area

Like most local authorities in Ghana, Sekondi-Takoradi Metropolitan Assembly started as Sekondi-Takoradi Town Councils on 1st October, 1903 by proclamation in the Gold Coast Colony. The proclamation was dated 15th September 1903 and was made under the town Council ordinance of 1894. Over the time, the population and the geographical area expanded. Many villages such as Ketan and Tanokrom were included in the Council's administrative jurisdiction. The status and the name of the Council changed from Town Council to City Council in 1976. The name again changed to Shama Ahanta East Metropolitan

Area, which later changed to Sekondi-Takoradi Metropolitan Area in December

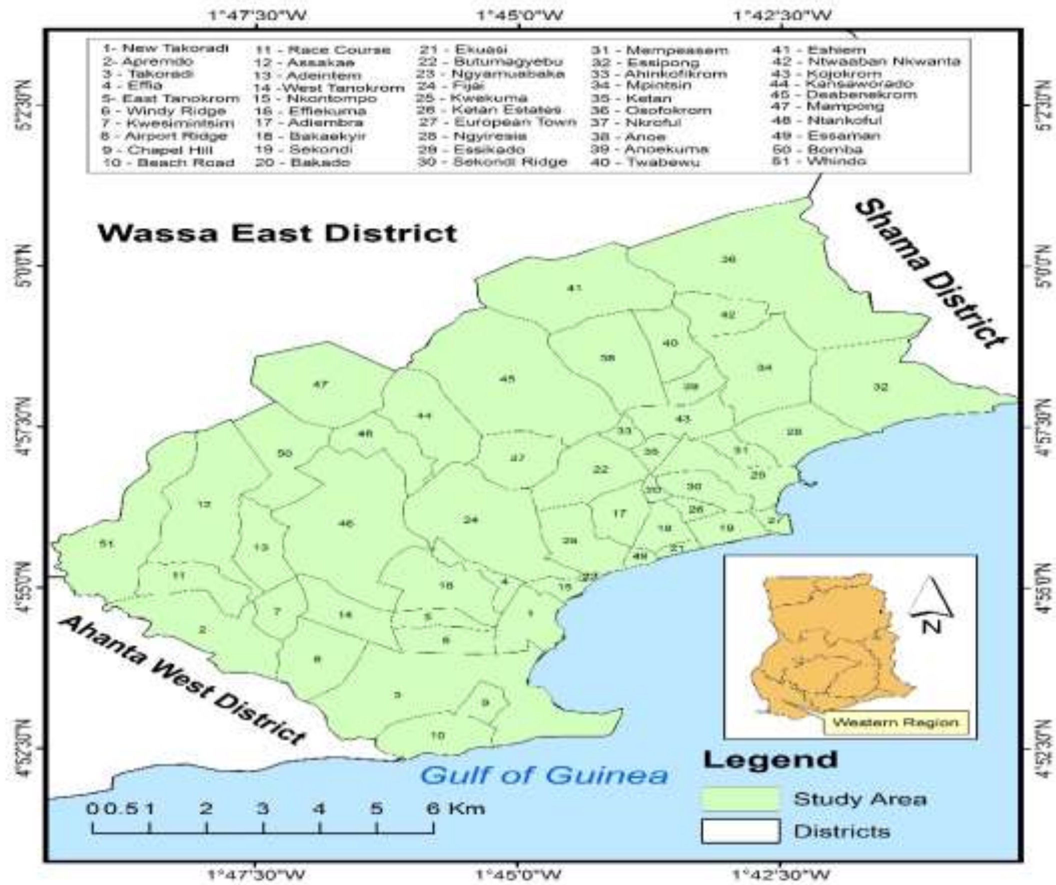


Figure 2: Map of the Study Area

Source: Author's Construct, 2016

2007 through Legislative Instrument 1933 when Shama was carved out of Shama Ahanta East Metropolitan Assembly (SAEMA).

Location and size

Figure 2 shows the area map of Sekondi-Takoradi Metropolis. The metropolis is located at the south-eastern part of the Western Region. The metropolis is bordered to the west by Ahanta West District and to the east by Shama District. At the south of the Metropolis is the Atlantic Ocean and at the northern part is Wassa East District. The Metropolis covers land size of 191.7 km^2 and Sekondi-Takoradi is the regional administrative capital. Though the smallest district in terms of land size, the Sekondi-Takoradi Metropolis is the most urbanised among the 22 districts in the region.

Demographic Characteristics

The indigenous people are predominately Akans (Ahantas). Fante is widely spoken in the Metropolis. There are also some other languages spoken. The indigenous people exhibit a high degree of cultural homogeneity in areas of lineage organization, inheritance and succession. Matrilineal inheritance system is what is conformed with. There are also non-indigenous settlers whose predecessors had migrated several years back from different parts of world into the Metropolis, primarily for economic reasons. The distribution of proportion of ethnic group in the Sekondi-Takoradi Metropolis is as follows Fantes 46.5 percent, Ahantas 12.2 percent, Asantes 12.2 percent, Nzemas 3.8 percent and Wassas 3.0 percent. The proportion of the rest of ethnic groups is below 3 percent.

The results of the 2010 Population and Housing Census (2010 PHC) show that the number of persons enumerated in the Sekondi-Takoradi Metropolis is 559,548. Figure 2.1 shows that, the population among urban and rural localities are 35,790 (96.1%) and 37,020 (3.9%) respectively. This shows that majority of the population in the Metropolis reside in the urban communities (GSS, 2013).

Political and Administrative Structure

The political head of the Metropolitan Assembly is the Chief Executive. The chief executive is appointed by the president of the republic in-line with the

1992 constitution supported by a presiding member and Assembly members. There are 72 Assembly members out of which 49 are elected by their constituents whilst 27 were appointed by the government. In order to ensure effective administration, the Metropolis has been divided into four (4) sub-metros. The four sub-metros in the Metropolis are Sekondi, Takoradi, Essikadu/Ketan and Effia/Kwesimintsim. There are five (5) constituencies in the Metropolis namely Effia, Kwesiminstim, Sekondi, Takoradi and Essikadu/Ketan.

Research Design

The research design presented a framework or blueprint for connecting the overall planning and organisation of the research. The design articulated the data required, methods used to collect and analyse the data, and how these answered the research questions. The study adopted a descriptive research design which is preferred due to the statistical nature of the data used.

Descriptive research is “aimed at casting light on current issues or problems through a process of data collection that enables them to describe the situation more completely than was possible without employing this method (Fox & Bayat, 2007). The study includes the use of statistical analysis, clustering analysis, regression analysis and weighted overlay analysis to establish the spatial patterns for the four kinds of crimes selected for the study which were reported in the Sekondi-Takoradi metropolis from 2007 to 2015. The selected crimes (robbery, assault, defrauding by false pretence and stealing) were the four most committed crimes in the metropolis according to the Regional Crime officer of the Western Regional Police Command.

The use of geographic information systems using ArcGIS tools and complemented by other software such as Microsoft Excel will ensure a positivist, bias-free outcome which reduces the likelihood of interpretation errors. Recognition should also be given in the research design to practical considerations and financial resources (Hedrick, Bickman & Rog, 1993). These considerations have determined the scope and nature of this research.

Data and Sources

Secondary data was used for this study, the data were of two kinds, spatial and non-spatial. The non-spatial data include crime ledger which contained the various crimes reported to the police stations. The spatial data include the shapefile of the road network in the metropolis was also taken from the regional office of the Ghana Highways Authority. The study also used the map of metropolis showing all the suburbs and the land use map of the metropolis which were collected from the Town and Country Planning Department of the Sekondi-Takoradi Metropolitan Assembly.

Data Collection

In accordance with the research objectives, crime data on the four forms of crimes have been collected. Commonly, data in crime research comes from four main sources; police; national statistics agencies, corrections or probation agencies and local government sources (Chainey & Ratcliffe, 2005). This research makes use of several different secondary data sources including data sourced from the police stations in the metropolis, the Town and Country Planning Department of the Sekondi-Takoradi Metropolitan Assembly and Ghana Statistical Service. Data on stealing, defrauding by false pretence, assaults and robbery was obtained from the nine police stations in the metropolis. This was done because, it is at the police stations that reported cases of the crimes are recorded. The data collection process was as follows:

Daily crime records from 2007 to 2015 from the Sekondi-Takoradi metropolis, shown in the Appendix A to Appendix I were retrieved. The researcher went to all the nine (9) police stations in the metropolis, that is crime statistics on stealing, assault, robbery and defrauding by false pretence from Kojokrom, Effiakuma, Adiembra, Market Circle, Beach Road, Central Police, Railways, Essikado, Anaji and Kwesimintsim Police Stations in the metropolis and. The type of crime and the suburb within which the crime was committed were taken from the records for the various years. The crime records which contribute to the attribute data were based on the data recorded by the Police department. The reported crime cases were contained in the station dairies of the various police stations, this was used because it was the first point at which all reported cases were recorded and it contains the location where the various crimes were perpetuated.

Secondly, a spatial dataset containing the information on the various suburbs of the Sekondi-Takoradi metropolis and the land use map of the metropolis was provided by the Town and Country Planning department of the metropolitan assembly. The dataset contained useful information on all the areas in the metropolis that allows for a wide range of analysis.

Data Processing and Analysis

The process used to analyse the data differs according to the strategy for each underlying method applied. There are however similarities in the type of software which is applied. These processes involve, spatially joining the crime data, and then finally, undertaking spatial analysis using most of the theoretical approaches outlined in the previous chapter.

Statistical Analysis

All the crime data collected which were collected from the police stations were then entered into the Microsoft excel. Since the data was collected on the suburb to suburb basis, the total crime for every suburb within the year was entered. Using the Line Chart, the trend analysis of the various crimes over the nine-year period was generated. This was repeated for all the years, then the statistical trends were generated in Microsoft excel.

A one-way repeated measures ANOVA test also performed on the data using Statistical Package for Social Sciences (SPSS) for windows version 25.0 software was employed. This analysis was done to test if there was any statistically significant difference between the study years. That is between 2007 and 2015. This analysis followed the steps that Almeida, Haddad, & Hewings (2005), Manolache, Totan, & Burcea (2011) and Vilalta (2013) used in their respective studies where they used one-way repeated measure ANOVA test to analysis their data.

Clustering Analysis Process

Clustering mapping is a popular analytical technique that is used to help identify where to target police and crime reduction resources. In essence, 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).

A number of different mapping techniques are used for identifying hotspots of crime, these include, point mapping, thematic mapping of geographic areas (e.g. census areas), spatial ellipses, grid thematic mapping, and kernel density estimation. Several research studies have discussed the use of these methods for identifying hotspots of crime, usually based on their ease of use and ability to spatially interpret the location, size, shape and orientation of clusters of crime incidents (Jefferis, 1999; Ratcliffe & McCullagh, 1999; Chainey et al 2002; Eck et al, 2005).

This study will use hotspot mapping which serves to supplement the crime density analysis and can assist in measuring the degree of association that the various crimes have with the various suburbs in the metropolis. The clustering analysis focuses only on the distribution of the four crimes. The application of this type of analysis to this study is particularly useful at an urban area level such as the Sekondi-Takoradi metropolis to highlight particular land uses including bars, nightclubs, residential areas and the fishing communities which are regarded as "crime opportunity" areas. The process in calculating how data clusters is as follows:

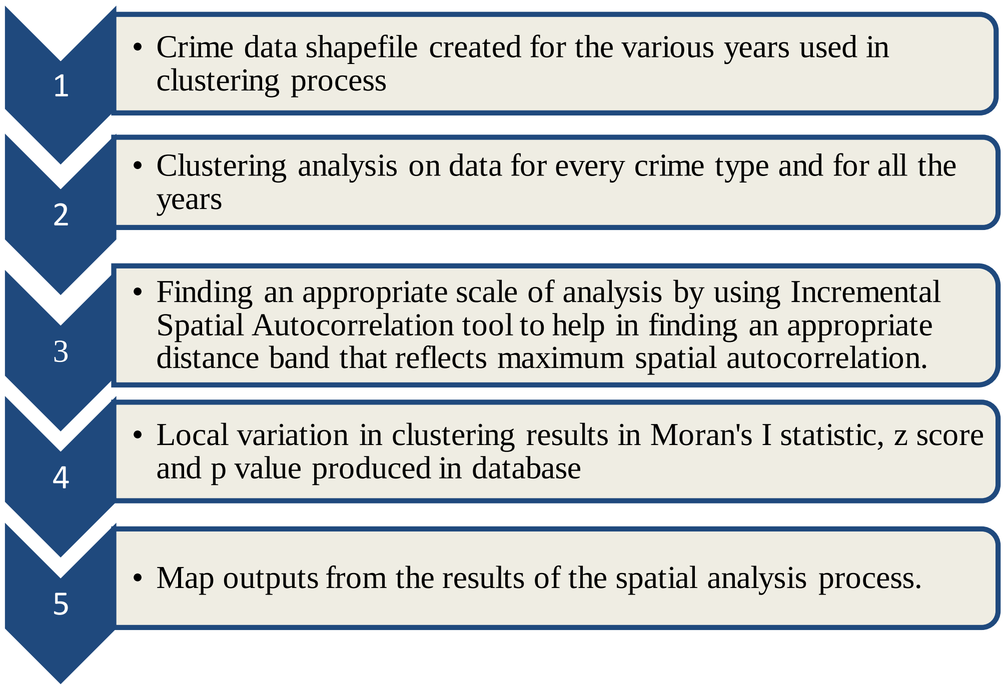


Figure 3: Process in conducting clustering analysis on the data

Source: Author's construct, 2016

Routine activity space

Brantingham and Brantingham's (2008) concept of activity spaces provides a framework for distinguishing between residential neighbourhoods as contexts for development and criminogenic activity spaces as contexts for (criminal) actions. Their discussion of activity spaces focuses on a person's daily activities as they unfold across space. Building on their approach, this study will view interactional settings or action contexts as consisting of two components that influence the probability of criminal acts. The first involves what individuals are doing, and the second involves the social and cultural characteristics of the space where they are doing it.

Although activities and spaces both influence the chances of crime through their effects on situational definitions involving provocation, threat, or criminal opportunity, the two constructs do so in different ways. The nature of an activity directly influences the probability that it will lead to social encounters favorable to crime, activity spaces contribute to criminogenic situational definitions by dictating the norms and social controls that govern social encounters within an area regardless of activity. Consistent with insights from Wikström et al. (2012) and drawing on cultural, structural/control (Sampson, 2012; Shaw & McKay, 1969 1942), and routine activities theories (Cohen & Felson, 1979; Felson and Cohen, 1980; Osgood et al., 2005).

The routine activity space analysis for the Sekondi-Takoradi metropolis was created using the road network, land use and population datasets for the Sekondi-Takoradi Metropolis which was acquired from the regional office of the roads and highways authority and the Town and Country Planning Authority and Ghana Statistical Service respectively. The network analyst tool in ArcGIS was used to create a network model for the road network, a point feature class for the roads and junctions were created. The weighted overlay tool was then used to combine the various raster datasets for the analysis.

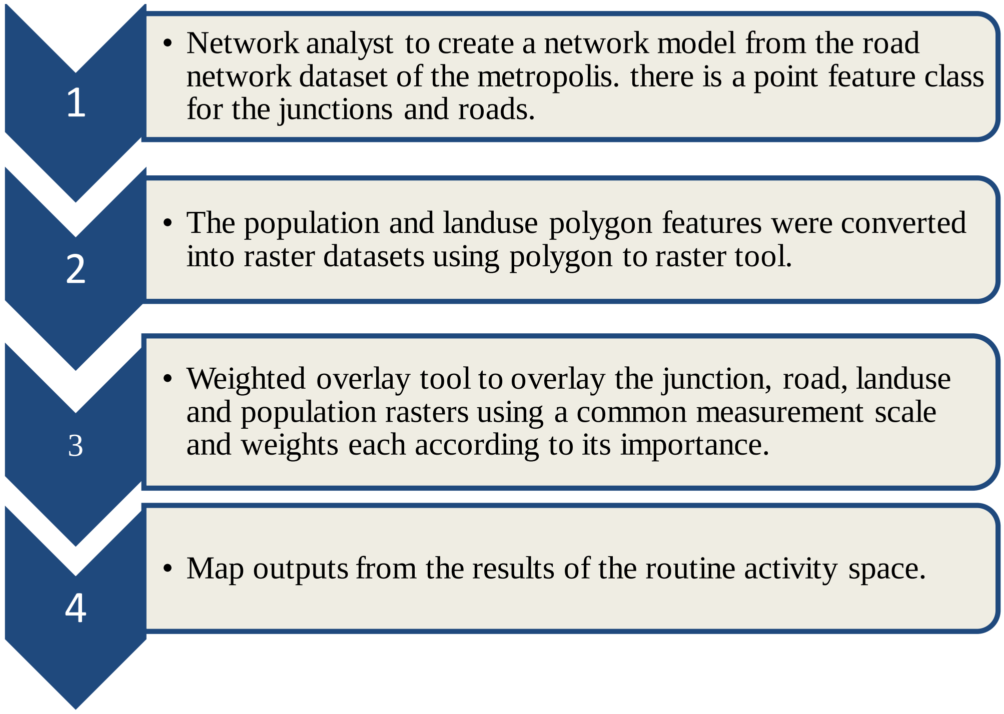


Figure 4: Routine Activity Space process

Source: Author's construct 2016

Regression Analysis Process

The ability to predict the locations of future crime events can serve as a valuable source of knowledge for law enforcement, both from tactical and strategic perspectives. From a traditional policing perspective, predictive mapping can inform a police department's deployment efforts, helping to allocate patrols more efficiently and reduce response times (Groff & La-Vigne, 2002). Predictive mapping holds promise for improving the identification of areas in which to focus interventions, but it also may improve the way those interventions are implemented (Hesseling, 2005).

Regression analysis is probably the most commonly used statistic in the social sciences. Regression is used to evaluate relationships between two or more feature attributes. Identifying and measuring relationships allows you to better understand what's going on in a place, predict where something is likely to occur, or begin to examine reasons why things occur where they do.

Data that is analysed using geographically weighted regression should initially be analysed using "Ordinary Least Squares" regression (Mitchell 2005) as "Ordinary Least Squares" regression explores the strength of relationship between two variables. Where a close relationship is found between variables of interest using Ordinary Least Squares regression, geographically weighted regression is then applied in analysing the spatial variation in the relationship between these variables. The process for conducting geographically weighted regression analysis of crime data thus is as follows:

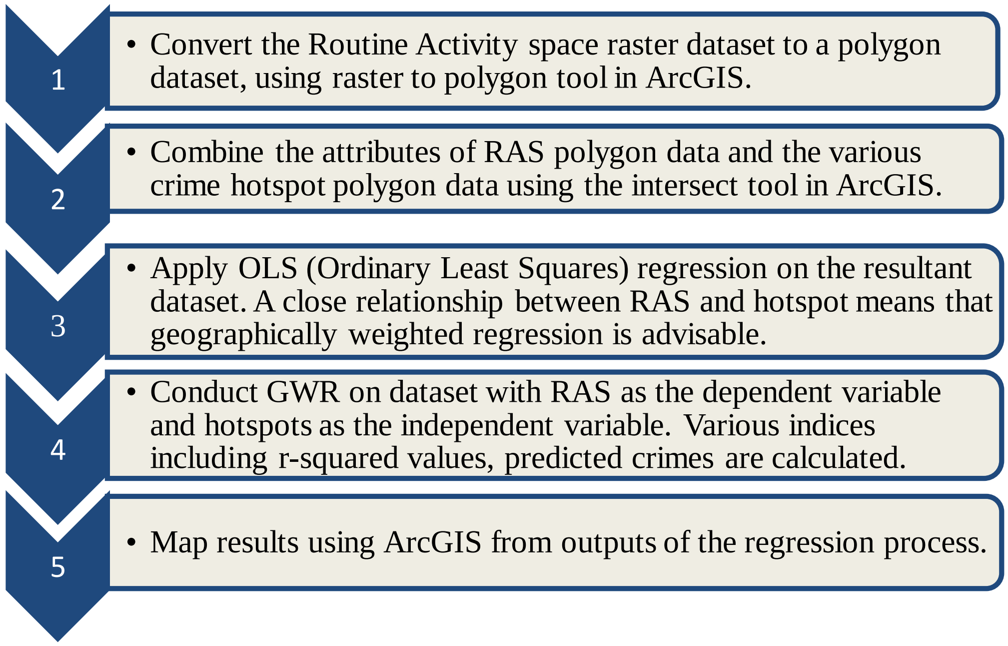


Figure 5: Process weighted regression of conducting geographically

Source: Author's construct, 2016

Chapter Summary

The chapter sought to present the research methods and design employed in the study. Thus, the chapter described the methodology that was developed to address the study's objective and research questions. The study's methodology gives insight into the spatial analysis of crime in the Sekondi-Takoradi metropolis in the Western region of Ghana, and sets out the research design and criteria applied. It also included the detailed description of how the data was collected. The chapter of the study was not without some limitations. Thus there was difficulty in going around all the nine police stations and sifting through the crime records to select the desired crime type for the analysis. However, appropriate method and procedure were employed in the study's design to ensure that the data collection was on schedule.

CHAPTER FOUR

RESULTS AND DISCUSSION

Introduction

The previous chapter gave the background information on the study area and the methodology adopted to accomplish the objectives of the study. This chapter focuses on the presentation of the results and the discussion of the findings of the crime data. It includes details of the results of the field work and these were segmented along the lines of the statistical analysis of the crime data, hotspot analysis, the routine activity space and the regression analysis of crime in the Sekondi-Takoradi Metropolis.

Statistical analysis of crime in Sekondi-Takoradi from 2007-2015

The study revealed that nine thousand seven hundred and three (9703) cases were recorded for the four different crimes over the nine-year period (2007 to 2015), with the year 2008 recording the lowest crime of 929 cases, for the four crimes which the study concentrated on. Several factors may have attributed to this figure, as it was also the period before the announcement of the discovery of oil in commercial quantities in the region. As such the population of the metropolis was comfortable for the Police to fight crime in the Metropolis (Aning, 2006). The 2010 figures saw the crime records drop to 1026 cases from the previous year's (2009) cases of 1143. The 2014 crime figures were the highest recorded among the other years, it reached a peak of 1280 cases (Figure 6).

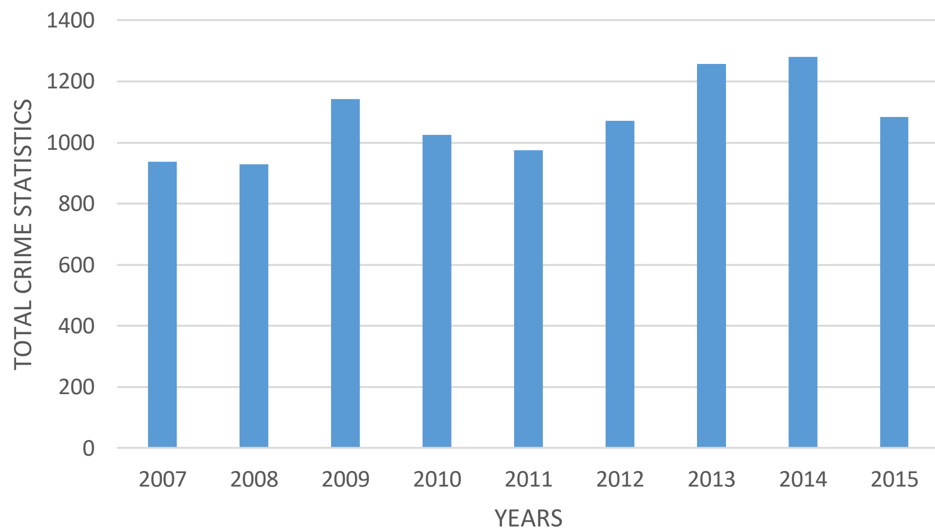


Figure 6: Total crime statistics for the study period

Source: Fieldwork, 2015

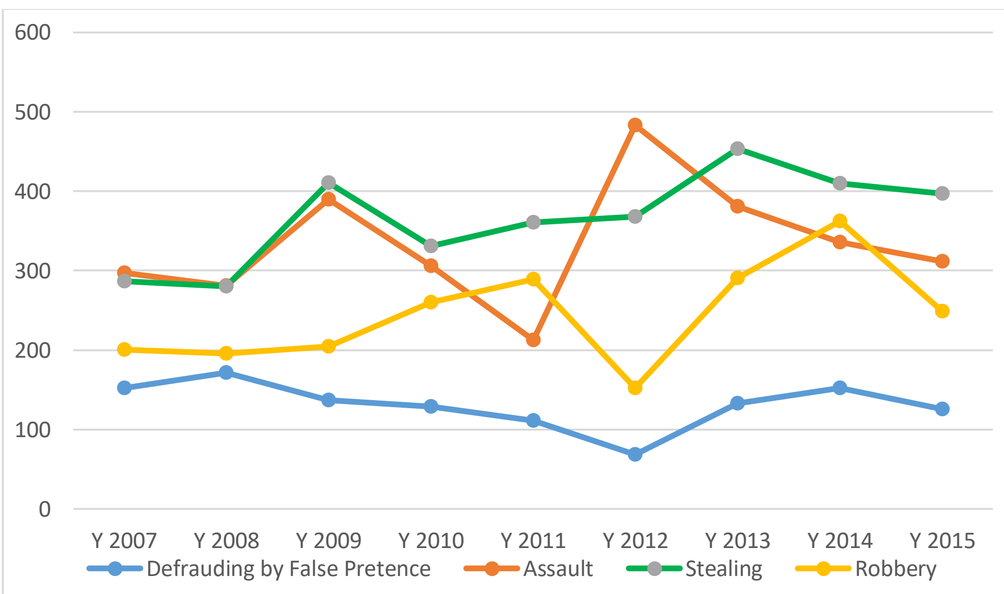


Figure 7: Yearly statistical trends of crime in STMA (2007 to 2015)

Source: Fieldwork, 2015

Results observed in Figure 7, indicated that defrauding by false pretence cases were the lowest among the other three crimes over the nine years, representing 12 percent of total crimes committed over the course of the nine years. In 2007, total reported cases of defrauding by false pretence was fifty-two (152) cases representing 16 percent of the total crimes committed in the metropolis. (Figure 6). Robbery, cases for that same year was 201 representing 21 percent, stealing eighty-seven (287) representing 31 percent. Assault recorded the highest reported cases of two hundred and ninety-seven (297) in 2007 representing 32 percent.

In 2008, which was the year Ghana co-hosted the African Cup of Nations Football tournament with Nigeria, the Police manpower was stretched in the metropolis, as such criminals had their field day in most parts of the metropolis. Lots of criminal activities occurred around the Essipong suburb of the metropolis as the stadium that hosted some of the matches was located there (Adinkrah, 2010). Assault for this particular year increased to 281 cases, most of these cases occurred in and around various bars and pubs. This is in line with the argument put forward by Andresen (2006) that most assault cases occurs at night at bars and pubs. Defrauding by false pretence had a total of one hundred and seventy-two (172) which was a 3% increase over the previous year, this is not surprising because this was the year that the African Cup of Nations football tournament was hosted in the Metropolis, lots of different people came into the metropolis who did not know their way around the metropolis, thus, they became victims of fraudulent activities. Robbery recorded a total of one hundred and ninety-six (196) cases in 2008 representing 21 percent of the total crime for the year. Stealing also recorded a total of two hundred and eighty (280) reported cases in the metropolis. This can also be partly attributed to the African Cup of Nations tournament which brought lots of people into the metropolis during the period (Adinkrah, 2010).

In 2009, the dynamics of the crime incidents changed in the metropolis, stealing was the most committed crime in the metropolis. It recorded a total of four hundred and eleven (411) cases, most of the theft cases were in areas around market areas where lots of business activities happen, as a result, perpetrators and victims converge without the presence of a capable guardian (Cohen & Felson, 1979). Assault, which used to be the most committed crime in the metropolis in the two previous years (2007 and 2008) had now fallen behind stealing, in the year 2009, three hundred and ninety (390) cases of assault was recorded across the metropolis. The total number of robbery cases recorded across the various police stations was two hundred and five (205), this represented 18 percent. The total number of cases recorded for defrauding by false pretence was one hundred and thirty-seven (137), this representing 12 percent. There was a total of a thousand one hundred and forty-three (1143) reported cases of the four crimes. This was an increase of 2 percent over the 2008 total.

Assault, unsurprisingly became the most committed crime in the metropolis in 2012, it recorded its highest ever mark of four hundred and eighty-three (483). It increased more than 100 percent over the previous year. This trend supports the assertion made by Amankwaah (2013) and Bob-Milliar (2014) that cases of assault rise exponentially during periods of national elections. This is especially true in the urban areas of the metropolis which recorded very high figures of assault during the 2012 national elections. Stealing continued to increase marginally, this time it increased to three hundred and sixty-eight (368) representing 34 percent of the reported cases. Robbery in 2012 reduced to one hundred and fifty-two (152) cases (Figure 7). Sixty-nine (69) cases of defrauding by false pretence was reported in 2012 across the metropolis. In total, one thousand and seventy-two (1072) cases were recorded for the four crimes in the study for 2012, showing an increase over the previous year which was nine hundred and seventy-four (974), this represented a 1 percent change between the two years.

In the year 2013, stealing overtook assault to become the most committed crime in the metropolis. It recorded four hundred and fifty-three (453) cases, representing 36 percent, this was a percentage increase of 2 percent above the previous year and the figure was highest over the nine-year period. Cases of assault reduced to three hundred and eighty-one (381), representing 30 percent of the total cases. Robbery this time show a significant increase, reaching a figure of two hundred and ninety-one (291) cases. This rise in robbery cases can be attributed to the assertion made by Akakpo (2012), Obeng-Odoom (2014) and Oteng-Ababio (2016) that the oil industry has given rise to the population of people in the metropolis, thus criminal elements have also moved into the metropolis. Defrauding by false pretence showed a substantial increase in 2013, reaching a figure of one hundred and thirty-three (133) cases representing 11 percent. The total number of reported cases for the year 2013 was one thousand two hundred and fifty-eight (1258) cases.

The year 2015 saw a general decline in crime from the previous year (2014), in total, one thousand and eighty-four cases were recorded across the metropolis for the four different crimes. The Police were very visible during this period as there was a lot of talk about the increasing rate of crime in the metropolis during the previous years. The Police in the metropolis therefore altered their tactics and were successful in pushing criminal elements out of the metropolis (Frimpong, 2016). Stealing continued to maintain its notorious position of being the most committed crime in the metropolis. It recorded three hundred and ninety-seven (397) reported cases. Assault also recorded three hundred and twelve (312) just like all the other crimes robbery saw a significant reduction during the year 2015 from the previous year, it reduced to two hundred and forty-nine (249) reported cases. Defrauding by false pretence also saw some reduction in terms of the number of reported cases. A total of one hundred and twenty-six (126) cases were recorded in the metropolis on defrauding by false pretence.

One-way ANOVA test for assault

A one-way between groups analysis of variance was conducted to explore the impact of time, in this case years (2007 to 2015) on the cases of assault. The assault cases for the nine-year period was therefore analysed. The Levene's test for homogeneity of variances, which tests whether the variance in assault cases in each of the years is the same for all the other years. A look at the significance value which was 0.031, which was less than 0.05 meant the assumption of homogeneity of variance was violated. Since the assumption was violated, a robust test of equality of means was conducted.

There was a statistically significant difference at the $p < .05$ level in the assault cases over the nine-year period: $F (8, 450) = 2.2$, $p = .025$. Despite reaching statistical significance, the actual difference in mean scores between the years was small. The effect size, calculated using eta squared, was 0.038. Post-hoc comparisons using the Tukey HSD test indicated that the mean score for 2007 (M = 6.75, SD = 5.47) was statistically different from that of 2012 (M = 11.47, SD = 8.17). Again, the mean score for 2011 (M= 6.88, SD = 6.07) was statistically significant from that of 2012 (M = 11.47, SD = 8.17).

One-way ANOVA test for stealing

A one-way between groups analysis of variance was conducted to explore the impact of time, in this case years (2007 to 2015) on the cases of stealing. The stealing cases for the nine-year period was therefore analysed. The Levene's test for homogeneity of variances, which tests whether the variance in stealing cases in each of the years is the same for all the other years. A look at the significance value which was 0.005, which was less than 0.05 meant the assumption of homogeneity of variance was violated. Since the assumption was violated, a robust test of equality of means was conducted.

There was a statistically significant difference at the $p < .05$ level in the stealing cases over the nine-year period: F: $(8, 450) = 3.6$, $p = 0.00$. Despite reaching statistical significance, the actual difference in mean scores between the years was small. The effect size, calculated using eta squared, was 0.060. Post-hoc comparisons using the Tukey HSD test indicated that the mean score for 2007 (M = 7.08, SD = 4.975) was statistically different from 2011 (M = 12.31, SD = 8.6), 2012 (M= 12.86, SD= 9.76) and 2015 (M = 12.31, SD = 12.04). Again, 2008 (M= 6.98, SD = 5.54) was statistically significant from 2011 (M = 12.31, SD = 8.6), 2012 (M= 12.86, SD= 9.76) and 2015 (M = 12.31, SD = 12.04). This indicates that most of the stealing cases that occurred over the years, there was little or no significant difference between the number of cases between the years over the study period (2007 to 2015).

One-way ANOVA test for robbery

Once again, a one-way between groups analysis of variance was conducted to explore the impact of time in this case years (2007 to 2015) on the cases of robbery in the metropolis. The robbery cases for the nine-year period was therefore analysed. The Levene's test for homogeneity of variances, which tests whether the variance in stealing cases in each of the years is the same for all the other years. A look at the significance value which was 0.258, which was greater than 0.05 meant the assumption of homogeneity of variance was not violated.

There was a statistically significant difference at the $p < .05$ level in the robbery cases over the nine-year period: F: (8, 450) = 1.96, p = 0.049. Despite reaching statistical significance, the actual difference in mean scores between the years was small. The effect size, calculated using eta squared, was 0.033. Post-hoc comparisons using the Tukey HSD test indicated that the mean score for 2007 (M = 4.80, SD = 3.58) was statistically different from that of 2014 (M = 8.00, SD = 5.89). Again, the mean score for 2009 (M = 4.96, SD = 4.44) was statistically different from that of 2014 (M = 8.00, SD = 5.89).

One-way ANOVA test for defrauding by false pretence

Lastly, a one-way between groups analysis of variance was conducted to explore the impact of time in this case years (2007 to 2015) on the cases of defrauding by false pretence in the metropolis. The defrauding by false pretence cases for the nine-year period were therefore analysed. The Levene's test for homogeneity of variances, which tests whether the variance in stealing cases in each of the years is the same for all the other years. A look at the significance value which was 0.334, which was greater than 0.05 meant the assumption of homogeneity of variance was not violated. There was no statistically significant difference between the means of any of the years which were studied in this research. This means that for defrauding by false pretence, the cases that were recorded between 2007 and 2015 were not statistically different.

Hotspot analysis

Hotspot analysis is a way of quantifying the level to which the various crime events relate to each other in the metropolis. That is identifying the suburbs which are hotspots from cold spot of the various crimes under investigation in this study. The hotspot analysis makes use of the Getis-Ord Gi* hot spot analyses, this type of analysis explains that areas with statistically significant positive z-scores, with a larger z-score is, have intense clustering of high values (hot spot). Contrary, statistically significant negative z-scores, with smaller z-score have intense clustering of low values (cold spot) (Ord and Getis, 1995).

Hotspot analysis serves to supplement the crime density analysis and can assist in measuring the degree of association that the various crimes have with the various suburbs in the metropolis. The hotspot analysis focuses only on the distribution of the four crimes. The application of this type of analysis to this study is particularly useful at an urban area level such as the Sekondi-Takoradi metropolis to highlight particular land uses including bars, nightclubs, residential areas and the fishing communities which are regarded as “crime opportunity” areas. Apart from the hotspot map, a table will be created for each crime year showing the z-score and p-value for every suburb in the metropolis and whether it is statistically significant or not.

Assault

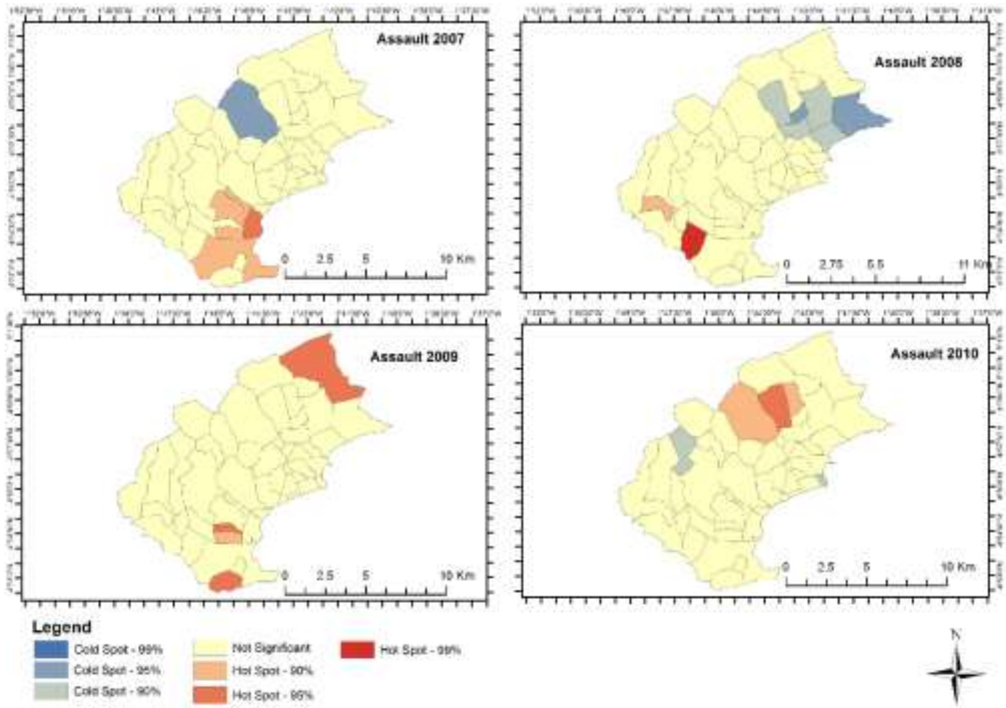


Figure 8*: Hotspot map of Assault 2007 to 2010*

Source: Fieldwork, 2015

The 2007 hotspot map of assault cases in Figure 8 showed that the five suburbs (Takoradi, Windy Ridge, New Takoradi, Effiekuma and Effia) were marked as hotspots. This was not surprising as these areas contained most of the nightclubs and pubs in the metropolis. As such during the night lots of activities occur in such suburbs. This assertion is in line with the argument put forward by Zhang & Peterson (2007) that areas that had pubs and night clubs are likely to have many assault cases than the place that had less of these pubs and night clubs. This is because most assault cases are as a result of people being intoxicated with alcohol thus, they are unable to manage their emotions. Only one suburb recorded a significant cold spot, and that is Deabenekrom, which is located at the periphery of the metropolis, thus fewer activities occur in such a place coupled with low population.

The 2008 assault hotspot map showed a surprising trend, the suburbs which were a hotspot for assault in 2007 were no longer hotspots, the hotspot had shifted to new areas. This situation might be because the Police worked hard in the hotspot areas for 2007, thus the situation shifted to other areas that the Police were not concentrating on. In terms of the spatial pattern, the 2009 map showed a different pattern, Osofokrom suburb was now a hotspot for assault, this is strange because it the suburb is at the periphery of the metropolis and thus it is a farming community where no a lot of people routine. This pattern can be attributed to the fact that the Police worked had to stop the rise in assault cases in the Central business area where this particular crime was rife, thus lost focus on other areas, the Police, therefore, dispersed the perpetrators of assault to other areas within the metropolis. This is in line with the assertion raised by Moeller (2009) that the tactics that most Police forces around the world adopt are the dispersion of criminals to other areas. That is when the crime rate of an area is increasing, the Police show up to disperse the criminal activity. But the criminals can go elsewhere to perpetrate crime.

In 2011, only two suburbs in the metropolis were hotspots (Figure 9), these

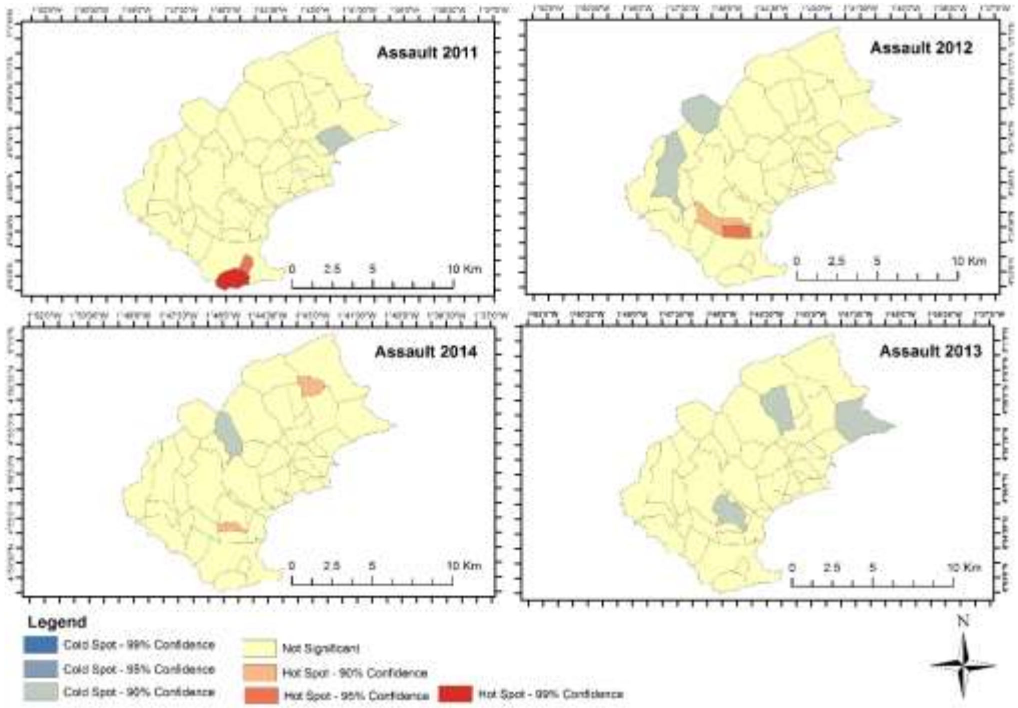


Figure 9*: Hotspot map of Assault 2011 to 2014*

Source: Fieldwork, 2015

were Beach Road with a z-score of 2.92 with a p-value of 0.00, Chapel Hill also recorded a z-score of 2.14 and p-value of 0.03. Ngyiresia was the only suburb in the metropolis that was a cold spot, recording a z-score of -1.65 and a p-value of 0.10. The pattern of the hotspot changes through the years is consistent with the argument raised by Moeller (2009) that most Police forces adopt the strategy of dispersing criminal elements from one location to the other. Thus, the hotspot patterns keep on changing from one location to another. That is why with this study, in terms of the hotspot pattern of the assault cases, there were changes in terms of the locations that were hotspots. The pattern continued to change for the 2012, 2013 and 2014. From Figure 9, it can be seen that the hotspots continued to shift from one suburb to another over the years. In 2013, there was no statistically significant hotspot suburb for assault in the Metropolis.

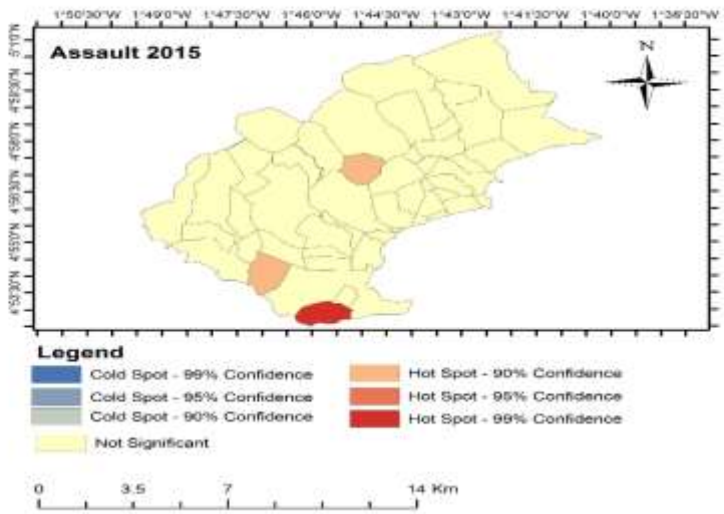


Figure 10*: Hotspot map of Assault 2015*

Source: Fieldwork, 2015

In 2015, Beach Road recorded the highest z-score of 2.70 with a p-value of 0.01, Nkroful had a z-score of 1.88 and a p-value of 0.06, Airport Ridge had a z-score of 1.77 and a p-value of 0.08. There was no cold spot for assault in 2015, the rest of the suburbs did not record z-score that were statistically significant.

Defrauding by false pretence

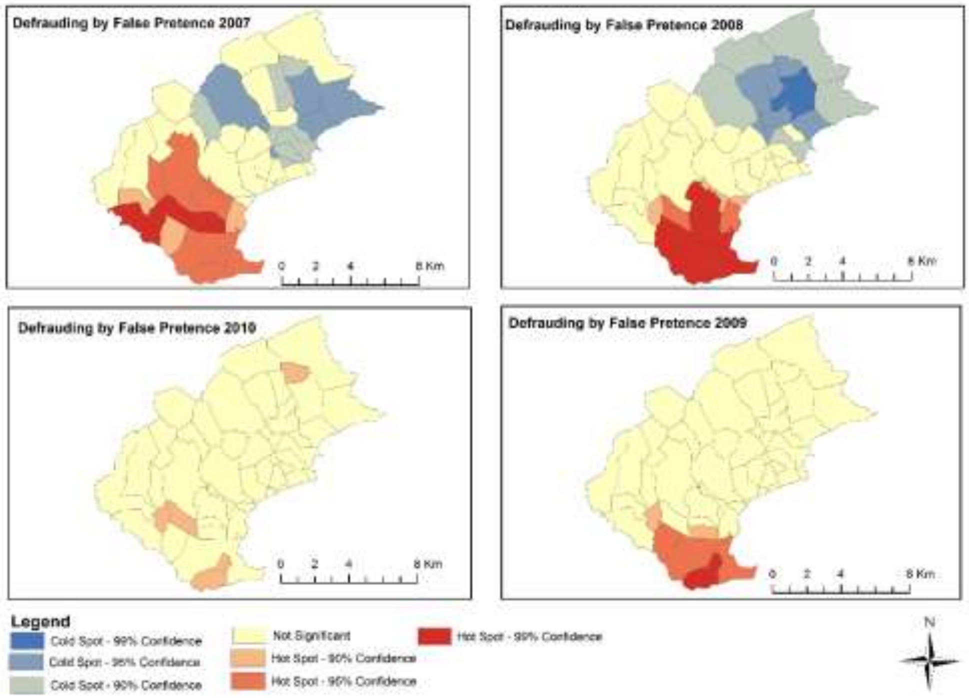
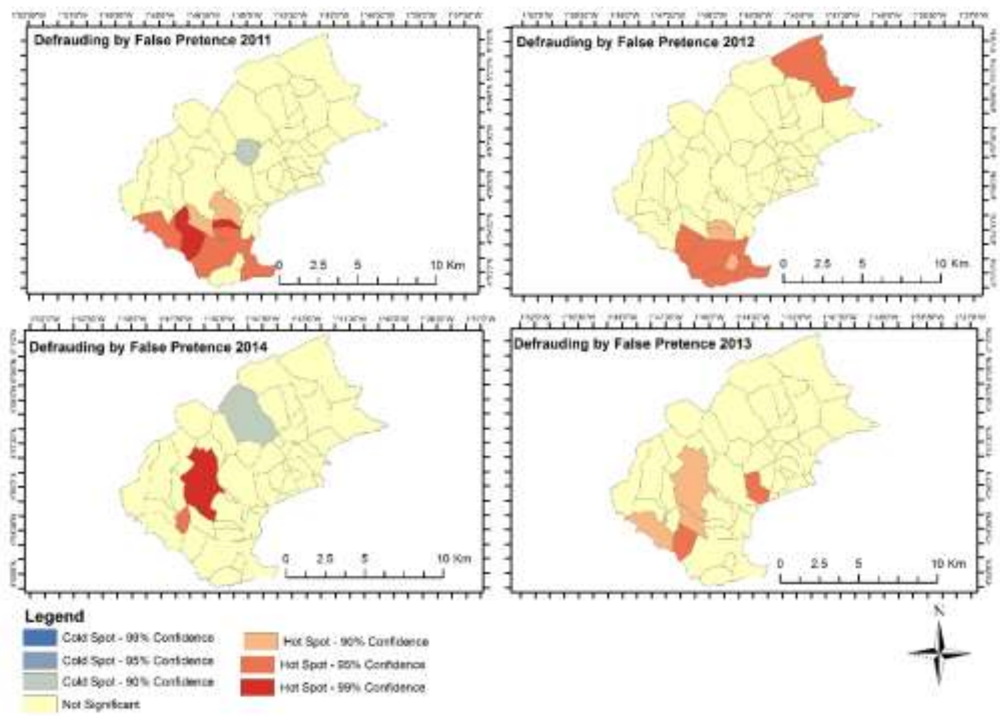


Figure 11*: Hotspot map of Defrauding by False Pretence 2007 to 2010*

Source: Fieldwork, 2015

The 2007 hotspot map of defrauding by false pretence from 2007 to 2010 showed that the hotspots were found in suburbs closer to the market areas of the metropolis. For instance, in 2008 from Figure 11, suburbs which were closer to Market Circle were hotspots with a high confidence level, this is in line with that assertion raised by Onwudiwe (2017) cases of defrauding by false pretence are normally high in areas that have market centres. A look at the cold spots for the metropolis over the years (2007 - 2010) indicates that areas at the periphery of the metropolis largely recorded negative statistically significant z-scores, making them cold spots. This is backed with the assertion raised by Marfo (2016) in which he argued that since economic activities are low in the periphery of the metropolitan, economic crimes are generally low in such areas. The z-scores for the suburbs that obtained statistically significant figures can be seen in Appendix A.

Figure 12: Hotspot map of Defrauding by False Pretence 2011 to 2014



Source: Fieldwork, 2015

The 2011 hotspot map of defrauding by false pretence in Figure 12 continued to show that most suburbs in the area around Market Circle were hotspots. Airport Ridge recorded the highest z-score of 3.20, Kwesimintsim recorded the next highest significant z-score of 2.78 with p-value of 0.01 (Table 14). The 2012 hotspot map showed a different pattern to the previous years, Osofokrom which is at the periphery of the metropolis and is predominantly a farming community was now a hotspot for crime, however this was not the case as argued by Marfo (2016), that hotspots for defrauding by false pretence are largely found in areas which are closer to busy markets centres. Tables 14 to 17 show the figures for the suburbs that recorded statistically significant z-score figures.

Robbery

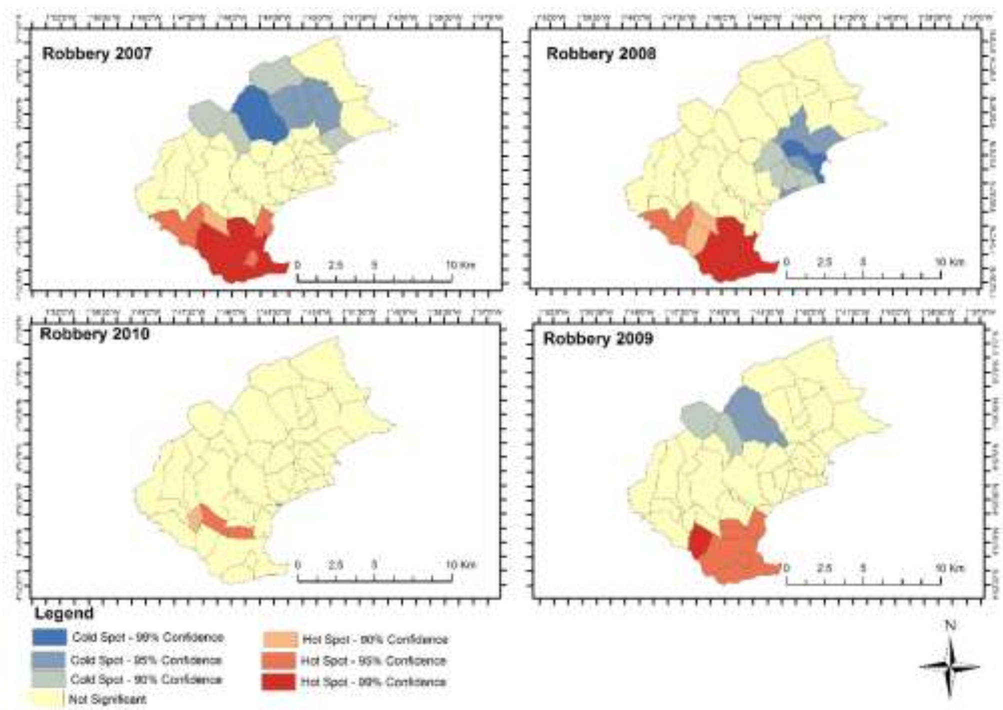


Figure 13*:Hotspot map of Robbery 2007 to 2010*

Source: Fieldwork, 2015

The robbery hotspot map (Fig 13) showed how spatial changes occurred throughout the four (4) year period. Spatially, robberies cases were concentrated in the Central Business District of the metropolis. That is the areas where business activities are quite high. Although in 2009 and 2012 robberies were at their lowest, there was still significant clustering of cases in the urban core. No hotspots in

2010(260) yet robberies were very high indicating that, policing effort is largely ad hoc and only manages to disperse robbers from the urban core with the dispersal effect lasting for only a year. High population to police ratio of about 976:1, inadequate logistical support and financing for the police may be responsible for this situation.

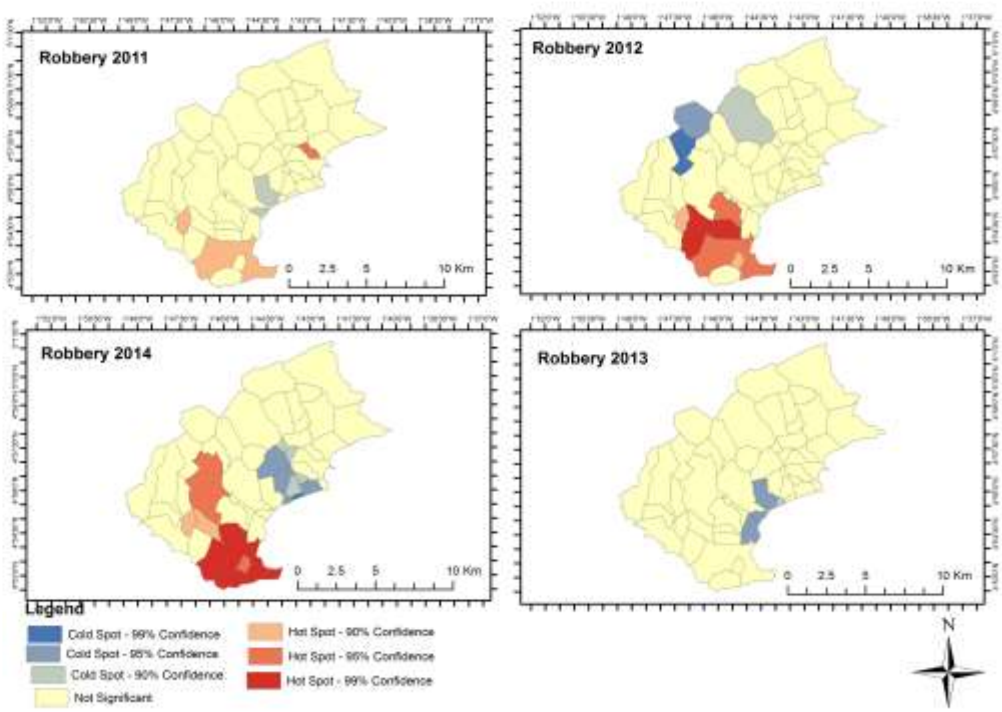


Figure 14: Hotspot map of Robbery 2011 to 2014

Source: Fieldwork, 2015

The 2011 to 2014 robbery hotspot map (Figure 14) showed that robberies have increased over the 4-year period particularly in the urban core and suggests that, the routine activity space function of the core and with its associated social disorganization is a strong draw for robberies even when absolute number of robberies decrease. There was a pattern change in the 2013 map, as there was no significant clustering of high z scores. This may be due to the fact that the Police had pushed the criminal elements to the other parts of the metropolis, thus spreading the robbery cases all over the metropolis evenly, therefore not a single suburb can have a significantly high z score.

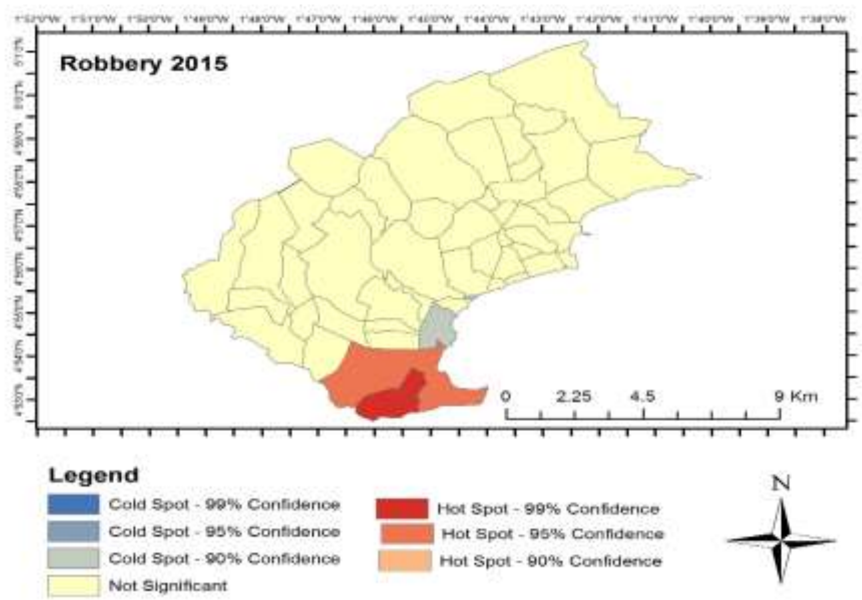


Figure 15: Hotspot map of Robbery 2015

Source: Fieldwork, 2015

The 2015 hotspot map of robbery cases showed that the spatial trend of hotspot cases was still clustered around the central business district of the metropolis. Beach Road had the highest z-score of 3.52 and a p-value of 0.00. Chapel Hill also had a z-score of 2.74 and a p-value of 0.01. New Takoradi had the lowest z-score of -1.91 and a p-value 0.06.

Stealing

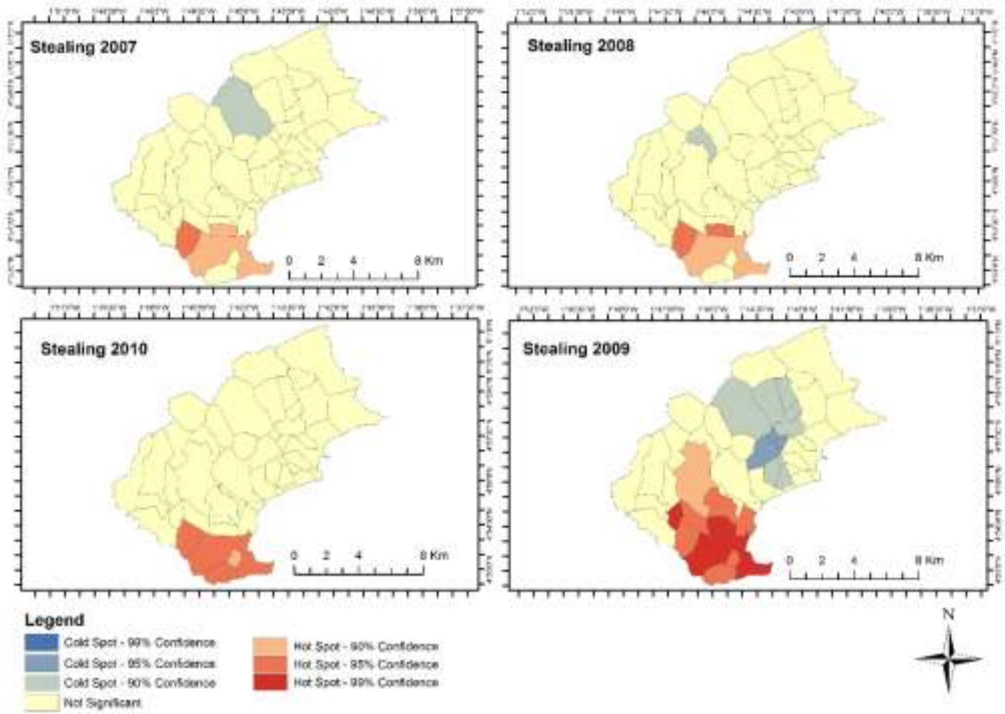


Figure 16: Hotspot map of Stealing 2007 to 2010

Source: Fieldwork, 2015

The 2007 to 2010 hotspot maps showed that like most crimes in the metropolis, hotspots of stealing were once again around the central business district. The paths of potential targets and criminals cross in these areas most of the time, as such the propensity of crime occurrence in these areas is quite high this explains why there is high clustering of stealing around the central business district (Figure 15). This is in line with the argument put forward by Cohen and Felson (1979) and Rengert (1997) that there is high clustering of crimes at locations where people frequent, as it is the same location that potential criminals and suitable target converge.

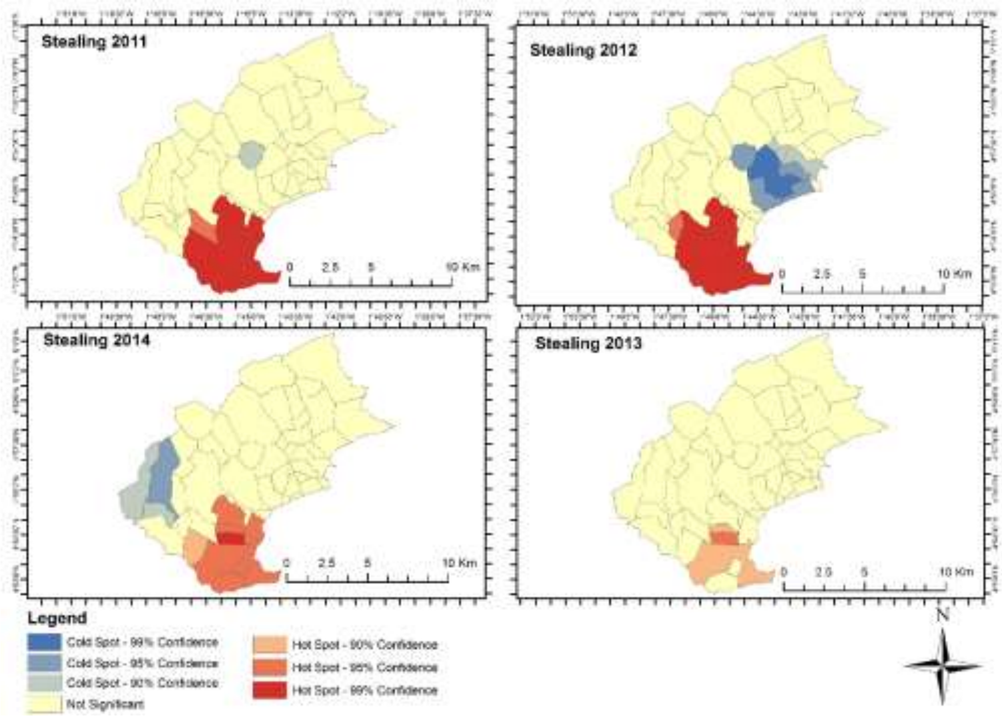


Figure 17: Hotspot map of Stealing 2011 to 2014

Source: Fieldwork, 2015

The 2011 to 2014 hotspot map was not spatially different from that of 2007 to 2010, once again there was high clustering around the central business district, this again confirms the assertion put forward by Block and Block (1995) that hotspots often surround elevated transit and major shopping sites. These areas are locations where potential victims can be located and potential offenders have options for escape. That is exactly the case with this study as lots of criminal activities take place in these areas and these criminals are always able to evade capture.

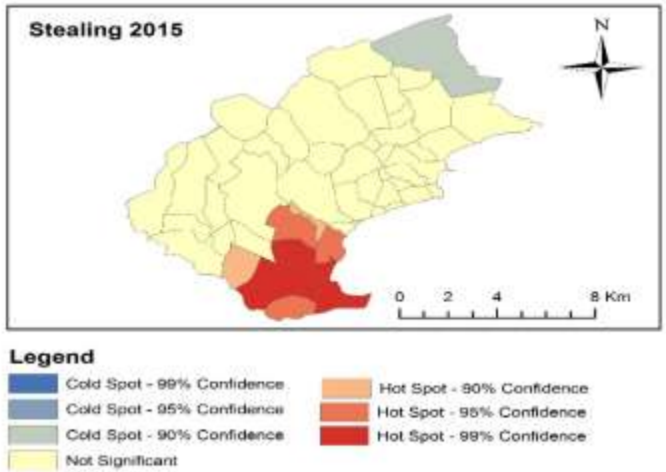


Figure 18: Hotspot map of stealing 2015

Source: Fieldwork, 2015

The 2015 hotspot map of stealing was no different from what we have seen in the previous years. There was once again high clustering around the central business districts, which contain Market Circle, the largest market in the region.

Total Crime

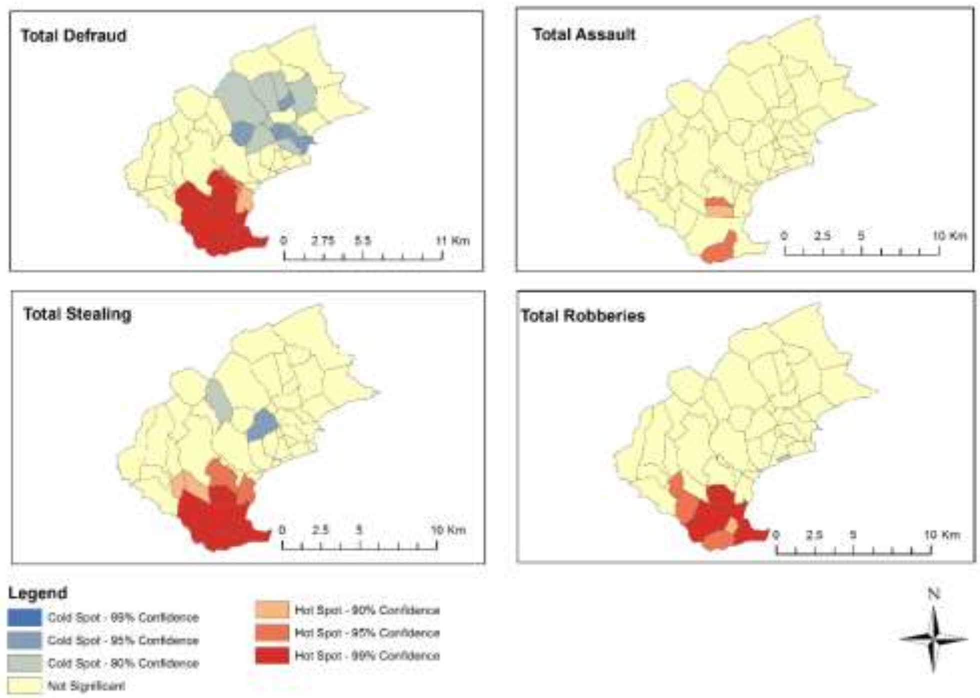


*Figure 19:*Hotspot map for total crime 2007 to 2015

Source: Fieldwork, 2015

The total crime cases from 2007 to 2015 for the four crimes were put together for the various suburbs and a hotspot map was generated. From the Figure 19, a look at the hotspot map of the total reported cases of defrauding by false pretence in the Sekondi-Takoradi metropolis between 2007 and 2015 showed that the southern part of the metropolis, around the Takoradi area (Figure 19). A look at the total assault cases revealed that majority of the suburbs recorded z-scores which were not statistically significant to either be a hotspot or a cold spot. From the map, only four suburbs obtained z-scores which were statistically significant to be hotspots. East Tanokrom obtained the highest z-score of 2.10 and a p-value of 0.04, whilst both Beach Road and Chapel Hill obtained z-scores of 1.97 and p-values of 0.05, Windy Ridge recorded the lowest z-score of 1.72 and a p-value of 0.09.

The hotspot map for the total cases of robbery showed that the highest clustering remained at the southern part of the metropolis, around the Takoradi area (Figure 13). Just like the hotspot map for assault, majority of the suburbs obtained z-scores which were not statistically significant. The only cold spot was found in Ekuasi, which obtained a z-score of -1.69 and a p-value of 0.09. Takoradi obtained the highest z-score of 3.39 and a p-value of 0.00.

Finally, the hotspot map for stealing continued to show that majority of the crimes reported in the metropolis continued to have their hotspots at the southern part of the metropolis. Takoradi recorded the highest z-score of 3.94 and a p-value of 0.00, Windy Ridge also recorded a z-score of 3.82 and a p-value of 0.00. Butumagyebu recorded the lowest z-score of -2.14 and a p-value of 0.03 whilst Kansaworado recorded -1.67 as z-score and a p-value of 0.10.

Routine activity space

The third objective which was the creation of a routine activity space map to show how certain suburbs in the Sekondi-Takoradi metropolis were highly or lowly routine. The aim was to show which suburbs in the metropolis was highly routine and which suburbs were not. The map (figure 20) showed the different level of busy activities that characterise the metropolis. As expected, areas around the central business district were coloured in deep colour, meaning they were highly routine.

Whilst the areas at the periphery of the metropolis were coloured in a light colour. Interestingly, as one moves northward away from the central business district, the colour becomes lighter. The deeply coloured parts of the metropolis are the suburbs within which a lot of people frequent. These are the same suburbs that host the big market places, hotels, nightclubs, pubs and many other places that people frequent. The results of the routine activity space map was a combination of population data, road network, and the land use data for the metropolis, with varying influences on the final map.

This result provides further justification to the assertion raised by Groff (2008) that areas that market places provide attraction to people in terms of economic activities. Again, people usually frequent entertainment centres such as nightclubs and pubs, thus a suburb that has any of these entertainment centres is likely to attract people. Furthermore, since one of the determinants of the routine activities in the population, areas that had higher population were likely to be coloured in deep orange.

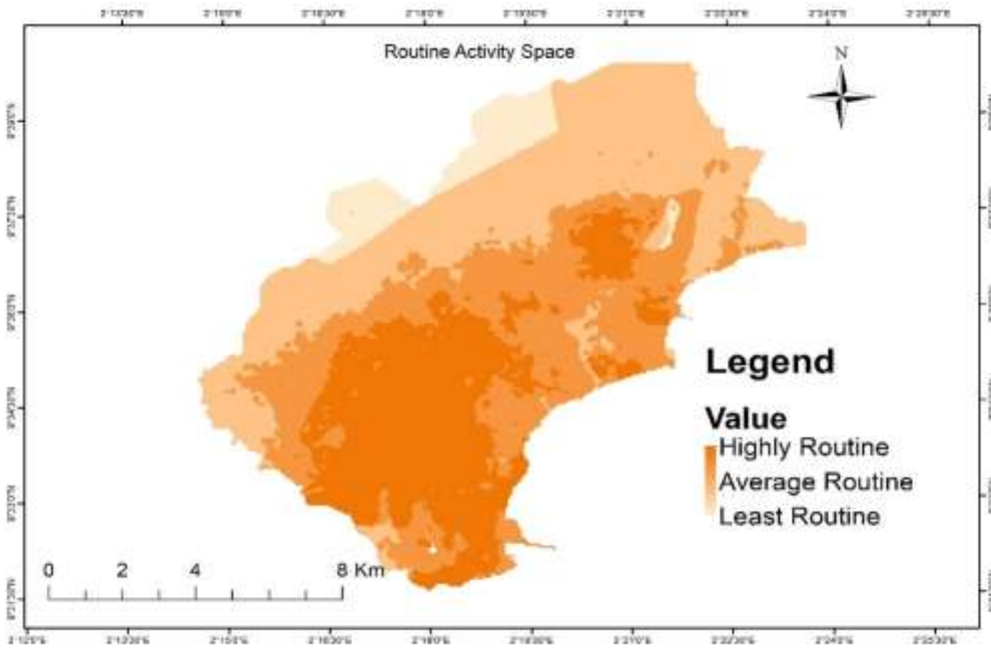


Figure 20: Routine activity space map of STMA

Source: Fieldwork, 2015

Regression Analysis

In this study, the global regression model Ordinary Least Squares (OLS) and the local regression model Geographically Weighted Regression (GWR) were applied to examine the influence of routine activity spaces in the metropolis and their effect on the location of the various crime hotspots. Separate models are estimated for the four crimes whereas the variables included in both analysis are the same.

The Exploratory Regression tool in ArcGIS 10.3.1 runs OLS regression analysis on all possible combinations of the input variables in order to find a properly specified OLS model (Rosenhein, Scott, & Pratt, 2011). Consequently, the Exploratory Regression tool was used to identify the explanatory variables generating the highest model performance when predicting crime hotspot in

Sekondi-Takoradi Metropolis; both in respect to the adjusted R^2 , AICc, BPK and VIF values.

Geographically weighted regression can be used to establish the level of variation between hotspots, land use and the distance to the nearest police post at the local level. The level of variation between these three variables is measured by the calculation of the r-squared statistic at a local level. Second, the geographically weighted regression technique is able to predict the number of crime hotspots (as the dependent variable) that occurs in different areas (routine activity spaces) and their distances to the nearest police stations. When analysing socio-economic data, this (geographically weighted) regression technique is commonly applied at the enumeration level (suburb level) (Mennis 2006).

In this study, the geographically weighted regression analysis is applied on the various crime (stealing, assault, robbery and defrauding by false pretence) of hotspot areas (dependent variable) and routine activity spaces (independent variable), the distance to the nearest police station (independent variable) present within the metropolis. When making predictions at the various suburbs, the model calculates an intercept value, routine activity space coefficient value and residual error value per hotspot suburb.

Regression analysis will be presented for all the four crimes which this study investigated.

Stealing (OLS)

The results of the OLS test revealed that the coefficient of routine activity space (grid code) variable is positive. This means that as the higher the routine activity of the suburb, the higher the rate of crime. That is, when an area is highly routine, the rate of crime will also be higher. A look at the coefficient of the near distance variable showed that it was negative. This means that the location of the police stations did not have any effect on the stealing hotspots in the metropolis. Again, a look at the level of redundancy among the independent variables showed that the VIF (variance inflation factor) of all the independent variables was 1.09. The results of the OLS test also showed that all of the independent variables recorded statistically significant coefficients, the adjusted r squared showed a value of 0.14, again looking at the Akaike's Information Criterion (AICc) value which is a measure of model performance and is helpful for comparing different regression models, the OLS test recorded 1247.42.

Lastly, the Koenker test is statistically significant, it therefore indicates relationship between the explanatory variables and the dependent variable are non-stationary. This means that the near distance variable might be an important predictor of stealing hotspots in some locations in the metropolis but weak predictor in other locations. This means the model can be improved by applying geographically weighted regression. This test was used in the work by Vilalta (2013), where he tried to compare the results of the OLS and GWR tests. According to his research the OLS test has to deal with the global relationships.

Robbery OLS

The results of the OLS test revealed that the coefficient of routine activity space (grid code) variable is positive (0.065). This means that as the higher the grid code, the higher the rate of crime. That is, when an area has a high routine activity code, the higher the crime rate. A look at the coefficient of the near distance variable showed that it was negative. This means that the location of the police stations did not have any effect on the stealing hotspots in the metropolis. Again, a look at the level of redundancy among the independent variables showed that the VIF (variance inflation factor) of all the independent variables was 1.09, the adjusted r squared showed a value of 0.08. The Koenker test is statistically significant, it therefore indicates relationship between the explanatory variables and the dependent variable are non-stationary. This means that the near distance variable might be an important predictor of stealing hotspots in some locations in the metropolis but weak predictor in other locations, again looking at the Akaike's Information Criterion (AICc) value which is a measure of model performance and is helpful for comparing different regression models, the OLS test recorded 1104.41. This means the model can be improved by applying geographically weighted regression.

Assault OLS

The results of the OLS test revealed that the coefficient of routine activity space (grid code) variable is positive. This indicates the higher the grid code, the higher assault hotspot. A look at the coefficient of the near distance variable showed that it was negative. This means that the assault rate increases, as the location of the nearest police station moves further from the hotspot. Again, a look at the level of redundancy among the independent variables showed that the VIF (variance inflation factor) of all the independent variables was 1.09, the adjusted r squared showed a value of 0.01, again looking at the Akaike's Information

Criterion (AICc) value which is a measure of model performance and is helpful for comparing different regression models, the OLS test recorded 407.87.

Lastly, the Koenker test is statistically significant, it therefore indicates relationship between the explanatory variables and the dependent variable are non-stationary. This means that the near distance variable might be an important predictor of stealing hotspots in some locations in the metropolis but weak predictor in other locations. This means the model can be improved by applying geographically weighted regression.

Defrauding by false pretence OLS

The results of the OLS test revealed that the coefficient of routine activity space (grid code) variable is positive. This indicates the higher the grid code, the higher the rate of crime. That is, when an area has a high routine activity code, the higher the crime rate. A look at the coefficient of the near distance variable showed that it was negative. This means that as the crime rate increases, the location of the nearest police station moves further from the hotspot. Again, a look at the level of redundancy among the independent variables showed that the VIF (variance inflation factor) of all the independent variables was 1.09. The results of the OLS test also showed that all of the independent variables recorded statistically significant coefficients, the adjusted r squared showed a value of 0.15, again looking at the Akaike's Information Criterion (AICc) value which is a measure of model performance and is helpful for comparing different regression models, the OLS test recorded 1291.93.

Lastly, the Koenker test is statistically significant, it therefore indicates relationship between the explanatory variables and the dependent variable are non-stationary. This means that the near distance variable might be an important predictor of stealing hotspots in some locations in the metropolis but weak predictor in other locations. This means the model can be improved by applying geographically weighted regression.

Stealing GWR

The results of the application of geographically weighted regression model at the suburb level showed an r-squared value of up to 84 percent. This means that around 84 percent of the stealing hotspots can be explained by the routine activity spaces and the distance to the nearest police station in the metropolis, this provides a reasonably accurate basis for predicting stealing hotspots at the routine activity space level and the distance to the nearest police station. Again, a look at the AICc which recorded 631.61 showed that this figure was much lower than the AICc in the OLS model, indicating that the GWR model is a better fit for this data than the OLS model.

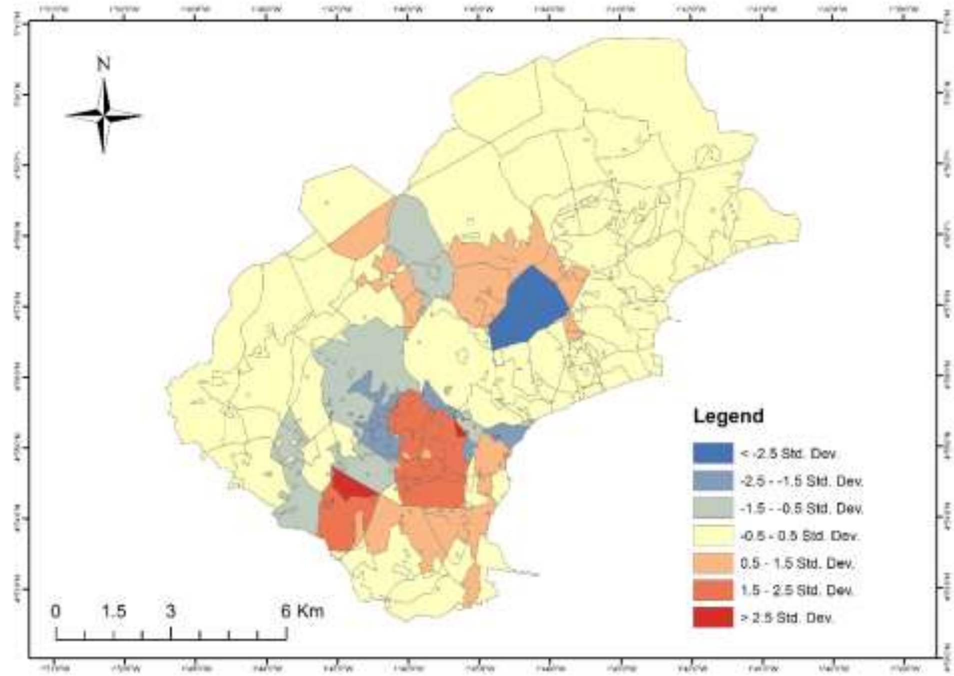


Figure 21: Geographical weighted regression of Routine activity space, stealing and nearest police stations

Source: Fieldwork, 2015

Robbery GWR

The results of the application of geographically weighted regression model at the suburb level showed an r-squared value of up to 79 percent. This means that around 79 percent of the total robbery hotspots can be explained by the routine activity spaces and the distance to the nearest police station in the metropolis, this provides a reasonably accurate basis for predicting stealing hotspots at the routine activity space level and the distance to the nearest police station. Again, a look at the AICc which recorded 579.10 showed that this figure was much lower than the AICc in the OLS model, indicating that the GWR model is a better fit for this data than the OLS model. The areas with the standard deviation of more than 2.5 indicates that there is a strong relationship between the level of robbery hotspots, routine activity space and the distance to the nearest police station. This result is in line with that of Cahill & Mulligan (2007) who examined a structural model of violent crime in Portland, Oregon, exploring spatial patterns of both crime and its covariates. The GWR was used to estimate a local model, producing a set of mappable parameter estimates and t-values of significance that vary over space. In their work, it was found out that there is a strong relationship between places that are highly routine and the occurrence of robbery.

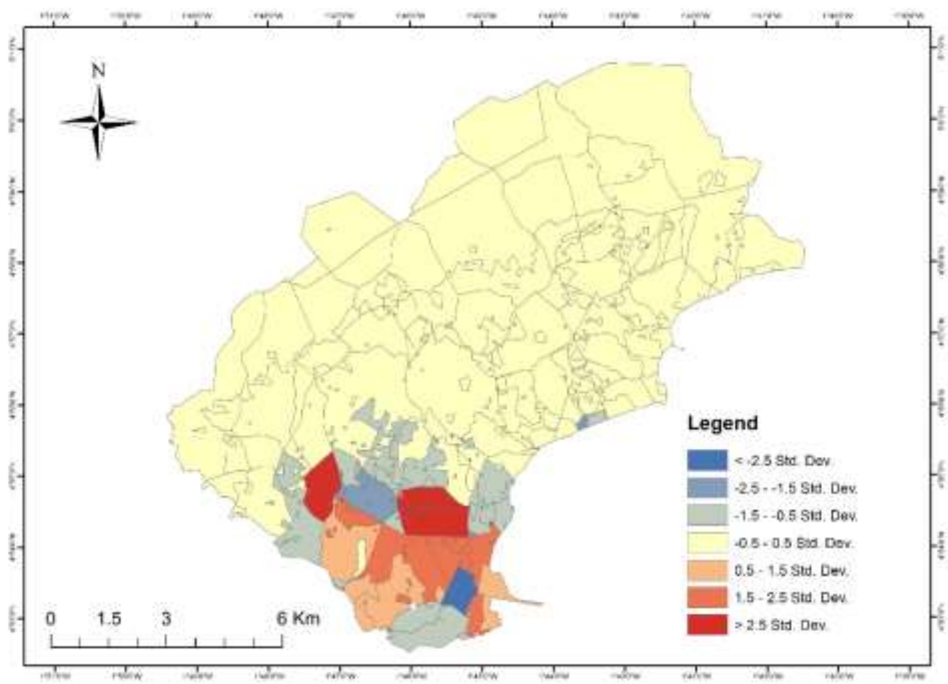


Figure 22: Geographical weighted regression of Routine activity space, robbery and nearest police stations

Source: Fieldwork, 2015

Defrauding by false pretence GWR

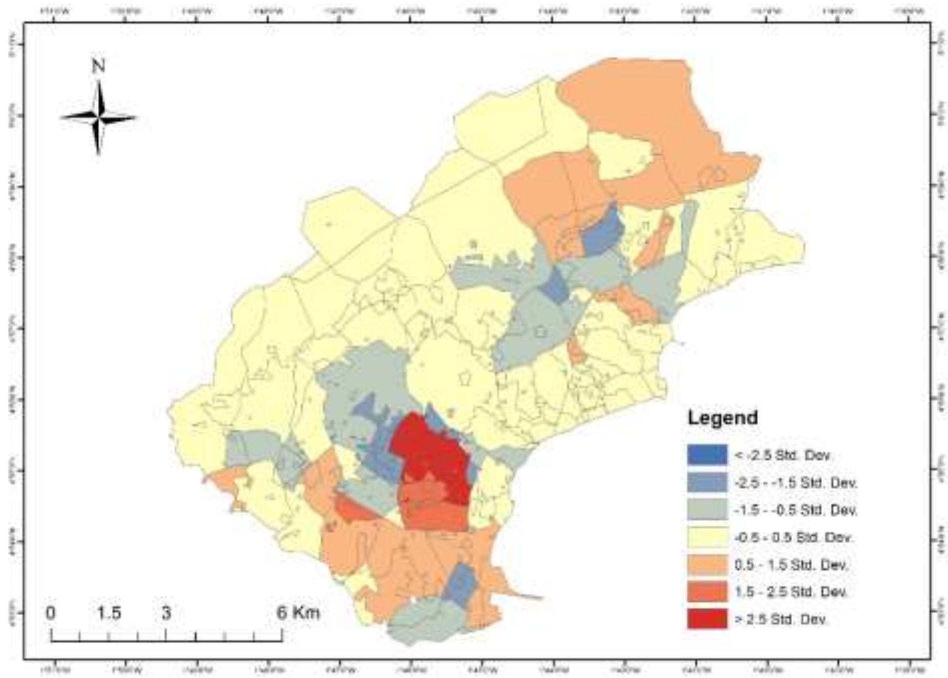


Figure 23: Geographical weighted regression of Routine activity space, defrauding by false pretence and nearest police stations

Source: Fieldwork, 2015

The results of the application of geographically weighted regression model at the suburb level showed an r-squared value of up to 78 percent. This means that around 78 percent of the total defrauding by false pretence hotspots can be explained by the routine activity spaces and the distance to the nearest police station in the metropolis, this provides a reasonably accurate basis for predicting defrauding by false pretence hotspots at the routine activity space level and the distance to the nearest police station. Again, a look at the AICc which recorded 812.73 showed that this figure was much lower than the AICc in the OLS model, indicating that the GWR model is a better fit for this data than the OLS model. The areas with the standard deviation of more than 2.5 indicates that there is a strong relationship between the defrauding by false pretence hotspots, routine activity space and the distance to the nearest police station, whilst the areas in the blue colour indicates a weak relationship between the variables.

Assault GWR

The results of the application of geographically weighted regression model at the suburb level showed an r-squared value of up to 54 percent. This means that around 54 percent of the total assault hotspots can be explained by the routine activity spaces and the distance to the nearest police station in the metropolis, this provides a reasonably accurate basis for predicting assault hotspots at the routine activity space level and the distance to the nearest police station. Again, a look at the AICc which recorded 178.80 showed that this figure was much lower than the AICc in the OLS model, indicating that the GWR model is a better fit for this data than the OLS model. The areas with the standard deviation of more than 2.5 indicates that there is a strong relationship between the assault hotspots, routine activity space and the distance to the nearest police station, whilst the areas in the blue colour indicates a weak relationship between the variables.

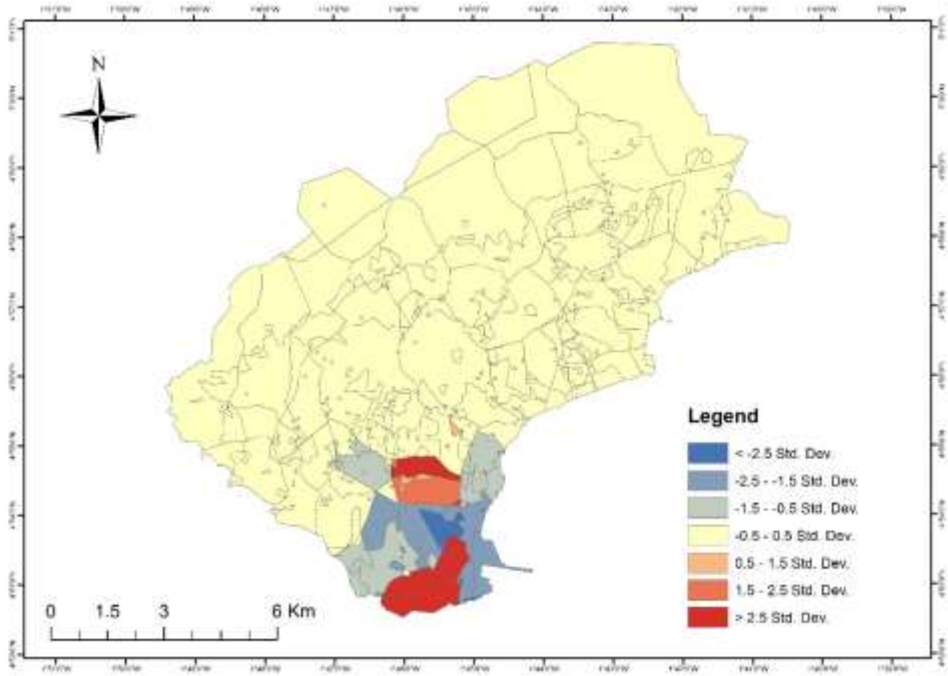


Figure 24: Geographical weighted regression of Routine activity space, assault and nearest police stations

Source: Fieldwork, 2015

Discussions

The main hypothesis of this study was that a higher level of routine activity would increase crime rate and that this relationship would remain when controlling for further spatial and socio-economic variables. Furthermore, the relationship was not expected to be spatially uniform, thus a spatial regression model such as the GWR was expected to better predict crime hotspots compared to a non-spatial OLS. Consequently, the results obtained in Sekondi-Takoradi indicate some support for the hypothesis; both in respect to the crime hotspots and in respect to the model performance of the spatial GWR model. The results in Sekondi-Takoradi demonstrated that routine activity space is positively associated with crime hotspot and that the spatial regression model of GWR was a better fit to the data than the non-spatial regression model of OLS. This highlights the importance of using a global regression model to assess statistically significant relationships and the use of a local regression model to examine regional variations within the data; revealing spatial patterns that were not identified by the global model. These results coincide with the suggestions by Fotheringham, Brunsdon, & Charlton (2003) implying that the local GWR model would generate higher model performance than a global model when modelling spatial data.

OLS results for the four crimes hotspots in Sekondi-Takoradi implied the data to possess regional variations, thus motivating the use of the spatial regression model of GWR to allow regional variations within the data (Gao & Li, 2011). Comparing the OLS and GWR models for the four crimes, there are differences both in respect to model structure and performance. Additionally, results vary in respect to modelling the same data with the global regression model of OLS and the local regression model of GWR. The explanatory variables possessing a statistically significant relationship (at the 5% level) with crime hotspots in Sekondi-Takoradi Metropolis was routine activity space and the distance to the nearest Police Station. Both the variables of routine activity and the distance to the nearest Police Station concerns the physical causes of crime hotspots, thus the association between these variables show support for the theory that crime occurrence is a derived effect; where ultimately routine activity space is what matters Ahmadi (2003).

Except for generating higher model performance, one of the key benefits of utilising the GWR model was the computation of coefficient raster surfaces that displayed the relationship between crime hotspots and each explanatory variable exclusively (Fotheringham, Brunsdon, & Charlton, 2003). By analysing the coefficient surfaces of the variables possessing a statistically significant relationship with crime hotspots, it is possible to detect trends and inform both local and region wide policy (Ali, Partridge, & Olfert, 2007).

Chapter Summary

This chapter focussed on the presentation of the results and the analysis of the findings of the survey. It included details of the results of the field work and these were segmented along the lines of statistical analysis of reported crimes, hotspot analysis, routine activity space and regression analysis. It was further found that the southern part of the metropolis was where most of the crime hotspots were found, especially the suburbs surrounding Takoradi, which is the busiest suburb in the metropolis. The study also covered the regression analysis of the various crimes and their relationship with other variables such as the distance to the closest police station and how routine the area is. It was found out that areas which were crime hotspot were also areas which were highly routine for people.

CHAPTER FIVE

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

Introduction

Chapter Five of the study primarily focussed on presenting the results of the study which addresses the study objectives. It gives a blueprint within which to place spatial analysis of crime in relation to crime mapping especially in a metropolitan city such as Sekondi-Takoradi Metropolis. Attempts were made to juxtapose the findings within the strategic framework of the Ghana Police Service. Based on the analysis and summary of findings, conclusions and inferences were made. The chapter ends with recommendations put forward to inform policy decisions.

Summary of major findings

The overarching objective of this study was to analyse the spatial patterns crime in the Sekondi-Takoradi metropolis and to see which suburbs in the metropolis are hotspots for the selected crimes investigated in this study. As part of efforts to achieve the overall objective of the study, the researcher set out to collect crime data from the various police stations within the metropolis over a nine (9) year period and spatially analyse them.

The study further endeavoured to analyse statistically the temporal variations in robbery, stealing, assault and defrauding by false pretence in Sekondi-Takoradi Metropolis. Attempts were also made to identify the hotspots and cold spots for the four crimes in the metropolis. In addition to this, the routine activity spaces within the metropolis was also mapped. The study then examined the influence of the routine activity space theory on the location of crime hotspots in the metropolis.

It was highlighted succinctly from reviewed literature, that the basic unit that breeds crime and disorder in the society is a breakdown in formal and informal community control as well as broad changes in the society. These changes have altered the way people live their lives, that is changes in the routine activities of people have increased the number of suitable targets as people continually work to amass wealth.

Also, as people work away from their homes, their property is left without any capable guardian and this seems to be the attraction points for a motivated offender to commit crime like burglary (Cohen and Felson, 1979). In a similar vein, Shaw and McKay (1969) adopted the neighbourhood structure to define the characteristics of a socially disorganised society. A socially disorganised community is characterised by the inability of that community to identify with the common values of its residents and maintain effective social controls.

In line with this claim, the study was designed to spatially analyse crime in STMA. The establishment of an appreciable context for the research work and further investigation into the gaps in existing research works was done through the review of various empirical and theoretical literatures concerning the subject matter. The study was conducted within the Sekondi-Takoradi Metropolis and specifically focused on four different crimes which were the highest recorded crimes in the metropolis.

In the following, some of the study's objectives were restated and the key findings and conclusions reached are presented:

i. *To conduct a statistical analysis of crime from 2007 to 2015*

It was found out that between the years 2007 and 2015, stealing was the most committed crime in the metropolis, followed closely by assault. Robbery, which is a violent crime increased over the 9-year period particularly in the urban core and suggests that, the routine activity space function of the core and with its associated social disorganization is a strong draw for robberies even when absolute number of robberies decrease. Crime in the metropolis generally increased over the study period, the metropolis being one of the fastest growing metropolis in Ghana, coupled with the fact that workers oil companies were now moving in to the area, it thus became a major attraction point for criminals (Owusu & Afutu-Kotey, 2010).

ii. To identify crime hotspots in the metropolis

The nature and dynamics of certain suburbs within the metropolis made those suburbs to be hotspots for the crimes reviewed in this study. The Central Business District of the metropolis was constantly a crime hotspot for stealing throughout the years. Suburbs such as Market Circle, Beach Road, Chapel Hill, Takoradi and Airport Ridge were crime hotspots because of the special characteristics that they had.

iii. To map the locations of routine activity spaces of the metropolis

The areas closer to the Central Business District were highly routine whilst the areas further away from the Central Business District were less routine. The highly routine areas were coloured in deep colours to indicate their level of activities. These highly routine areas had high population, big market centres coupled with entertainment spots. These characteristics were thus a major attractor of people into these suburbs.

iv. To examine the influence of routine activity spaces on crime hotspots

The influence of the routine activity spaces in the metropolis on the various crime hotspots cannot be over emphasised. From analysis, it was seen that where the routine activities were high, the level of crime were also high. It was also noted that in some areas, the distance to the nearest Police Station did not have any effect on the hotspots, that is, the Police Stations were in the suburbs yet crime rate was still high.

Conclusions

From the summary findings, it can be concluded that the statistical analysis of the four crimes, namely, assault, theft, robbery and defrauding by false pretence in the metropolis showed varying results. Robbery was on the ascendency in the urban core of metropolis suggesting that the routine activity space function of the core is a strong draw for criminals who are bent on perpetrating this heinous crime. With the brisk economic activities going on in the metropolis, it was surprising that defrauding by false pretence was the least committed crime in the metropolis among the four crimes that the study investigated.

In some years, there were no hotspots for some of the crimes in the metropolis yet the crime rate was very high indicating that, policing effort is largely ad hoc and only manages to disperse robbers from the urban core with the dispersal effect lasting for only a year. This dispersal sometime leads the criminals to find solace in the periphery of the metropolis and to continue their criminal activities there.

Most of the suburbs around the Central Business District were highly routine, that is, these suburbs possessed special characteristics that made it attractive for people to go to these places. These are the same suburbs that host the big market places, hotels, nightclubs, pubs and many other places that people frequent. The results of the routine activity space map were a combination of population data, road network, and the land use data for the metropolis, with varying influences on the final map.

The study shows that the characteristics of a place clearly influence crime distributions. In this study, assault hotspots were generally located in the urban areas, especially at market centres and places that people frequent. These results are similar to patterns highlighted in the research of Gruenewald, Freishthler, Remer, LaScala and Treno (2006) who, through statistical analysis, established a strong relationship between assaults and place which were modified by population characteristics. Defrauding by false pretence hotspots were also generally located in the most urban suburbs of the metropolis, just as the total robbery hotspots which were also generally located at suburbs where there was a lot of routine activities. In this study, the influence of population was obvious with very high associations identified between the various crimes and the selected predicting variable of routine activity spaces which included the population densities of all the suburbs.

Recommendations

Based on the findings and conclusions of the study, the following recommendations were made:

1. The Ghana police service should set up GIS departments in all police stations to provide spatial analysis of resource allocation for administrative planning.
2. The patrol units should be equipped with GPS so that their locations could be known. This will make it easier for the police to pin point the locations of on-going crimes in the metropolis.
3. When building new police stations, the communities or neighbourhoods are generally divided according to boundaries of neighbourhoods or roadways. But the level of service needed, number of incidents and also the land use are more important factors that should be looked at while building the police new police stations. In addition, dividing the police stations based on only demographics, the resources may be allocated improperly. Because there may be several areas where there are thousand inhabitants but they generate few criminal incidents for service, while there are less people that require much greater levels of service. For example, commercial areas do not have any inhabitants especially at the nights but they are more prone to incidents.
4. In addition to the police, many organisations can influence the extent of crime incidents. Professional organisations such as town and country planning department, and Ghana highway authority come into picture when one is talking about physical environment within which crime takes place. Both short and long-term measures can be taken by these organisations which will reduce the

likelihood of crime and the fear of crime. For instance, highway authority may improve street lightning in a particularly vulnerable areas, or the planners might design a residential layout so as to avoid the creation of crime-prone areas.

5. Substantially decrease the population to police ratio to UN recommended levels of 500 citizens to 1 police personnel.

Opportunities for further research

The research has highlighted that there even though there is a wide range of literature on urban crime; there are very few comparable available studies that focus on urban crime using contemporary mapping techniques. It is noted that published, reputable studies on spatial crime analysis have to date, been limited mainly to Australia and the United States, such as urban centres of Sydney, Melbourne, Los Angeles, Cincinnati and Chicago. The failure to replicate such studies in different geographic environments is a particular concern as it is difficult to gain an impression as to whether urban crime is a peculiarly Anglo-American, metropolitan or large urban phenomenon as distinct from Ghanaian metropolitan and rural areas.

The lack of spatial analysis to date is surprising given the generally high level of community and academic interest in crime and the wider significance of a critical social and geography related issue. Studies of this type could be replicated effectively throughout other metropolitan areas in Ghana, and the availability of source data means that there is no impediment to such studies being carried out in this country, to see if the same patterns of crime in Australia and the United States are reproduced at the urban and at the rural level here in Ghana. Different or unusual patterns from that found in the United States could point to other local influences on the various crimes.

There is still opportunity for research into the development of a better integrated geographic information system that allows for the automation not only of spatial analysis processes but also of data aggregation processes taking place in Microsoft Excel. Although there has been recent development of automated procedures in ArcGIS in the form of scripting tools, a completely integrated Geographic Information System combining the functionality of Excel with ArcGIS software allowing the complete automation of spatial analysis, data aggregation, cartographic design and map presentation within one module has not yet been developed. With recent technological advancements, it is feasible to suggest that the possibility for an integrated system is not too far away.

Finally, this research has illustrated that geographic information systems enable the effective analysis and description of crime data using maps. The old adage of “A picture is worth a thousand words” (Anon) is particularly relevant when analysing data as maps are able to provide detail on the location and relationship between crime and location. It is also significant to this research study that maps also provide an aesthetically appealing way of presenting information in ways that is easily understood through the application of correct cartographic principles such as balance, the use of colour, data classification, etc. With further developments in Geographic Information Systems and spatial analysis it can safely be expected that there will continue to be widespread and effective use of mapping in crime research.

Limitations

Although GIS is a useful tool in the investigation of spatial patterns of crime, it is inevitably limited by the amount of spatial data that are available. In the process of collecting the necessary data the most important problem that was encountered in the thesis is to get the incident data. It is a very difficult process to receive the required data from the related institutions in Ghana. Especially police would not like to provide the incident data to any outsource since they keep them in a secret and think that if the information of where the incidents take place is published, personal privacy may be damaged or they do not want to worry inhabitants about the safety of their neighbourhood or they do not want people to doubt about their performance or the efficiency of their work.

Furthermore, the information of the incidents is not related to the happened but only reported incidents. That means the amount of the incidents may not reflect the existing status since there may be more incidents, but are not reported. In addition, the definite rate of the victimisation is not known. For this problem in order to find the amount of wronged people, a victimisation survey in which questionnaires are prepared and ask people if they are exposed to any incidence should be realised.

In addition, for land use dataset it is also not possible to obtain detail information about the usage of the functions. For instance, if the information of the number and locations of the restaurants or nightclubs with alcohol or the ratio of the commerce and residence usage of a building or the type of the commercial usage such as shop, market, stadium, factory, restaurant or bar are received the results will be more meaningful, accurate and realistic.

REFERENCES

Adebayo, A. A. (2013). Social factors affecting effective crime prevention and control in Nigeria. *International Journal of Applied Sociology, 3(4)*, 71 - 75.

Adinkrah, M. (2010). Vigilante homicides in contemporary Ghana Justice, 33(5). *Journal of Criminal*, 413 – 427.

Ahmadi, M. (2003). *Crime Mapping and Spatial Analysis.* Thesis submitted to INTERNATIONAL INSTITUTE FOR GEO-INFORMATION SCIENCE AND EARTH OBSERVATION, ENSCHEDE, THE NETHERLANDS.

Ahmed, M., & Salihu, R. S. (2013). *Spatiotemporal Pattern of Crime Using Geographic Information System (GIS) Approach.* Kano State: AJER.

Akakpo, G. S. (2012). Social Impact Assessment of Oil and Gas Exploration In The Western Region of Ghana: A Case of Sekondi-Takoradi Metropolis. *Regional Maritime University Journal, 2*, 44 - 62.

Akpinar, E. (2005). *Using geographic informations systems in analysing the pattern of crime incidents and the relationship between landuse and incidents.* Ankara, Turkey: Middle East Technical University Graduate School of Natural and Applied Sciences.

Akpinar, E., & Usul, N. (2003). *Geographic Information Systems Technologies in Crime Analysis and Crime Mapping.*

Ali, K., Partridge, M. D., & Olfert, M. R. (2007). Can Geographically Weighted Regressions Improve Regional Analysis and Policy Making? *International Regional Science Review, 30*, 300 - 329.

Almeida, E. S., Haddad, E. A., & Hewings, G. J. (2005). The spatial pattern of crime in Minas Gerais: an exploratory analysis. *Economia Aplicada, 9(1)*, 39 - 55.

Amankwaah, C. (2013). Election-related violence: The case of Ghana. *Nordiska Afrikainstitutet*.

Andresen, M. A., & Malleson, N. (2015). Intra-week spatial-temporal patterns of crime. *Crime science, 4(1)*, 1-11.

Aning, E. K. (2006). An Overview of the Ghana Police Service. *Journal of Security Sector Management, 4(2)*, 1-37.

Anselin, L., Griffiths, E., & Tita, G. (2008). Crime mapping and hot spot analysis. *Environmental criminology and crime analysis*, 97-116.

Appiahene-Gyamfi, J. (2009). Crime and Punishment in the Republic of Ghana: A Country Profile. *International Journal of Comparative and Applied Criminal Justice, 33:2*, 309 - 324.

Badiora, A. I., & Afon, A. O. (2013). Spatial pattern of crime in Nigerian traditional city: The Ile-Ife experience. *International Journal of Criminology and Sociological Theory 6*, 14 - 29.

Bailey, T. C., & Gatrell, A. C. (1995). *Interactive Spatial Data Analysis.* England: Addison Wesley Longman Limited.

Barak, G. (2009). *Criminology: An integrated approach.* New York: Rowman & Littlefield Publishers.

Block, C. R. (1998). The Geoarchive: An Information Foundation for Community Policing. In D. Weisburd, & T. McEwen, *Crime Mapping and Crime Prevention* (pp. 27 - 81). Monsey, New York: Criminal Justice Press.

Block, R. L., & Block, C. R. (1995). "Space, Place and Crime: Hot Spot Areas and Hot Places of Liquor – Related Crime". In J. E. Eck, & D. (. Weisburd, *Crime and Place,*. Monsey, NY: Criminal Justice Press.

Bob-Milliar, G. M. (2014). Party youth activists and low-intensity electoral violence in Ghana: a qualitative study of party foot soldiers' activistim. *African studies quartely, 15(1)*, 125.

Bowers, K. J., Johnson, S. D., & Pease, K. (2004). Prospective Hotspotting: The Future of Crime Mapping. *British Journal of Criminology, 44*, 641 - 658.

Boylan-Kemp, J. (2013). Catherine Elliott and Frances Quinn. *Criminal Law*, 119-121.

Brantingham, P. J. (1984). *Patterns in crime.* New York, NY: Macmillian Publishing Company.

Brantingham, P. J., & Tita, G. (2008). Offender mobility and crime pattern formation from first principles . *Artificial crime analysis systems: using computer simulations and geographic information systems*, 193-208.

Brookman-Amissah, M., Wemegah, T. D., & Okyere, F. T. (2014). Crime Mapping and Analysis in the Dansoman Police Subdivision, Accra, Ghana - A Geographic Information Systems Approach. *Journal of Environment and Earth Science*, 28-38.

Bruce, C. W., Hick, S. R., & Cooper, J. P. (2004). *Exploring Crime Analysis: Readings On Essential Skills.* Overland Park, KS: International Association of Crime Analysts.

Brunsdon, C., Fotheringham, S., & Charlton, M. (1998). Geographically weighted regression. *Journal of the Royal Statistical Society: Series D (The Statistician), 47(3)*, 431-443.

Burkhardt, B. C., & Connor, B. T. (2015). Durkheim, punishment, and prison privatization. *Social Currents, 3(1)*, 84-99.

Cahill, M., & Mulligan, G. (2007). Using geographically weighted regression to explore local crime patterns. *Social Science Computer Review, 25(2)*, 174-193.

Carson, D. C., & Felthous, A. R. (2003). Mens rea. *Behavioral sciences & The Law, 21(5)*, 559-562.

Ceccato, V. &. (2008). Comparing Spatial Patterns of Robbery: Evidence from A Western and an Eastern European City. *Cities*, *25*, 185-196.

Chainey, S., & Ratcliff, J. (2005). *GIS and crime mapping.* Washington DC: John Wiley & Sons, Inc.

Chainey, S., Tompson, L., & Uhlig, S. (2008). The utility of hotspot mapping for predicting spatial patterns of crime. *Security Journal, 21 (1-2)*, 4 - 28.

Chang, D. H., & Janeksela, G. M. (1996). An analysis of the Korean criminal justice system. *Comparative Criminal Justice*, 411-425.

Charron, M. (2009). *Neighbourhood characteristics and the distribution of police-reported crime in the City of Toronto.* Toronto: Canadian Centre for Justice Statistics.

Christie, N. (2004). *A suitable amount of crime.* Makato: Psychology Press.

Clark, P. J., & Evans, F. C. (1954). Distance to nearest neighbor as a measure of spatial relationships in populations. *Ecology, 35 (4),* 445-453.

Cohen, L. E., & Felson, M. (1979). Social change and crime rate trends: A routine's activity approach. *American Sociological Review, 44(4)*, 588-608.

Cohen, L. E., Kluegel, J. R., & Land, K. C. (1981). Social inequality and predatory criminal victimization: An exposition and test of a formal theory. *American Sociological Review*, 505-524.

Costanzo, M. A., & Gerrity, E. (2009). The effects and effectiveness of using torture as an interrogation device: Using research to inform the policy debate. *Social Issues and Policy Review, 3(1)*, 179 - 210.

Criminal Code, The (Act 29). (1960). Tema: Ghana Publishing Corp.

Dale, M. R., & Fortin, M. J. (2014). *Spatial analysis: a guide for ecologists.* Cambridge University Press.

Douglas, J., Burgess, A. W., Burgess, A. G., & Ressler, R. K. (2013). *Crime classification manual: A standard system for investigating and classifying violent crime.* John Wiley & Sons.

Eck, J. E., & Weisburd, D. L. (2015). *Crime places in crime theory*. Maryland: Adventure Press.

Fafa, H. B. (2010). High crime rate in Ghana. *Jayee University College.* Mallam, Ghana.

Fayeye, J. (2010). Ethnic militia: National security, democracy and development. *Department of Sociology, University of Ilorin, Ilorin*, 13 - 26.

Fitzgerald, R., Wisener, M., & Savoie, J. (2004). Neighbourhood characteristics and the distribution of crime in Winnipeg. *Canadian Centre for Justice Statistics, Statistics Canada*, 1-63.

Fotheringham, A. S., Brunsdon, C., & Charlton, M. (2003). *Geographically weighted regression: the analysis of spatially varying relationships.* New York: John Wiley & Sons.

Fox, W., & Bayat, M. S. (2007). *A guide to managing research.* San Francisco: Juta Publications.

Frimpong, L. K. (2016). Geography of fear of crime: Examining intra-urban differentials in Sekond-Takoradi Metropolis, Ghana. *Ghana Journal of Geography, 8(1),* 79 - 102.

Gao, J., & Li, S. (2011). Detecting spatially non-stationary and scale-dependent relationships between urban landscape fragmentation and related factors using Geograpphically Weighted Regression. *Applied Geography, 31 (1)*, 292 - 302.

Groff, E. R. (2008). Adding the temporal and spatial aspects of routine activities: A further test of routine activity theory. *Security Journal, 21 (1-2)*, 95 - 116.

Groff, E. R., & La Vigne, N. G. (2002). Forecasting the future of predictive crime mapping. *Crime Prevention Studies, 13*, 29-58.

Groff, E. R., & LaVigne, N. G. (2001). Mapping an opportunity surface of residential burglary. *Journal of Research in Crime and Delinquency, 38 (3)*, 257 - 278.

Gruenewald, P. J., Freishthler, B., Remer, L., LaScala, E. A., & Treno, A. (2006). Ecological models of alcohol outlets and violents: crime potentials and geospatial analysis. *Addiction, 101 (5)*, 666 - 677.

Hagan, F. E. (2010). *Crime types and criminals.* Crochard: Sage.

Haining, R. (1994). Designing spatial data analysis modules for geographical information systems. *Spatial Analysis in GIS*, 45-63.

Hale, C., Hayward, K., Wahidin, A., & Wincup, E. (2013). *Criminology (3rd edn).* Oxford University Press.

Harries, K. D. (1980). *Crime and the environment.* Springfield, Illinois: Charles C Thomas Publisher.

Havi, D. E. (2014). The economic impact of crime rate on economic performance in Ghana. *Academic Research International SAVAP International, Vol. 5*, 25 - 37.

Hayward, K. (2004). *City Limits: Crime Consumer Culture and the Urban Experience,.* London: Glasshouse Press.

Hedrick, T. E., Bickman, L., & Rog, D. J. (1993). *Applied research desing: A practical guide (Vol. 32).* Illinois: Sage Publications.

Hesseling, R. B. (2005). Displacement: A review of the empirical literature. In R. V. Clarke, *Crime Prevention Studies, vol. 3* (pp. 12 - 39). Monsey, NY: Criminal Justice Press.

Hiropoulos, A., & Porter, J. (2014). Visualising property crime in Gauteng: Applying GIS to crime pattern theory. *SA Crime Quarterly, (47)*, 17-28.

Hirschi, T. (1969). A control theory of delinquency. *Criminology Theory: Selected Classic Readings*, 289 - 305.

Jacquez, G. M. (2008). Spatial cluster analysis. *The Handbook of Geographic Information Science*, 395 - 416.

Jefferis, E. (1999). *A multi-method exploration of crime hot spots: A summary of findings.* Washington: U.S. Department of Justice, National Institute of Justice, Crime Mapping Research Center.

Julien, P. Y., Saghafian, B., & Ogden, F. L. (1995). Raster-based hydrologic modeling of spatially-varied surface runoff. *Journal of the American Water Resources Association, 31(3)*, 523-536.

Kubrin, C. E., & Weitzer, R. (2003). New directions in social disorganization theory. *Journal of Research in Crime and Delinquency, 40(4)*, 374-402.

Manolache, R., Totan, L., & Burcea, S. G. (2011). Analysis of crime rate in developing regions of Romana. *Management Research and Practice Vol. 3 Issue 3*, 63 - 70.

Marfo, S. (2016). Sustaining development through policing: Wa Municipality in Perspective. *Journal of Sociology 4*, 162 - 171.

Mennis, J. (2006). Mapping the results of geographically weighted regression. *The Cartographic Journal, 43(2)*, 171-179.

Miethe, T. D., & Meier, R. F. (1994). *Crime and its social context: Toward an integrated theory of offenders, victims, and situations.* Chicago: Suny Press.

Milovanovic, D. (2006). Legalistic definition of crime and an alternative view. *Annals of the Faculty of Law in Belgrade (54)3*, 78 - 86.

Mitchell, A. (2005). *The ESRI guide to GIS analysis: geographic patterns & relationships (Vol. 1).* New Orleans: ESRI, Inc.

Moeller, K. K. (2009). Police crackdown on Christiaia in Copenhagen. *Crime, Law and Social Change, 52(4)*, 337 - 345.

Numbeo. (2015, September 12). *Crime in Ghana. Safety in Ghana*. Retrieved from http://www.numbeo.com/crime/country_result

Obeng-Odoom, F. (2014). Oil, sex and temporary migration: The case of Vienna City, Sekondi-Takoradi, Ghana. *The Extractive Industries and Society, 1(1)*, 69 - 74.

Onwudiwe, I. D. (2017). Transnational crimes: The case of advanced fee fraud in Nigeria. *Pan-African Issues in Crime and Justice*, 99 - 120.

Ord, J. K., & Getis, A. (1995). Local spatial autocorrelation statistics: distributional issues and an application. *Geographical Analysis, 27(4)*, 286-306.

Osei-Tutu, E., Badu, E., & Owusu-Manu, D. (2010). Exploring corruption practices in public procurement of infrastructural projects in Ghana. *International Journal of Managing Projects in Business, 3(2)*, 236-256.

Oteng-Ababio, M. (2016). The Oil is Drilled in Takoradi, but the money is counted in Accra: The Paradox of plenty in the oil city, Ghana. *Journal of Asian and African studies*, 2 - 19.

Oteng-Ababio, M., Owusu, A. Y., Owusu, G., & Wrigley-Asante, C. (2016). Geographies of crime and collective efficacy in urban Ghana. *Territory, Politics, Governance*, 1 - 19.

Owusu, G., & Afutu-Kotey, R. L. (2010). Poor urban communities and municipal interface in Ghana: A case study of Accra and Sekondi-Takoradi metropolis. *African Studies Quarterly, 12(1)*, 1-16.

Owusu, G., Wrigley-Asante, C., Oteng-Ababio, M., & Adobea, Y. O. (2015). Crime prevention through environmental design (CPTED) and built-environmental manifestations in Accra and Kumasi , Ghana. *Crime Prevention and Community Safety 17 (4)*, 249-269.

Prades, J. A. (2013). *An Introduction to four major works 1984. Archives de sciences sociales des religions.* Beverly Hills,: Sage Publications.

Rengert, G. F. (1997). Auto theft in central Philadelphia. *Policing for prevention: Reducing crime, public intoxication and injury, 7*, 199 - 219.

Ripley, B. D. (1977). Modelling spatial patterns. *Journal of the Royal Statistical Society. Series B Methodological*, 172-212.

Rosenhein, L., Scott, L., & Pratt, M. (2011). *Exploratory Regression: A Tool for Modeling Complex Phenomena.* ESRI.

Rossmo, K. (2000). *Geographic profiling.* Boca Raton, Florida: CRC Press.

Schmalleger, P. F. (2009). *Criminal Justice Today: An Introductory Text for the 21st Century.* NJ: Pretence Hall.

Schwendinger, H., & Schwendinger, J. (2001). *Defenders of Order or Guardians of. What Is Crime?: Controversies over the Nature of Crime and What to Do about It.* NJ: Pretence Hall.

Service, G. S. (2014). *2010 population and housing census report.* Accra.

Shaw, C. R., & McKay, H. D. (1942). *Juvenile delinquency and urban areas.* Cincinnati, OH: Anderson Publishing Co.

Simons, R. L. (2003). Incidents of discrimination and risk for deliquency: A longitudinal test of strain theory with an African American sample. *Justice Quarterly, 20(4)*, 827 - 854.

Van Gyampo, R. E. (2011). Saving Ghana from its oil: A critical assessment of preparations so far made. *Africa Today, 57(4)*, 48-69.

Vilalta, C. J. (2013). How exactly does place matter in crime analysis? Place, space and spatial heterogeneity. *Journal of Criminal Justice Education 24(3)*, 290 - 315.

Walker, R. (2011, March 8). *Oil boom changes face of Ghana city.* Retrieved from BBC: http://www.bbc.co.uk/news/world-africa-12646359

Wilcox, P., Land, K., & Hunt, S. A. (2004). Criminal circumstance: a multicontextual criminal opportunity theory. *Symbolic Interaction, 27(1)*.

Wiles, P., & Costello, A. (2000). *The road to nowhere: The evidence for traveling criminals.* UK: Development and Statistics Directorate, Home Office.

Zhang, H., & Peterson, M. P. (2007). A spatial analysis of neighbourhood crime in Omaha, Nebraska using alternative measure of crime rates. *Internet Journal of Criminology*, 1 - 28.

Zhang, S. X., Roberts, R. E., & McCollister, K. E. (2011). Therapeutic community in a California prison: Treatment outcomes after 5 years. *Crime & Delinquency*, *57(1)*, 82-101.

Appendix A

Table 1: Crime data for 2007

Suburb	Defrauding	Stealing	Assault	Robbery
New Takoradi	3	7	4	2
Apremdo	5	8	4	5
Takoradi	6	17	19	14
Effia	5	6	4	3
East Tanokrom	5	3	2	4
Windy Ridge	1	3	6	4
Kwesimintsim	3	9	3	5
Airport Ridge	6	7	5	9
Chapel Hill	9	4	8	9
Beach Road	5	8	4	6
Race Course	7	5	3	6
Assakae	2	5	5	5
Adientem	8	9	11	6
West Tanokrom	7	7	6	6
Nkontompo	3	4	11	5
Effiekuma	5	10	20	9
Adiembra	3	2	3	5
Bakaekyir	0	5	3	4
Sekondi	3	6	9	9
Bakado	3	8	14	5
Ekuasi	7	3	2	6
Butumagyebu	3	10	12	7
Ngyamuabaka	0	3	6	1
Fijai	6	2	5	4
Kwekuma	4	7	5	5
Ketan Estates	2	7	7	4
European Town	0	0	0	0
Ngyiresia	1	4	5	2
Essikado	3	8	6	2
Sekondi Ridge	4	9	5	6
Mempeasem	1	4	9	1
Essipon	0	8	7	6
Ahinkofikrom	2	7	4	2
Mpintsin	0	5	3	0
Ketan	1	7	9	3
Osofokrom	1	8	6	2
Nkroful	0	6	3	3
Anoe	3	2	1	1
Anoekuma	0	5	1	3
Twabewu	2	4	2	1
Eshiem	0	1	2	0
Ntwaaban Nkwanta	5	9	13	5
Kojokrom	2	6	1	2
Kansaworado	3	4	1	0
Anaji	8	6	7	3
Mampong	0	4	6	1
Ntankoful	1	6	8	5
Essaman	0	4	7	1
Bomba	0	2	3	1
Whindo	1	1	2	1

Source: Fieldwork (2015)

Table 2: Crime data for 2008

Suburb	Defrauding	Stealing	Assault	Robbery
New Takoradi	5	6	3	4
Apremdo	6	5	12	3
Takoradi	19	16	11	16
Effia	6	4	7	0
East Tanokrom	7	3	7	5
Windy Ridge	7	4	7	4
Kwesimintsim	8	10	15	6
Airport Ridge	8	8	3	8
Chapel Hill	1	8	3	9
Beach Road	8	4	5	6
Race Course	0	5	7	6
Assakae	5	6	8	0
Adientem	4	6	3	4
West Tanokrom	2	6	3	9
Nkontompo	8	4	4	3
Effiekuma	5	9	4	6
Adiembra	6	7	6	0
Bakaekyir	6	4	8	3
Sekondi	5	6	7	4
Bakado	1	2	3	0
Ekuasi	6	3	4	0
Butumagyebu	3	7	9	6
Ngyamuabaka	2	3	5	0
Fijai	2	5	7	5
Kwekuma	4	7	5	5
Ketan Estates	2	8	5	3
European Town	3	5	9	3
Ngyiresia	0	4	7	1
Essikado	1	8	7	3
Sekondi Ridge	0	4	2	2
Mempeasem	0	2	4	1
Essipon	1	5	2	3
Ahinkofikrom	0	7	5	2
Mpintsin	0	4	1	2
Ketan	2	4	3	2
Osofokrom	0	8	5	8
Nkroful	0	4	6	3
Anoe	0	3		2
Anoekuma	1	6	0	3
Twabewu	0	6	7	5
Eshiem	3	6	9	3
Ntwaaban Nkwanta	1	6	8	3
Kojokrom	4	3	6	3
Kansaworado	4	3	8	5
Deabenekrom	3	8	2	5
Anaji	3	3	6	4
Mampong	2	4	7	4
Ntankoful	0	1	6	2
Essaman	0	9	6	6
Bomba	3	8	3	4

Source: Fieldwork (2015)

Table 3: Crime data for 2009

Suburb	Defrauding	Stealing	Assault	Robbery
New Takoradi	4	11	6	5
Apremdo	5	7	3	8
Takoradi	18	18	25	19
Effia	0	5	6	3
East Tanokrom	0	5	8	4
Windy Ridge	0	6	5	3
Kwesimintsim	9	15	11	5
Airport Ridge	8	15	6	6
Chapel Hill	6	22	9	9
Beach Road	6	13	3	2
Race Course	0	6	6	3
Assakae	0	3	8	5
Adientem	3	7	3	5
West Tanokrom	5	24	9	8
Nkontompo	5	6	8	5
Effiekuma	3	23	15	4
Adiembra	3	6	3	0
Bakaekyir	0	6	8	3
Sekondi	8	14	9	8
Bakado	2	13	9	4
Ekuasi	0	4	4	3
Butumagyebu	3	7	3	8
Ngyamuabaka	1	4	4	2
Fijai	0	4	9	4
Kwekuma	0	6	6	0
Ketan Estates	1	5	2	3
European Town	3	6	8	3
Ngyiresia	1	7	9	4
Essikado	3	6	8	3
Sekondi Ridge	3	5	8	5
Mempeasem	0	4	1	1
Essipon	3	15	6	5
Ahinkofikrom	5	3	8	2
Mpintsin	0	3	6	3
Ketan	5	8	8	4
Osofokrom	2	9	14	8
Nkroful	1	5	9	3
Anoe	0	2	5	2
Anoekuma	1	5	3	5
Twabewu	0	3	6	4
Eshiem	0	4	8	0
Ntwaaban Nkwanta	5	12	14	8
Kojokrom	2	7	14	2
Kansaworado	0	7	7	0
Deabenekrom	2	6	12	0
Anaji	7	12	16	2
Mampong	0	8	5	3
Ntankoful	1	7	8	3
Essaman	1	4	8	2
Bomba	2	5	4	2
Whindo	0	3	7	2

Source: Fieldwork (2015)

Table 4: Crime data for 2010

Suburb	Defrauding	Stealing	Assault	Robbery
New Takoradi	6	7	4	4
Apremdo	0	8	5	4
Takoradi	11	18	12	9
Effia	2	2	7	0
East Tanokrom	0	6	3	0
Windy Ridge	5	14	16	2
Kwesimintsim	9	8	6	4
Airport Ridge	4	9	1	16
Chapel Hill	1	7	5	9
Beach Road	0	6	5	2
Race Course	3	6	11	6
Assakae	2	2	5	0
Adientem	0	3	2	5
West Tanokrom	3	4	7	12
Nkontompo		4	1	5
Effiekuma	2	10	15	21
Adiembra	0	2	2	5
Bakaekyir	1	5	1	0
Sekondi	6	9	9	5
Bakado	7	14	8	11
Ekuasi		3	0	0
Butumagyebu	4	12	9	6
Ngyamuabaka	3	1	4	0
Fijai	6	6	7	8
Kwekuma	3	2	7	0
Ketan Estates	0	5	4	9
European Town	3	5	7	6
Ngyiresia	2	6	1	0
Essikado	4	6	7	3
Sekondi Ridge	2	9	7	5
Mempeasem	0	6	4	4
Essipon	1	9	6	9
Ahinkofikrom	3	6	9	7
Mpintsin	0	1	6	4
Ketan	1	2	7	5
Osofokrom	0	9	0	9
Nkroful	0	6	8	4
Anoe	2	7	5	6
Anoekuma	3	13	9	7
Twabewu	0	4	8	5
Eshiem	2	7	9	4
Ntwaaban Nkwanta	7	6	11	9
Kojokrom	5	6	8	0
Kansaworado	2	3	6	3
Deabenekrom	4	8	12	7
Anaji	0	7	2	1
Mampong	2	12	7	6
Ntankoful	5	4	4	5
Essaman	0	7	3	5
Bomba	3	5	1	3
Whindo	0	4	3	0

Source: Fieldwork (2015)

Table 5: Crime data for 2013

Suburb	Defrauding	Stealing	Assault	Robbery
New Takoradi	1	9	3	1
Apremdo	2	12	5	14
Takoradi	5	27	16	8
Effia	5	0	5	7
East Tanokrom	1	16	3	1
Windy Ridge	2	4	2	3
Kwesimintsim	7	6	19	5
Airport Ridge	5	8	11	7
Chapel Hill		14	5	5
Beach Road	1	12	7	15
Race Course	0	7	9	5
Assakae	3	3	9	2
Adientem	2	9	10	1
West Tanokrom	9	5	5	4
Nkontompo	3	5	4	0
Effiekuma	3	42	16	17
Adiembra		15	15	7
Bakaekyir	4	5	3	3
Sekondi	8	25	11	9
Bakado	4	16	3	14
Ekuasi	7		9	0
Butumagyebu	8	13	19	5
Ngyamuabaka	0	1	6	1
Fijai	9	9	0	9
Kwekuma	3	4	7	2
Ketan Estates	0	7	3	2
European Town	0	14	14	8
Ngyiresia	5	3	3	4
Essikado	0	8	11	5
Sekondi Ridge	3	7	8	6
Mempeasem	0	5	12	3
Essipon	1	9	5	8
Ahinkofikrom	0	6	8	4
Mpintsin	0	5	0	7
Ketan	0	7	0	4
Osofokrom	5	5	8	6
Nkroful	0	6	7	8
Anoe	0	8	9	0
Anoekuma	0	6	5	4
Twabewu	4	7	4	7
Eshiem	6	7	0	5
Ntwaaban Nkwanta	3	19	23	13
Kojokrom	5	12	7	8
Kansaworado	4	6	5	2
Deabenekrom	0	9	4	5
Anaji	4	1	6	10
Mampong	0	7	5	8
Ntankoful	0	3	8	6
Essaman	0	7	11	4
Bomba	0	7	9	7
Whindo	1	5	4	2

Source: Fieldwork (2015)

Table 6: Crime data for 2014

Name	Defrauding	Stealing	Assault	Robbery
New Takoradi	3	9	9	7
Apremdo	3	4	3	5
Takoradi	6	28	7	7
Effia	0	8	4	6
East Tanokrom	2	3	2	10
Windy Ridge	0	12	15	6
Kwesimintsim	9	12	14	13
Airport Ridge	1	4	0	9
Chapel Hill	1	13	9	16
Beach Road	3	10	6	23
Race Course	0	4	5	4
Assakae	4	3	8	5
Adientem	6	5	3	13
West Tanokrom	10	18	13	7
Nkontompo	2	4	1	4
Effiekuma	11	18	17	16
Adiembra	5	8	2	3
Bakaekyir		7	0	1
Sekondi	7	14	19	15
Bakado	7	15	17	5
Ekuasi	0	9		0
Butumagyebu	3	7	12	3
Ngyamuabaka	0	4	2	2
Fijai	0	16	9	14
Kwekuma	7	6	7	2
Ketan Estates	4	2	5	4
European Town	0	3	6	5
Ngyiresia	1	10	3	7
Essikado	8	6	11	7
Sekondi Ridge	6	7	7	6
Mempeasem	0	8	2	8
Essipon	1	11	6	5
Ahinkofikrom	0		3	6
Mpintsin	0	12	6	8
Ketan	2	3	6	4
Osofokrom	6	0	14	7
Nkroful	0	0	0	5
Anoe	0	12	8	4
Anoekuma	4	11	13	8
Twabewu	1	4	12	1
Eshiem	0	13	0	4
Ntwaaban Nkwanta	7	11	7	8
Kojokrom	7	12	9	13
Kansaworado	0	9	3	3
Deabenekrom	3	6	4	9
Anaji	2	6	8	13
Mampong	2	2	5	6
Ntankoful	4	8	3	4
Essaman	0	6	3	7
Bomba	4	6	4	9
Whindo	0	1	4	5

Source: Fieldwork (2015)

Table 7: Crime data for 2015

Name	Defrauding	Stealing	Assault	Robbery
New Takoradi	5	6	7	7
Apremdo	3	6	8	2
Takoradi	13	30	25	27
Effia	0	19	2	0
East Tanokrom	0	9	5	1
Windy Ridge	0	6	3	2
Kwesimintsim	3	10	17	6
Airport Ridge	8	10	5	8
Chapel Hill	4	8	16	6
Beach Road	1	11	3	8
Race Course	0	9	7	2
Assakae	2	5	0	3
Adientem	0	9	5	2
West Tanokrom	5	8	6	5
Nkontompo	0	5	0	0
Effiekuma	2	19	9	7
Adiembra	1	5	0	1
Bakaekyir	0	5	0	0
Sekondi	8	13	8	11
Bakado	0	5	13	11
Ekuasi	0	4	1	1
Butumagyebu	3	6	19	8
Ngyamuabaka	0	2	0	0
Fijai	3	9	11	7
Kwekuma	7	9	17	4
Ketan Estates	2	12	5	5
European Town	6	5	2	4
Ngyiresia	0	15	1	3
Essikado	3	5	7	5
Sekondi Ridge	0	8	3	8
Mempeasem	3	9	9	4
Essipon	0	13	6	7
Ahinkofikrom	3	4	5	2
Mpintsin	0	0	4	6
Ketan	0	7	4	7
Osofokrom	3	2	13	7
Nkroful	5	3	9	2
Anoe	0	5	4	3
Anoekuma	0	8	3	6
Twabewu	0	6	4	5
Eshiem	1	4	8	5
Ntwaaban Nkwanta	5	9	7	12
Kojokrom	0	10	5	0
Kansaworado	1	2	0	0
Deabenekrom	3	11	8	2
Anaji	3	8	3	3
Mampong	8	7	2	8
Ntankoful	4	3	0	5
Essaman	0	6	8	6
Bomba	2	3	0	3
Whindo	6	4	5	2

Source: Fieldwork (2015)

Table 8: Total crime data

Suburb	Defrauding	Stealing	Assault	Robbery
New Takoradi	51	82	52	46
Apremdo	26	69	55	53
Takoradi	154	345	290	189
Effia	19	61	43	27
East Tanokrom	17	81	37	34
Windy Ridge	17	76	67	34
Kwesimintsim	65	159	136	80
Airport Ridge	52	88	43	85
Chapel Hill	69	193	144	149
Beach Road	32	101	42	80
Race Course	11	84	64	41
Assakae	27	34	53	21
Adientem	35	65	43	50
West Tanokrom	69	211	131	80
Nkontompo	24	52	40	22
Effiekuma	166	368	262	172
Adiembra	32	56	38	21
Bakaekyir	11	49	27	14
Sekondi	66	176	183	108
Bakado	29	135	133	80
Ekuasi	20	35	27	10
Butumagyebu	33	89	111	54
Ngyamuabaka	12	25	33	9
Fijai	27	90	63	65
Kwekuma	29	50	69	29
Ketan Estates	15	74	46	39
European Town	23	70	78	41
Ngyiresia	12	94	83	43
Essikado	24	98	98	44
Sekondi Ridge	23	78	66	54
Mempeasem	8	56	85	33
Essipon	15	97	52	53
Ahinkofikrom	13	47	61	38
Mpintsin	3	53	54	44
Ketan	11	67	74	47
Osofokrom	23	99	106	62
Nkroful	8	48	55	37
Anoe	8	79	77	30
Anoekuma	9	69	61	47
Twabewu	8	46	56	33
Eshiem	18	57	61	22
Ntwaaban Nkwanta	62	171	165	109
Kojokrom	32	78	56	44
Kansaworado	15	50	40	22
Deabenekrom	19	77	74	55
Anaji	28	109	57	53
Mampong	19	72	71	49
Ntankoful	15	60	55	43
Essaman	1	65	60	39
Bomba	18	69	65	42
Whindo	25	52	44	30

Source: Fieldwork (2015)

Appendix B: Calculation of Moran's I statistic

Moran's I statistic is calculated using the following formula:

$I= [\Sigma_{i=1}\Sigma_{j=1} W_{ij} Z_i Z_j /S0] / [\Sigma_i Z_i {}^2/n]$

(Anselin, Griffiths & Tita 2008)

W_{ij} = spatial weighting matrix

$S_0= \Sigma_i \Sigma_j W_{ij}$ = sum of weights

n = number of regions

z = ($y_{i, j}$) – mean ($_{i, j}$)

Z_i^2= deviations from the mean

n= number of spatial units of observations

Areas i and j = adjacent areas

Moran's Z score = $(I_O – I_E) / SD_{IE}$

Where I_O = observed Moran's coefficient

I_E = expected Moran's coefficient for a random distribution

SD_{IE} = Standard Deviation for expected Moran's coefficient

(Mitchell, 2005).

Appendix C

Table 9: P-value and Z-score for Assault 2007

Suburb	Assault	Z-Score	P-Value	Bin
New Takoradi	4	2.06	0.04	2
Takoradi	19	1.69	0.09	1
Effia	4	1.85	0.06	1
Windy Ridge	6	1.71	0.09	1
Effiekuma	20	1.68	0.09	1
Deabenekrom	5	-2.36	0.02	-2

Source: Fieldwork (2015)

Table 10: P-value and Z-score for Assault 2008

Suburb	Assault	Z-Score	P-Value	Bin
Airport Ridge	3	2.65	0.01	3
Race Course	7	1.88	0.06	1
Ngyiresia	7	-1.66	0.10	-1
Essipon	2	-2.10	0.04	-2
Mpintsin	1	-1.78	0.07	-1
Anoe	0	-1.66	0.10	-1
Anoekuma	0	-2.43	0.02	-2

Source: Fieldwork (2015)

Table 11: P-value and Z-score for Assault 2009

Suburb	Assault	Z-Score	P-Value	Bin
East Tanokrom	8	1.99	0.05	2
Windy Ridge	5	1.77	0.08	1
Beach Road	3	1.99	0.05	2
Osofokrom	14	2.19	0.03	2

Source: Fieldwork (2015)

Table 12: P-value and Z-score for Assault 2010

Suburb	Assault	Z-Score	P-Value	Bin
European Town	7	-1.71	0.09	-1
Anoe	5	2.51	0.01	2
Twabewu	8	1.67	0.09	1
Deabenekrom	12	1.91	0.06	1
Bomba	1	-1.67	0.10	-1

Source: Fieldwork (2015)

Table 13: Z-values and P-values of Assault 2011

Suburb	Assault	Z-Score	P-Value	Bin
Chapel Hill	8	2.14	0.03	2
Beach Road	2	2.92	0.00	3
Ngyiresia	4	-1.65	0.10	-1

Source: Fieldwork (2015)

Table 14: Z-values and P-values of Assault 2012

Suburb	Assault	Z-Score	P-Value	Bin
East Tanokrom	6	1.89	0.06	1
Windy Ridge	6	1.96	0.05	2
Assakae	6	-1.84	0.07	-1
West Tanokrom	19	1.82	0.07	1
Mampong	3	-1.64	0.10	-1

Source: Fieldwork (2015)

Table 15: Z-values and P-values of Assault 2013

Suburb	Assault	Z-Score	P-Value	Bin
Effiekuma	16	-1.66	0.10	-1
Essipon	5	-1.67	0.09	-1
Anoe	9	-1.71	0.09	-1

Source: Fieldwork (2015)

Table 16: Z-values and P-values of Assault 2014

Suburb	Assault	Z-Score	P-Value	Bin
East Tanokrom	2	1.67	0.09	1
Eshiem	7	1.79	0.07	1
Kojokrom	3	-1.81	0.07	-1

Source: Fieldwork (2015)

Table 17: Z-scores and P-value of 2015 Assault Hotspot

Suburb	Assault	Z-Score	P-Value	Bin
Airport Ridge	5	1.77	0.08	1
Beach Road	3	2.70	0.01	3
Nkroful	9	1.88	0.06	1

Source: Fieldwork (2015)

Table 18: Z-score and p value of Defrauding by False Pretence 2007

Suburb	Defrauding	Z-Score	P-Value	Bin
New Takoradi	3	1.94	0.05	1
Apremdo	5	2.76	0.01	3
Takoradi	6	2.46	0.01	2
Effia	5	2.20	0.03	2
East Tanokrom	5	3.21	0.00	3
Windy Ridge	1	2.91	0.00	3
Kwesimintsim	3	3.52	0.00	3
Airport Ridge	6	1.96	0.05	1
Chapel Hill	9	2.12	0.03	2
Beach Road	5	2.07	0.04	2
Race Course	7	1.96	0.05	1
Adientem	8	2.06	0.04	2
West Tanokrom	7	3.56	0.00	3
Effiekuma	5	2.20	0.03	2
Bakado	3	2.14	0.03	-2
Ketan Estates	2	1.82	0.07	-1
Ngyiresia	1	2.53	0.01	-2
Essikado	3	1.84	0.07	-1
Sekondi Ridge	4	1.70	0.09	-1
Mempeasem	1	1.87	0.06	-1
Essipon	0	2.25	0.02	-2
Ahinkofikrom	2	2.23	0.03	-2
Mpintsin	0	1.99	0.05	-2
Ketan	1	1.91	0.06	-1
Anoekuma	0	1.87	0.06	-1
Twabewu	2	1.86	0.06	-1
Ntwaaban Nkwanta	5	1.65	0.10	-1
Kansaworado	3	1.91	0.06	-1
Deabenekrom	3	2.01	0.04	-2
Anaji	8	2.12	0.03	2

Source: Fieldwork (2015)

Table 19: Z-score and p value of Defrauding by False Pretence 2008

Suburb	Defrauding	Z-Score	P-Value	Bin
New Takoradi	5	2.26	0.02	2
Takoradi	19	3.82	0.00	3
Effia	6	1.83	0.07	1
East Tanokrom	7	3.73	0.00	3
Windy Ridge	7	3.95	0.00	3
Kwesimintsim	8	1.67	0.09	1
Airport Ridge	8	3.96	0.00	3
Chapel Hill	1	3.49	0.00	3
Beach Road	8	3.45	0.00	3
West Tanokrom	2	1.98	0.05	2
Nkontompo	8	1.81	0.07	1
Effiekuma	5	3.20	0.00	3
Ngyiresia	0	-2.33	0.02	-2
Essikado	1	-1.77	0.08	-1
Essipon	1	-1.75	0.08	-1
Ahinkofikrom	0	-2.55	0.01	-2
Mpintsin	0	-2.89	0.00	-3
Ketan	2	-2.23	0.03	-2
Osofokrom	0	-1.77	0.08	-1
Anoe	0	-2.00	0.05	-2
Anoekuma	1	-3.34	0.00	-3
Twabewu	0	-2.29	0.02	-2
Eshiem	3	-1.68	0.09	-1
Ntwaaban Nkwanta	1	-2.02	0.04	-2
Kojokrom	4	-2.46	0.01	-2
Deabenekrom	3	-1.82	0.07	-1

Source: Fieldwork (2015)

Table 20: Z-score and p-values of Defrauding by False Pretence 2009

Suburb	Defrauding	Z-Score	P-Value	Bin
Takoradi	18	2.35	0.02	2
Windy Ridge	0	1.68	0.09	1
Kwesimintsim	9	1.82	0.07	1
Airport Ridge	8	2.50	0.01	2
Chapel Hill	6	3.02	0.00	3
Beach Road	6	3.93	0.00	3

Source: Fieldwork (2015)

Table 21: Z-score and p-values of Defrauding by False Pretence 2010

Suburb	Defrauding	Z-Score	P-Value	Bin
Kwesimintsim	9	1.94	0.05	1
Chapel Hill	1	1.94	0.05	1
Beach Road	0	1.66	0.10	1
West Tanokrom	3	1.94	0.05	1
Ntwaaban Nkwanta	7	1.75	0.08	1

Source: Fieldwork (2015)

Table 22: Z-score and p-values of Defrauding by False Pretence 2011

Suburb	Defrauding	Z-Score	P-Value	Bin
Apremdo	2	2.12	0.03	2
Takoradi	14	2.30	0.02	2
East Tanokrom	2	2.71	0.01	3
Windy Ridge	0	2.40	0.02	2
Kwesimintsim	9	2.78	0.01	3
Airport Ridge	7	3.20	0.00	3
West Tanokrom	7	1.67	0.09	1
Effiekuma	10	1.70	0.09	1
Nkroful	0	-1.66	0.10	-1

Source: Fieldwork (2015)

Table 23: Z-score and p-values of Defrauding by False Pretence 2012

Suburb	Defrauding	Z-Score	P-Value	Bin
Takoradi	11	2.14	0.03	2
East Tanokrom	0	1.94	0.05	1
Windy Ridge	2	1.85	0.06	1
Airport Ridge	1	2.35	0.02	2
Chapel Hill	3	1.71	0.09	1
Beach Road	0	2.18	0.03	2
Osofokrom	4	2.37	0.02	2

Source: Fieldwork (2015)

Table 24: Z-score and p-values of Defrauding by False Pretence 2013

Suburb	Defrauding	Z-Score	P-Value	Bin
Apremdo	2	1.71	0.09	1
Airport Ridge	5	2.05	0.04	2
West Tanokrom	9	1.70	0.09	1
Kwekuma	3	2.00	0.05	2
Anaji	4	1.88	0.06	1

Source: Fieldwork (2015)

Table 25: Z-score and p-values of Defrauding by False Pretence 2014

Suburb	Defrauding	Z-score	P-value	Bin
Kwesimintsim	9	2.04	0.04	2
Deabenekrom	3	-1.85	0.06	-1
Anaji	2	2.76	0.01	3

Source: Fieldwork (2015)

Table 26: Z-score and p-values of Robbery 2007

Suburb	Robbery	Z-Score	P-Value	Bin
New Takoradi	2	2.14	0.03	2
Apremdo	5	2.04	0.04	2
Takoradi	14	3.40	0.00	3
Effia	4	3.21	0.00	3
East Tanokrom	4	3.27	0.00	3
Windy Ridge	5	2.24	0.03	2
Kwesimintsim	9	2.74	0.01	3
Airport Ridge	9	2.32	0.02	2
Chapel Hill	6	2.83	0.00	3
Beach Road	6	1.69	0.09	1
Race Course	2	-1.93	0.05	-1
Adientem	0	-2.17	0.03	-2
West Tanokrom	1	-2.05	0.04	-2
Nkontompo	3	-2.04	0.04	-2
Effiekuma	1	-2.36	0.02	-2
Adiembra	0	-1.75	0.08	-1
Bakaekyir	5	-2.34	0.02	-2
Sekondi	0	-1.76	0.08	-1
Bakado	2	-2.61	0.01	-3
Ekuasi	1	-1.75	0.08	-1

Source: Fieldwork (2015)

Table 27: Z-score and p-values of Robbery 2008

Suburb	Robbery	Z-Score	P-Value	Bin
Apremdo	3	2.11	0.04	2
Takoradi	16	3.42	0.00	3
East Tanokrom	5	3.30	0.00	3
Windy Ridge	4	3.52	0.00	3
Kwesimintsim	6	2.01	0.04	2
Airport Ridge	8	1.82	0.07	1
Chapel Hill	9	3.18	0.00	3
Beach Road	6	3.58	0.00	3
West Tanokrom	9	1.92	0.05	1
Adiembra	0	-1.90	0.06	-1
Bakaekyir	3	-1.68	0.09	-1
Sekondi	4	-1.86	0.06	-1
Bakado	0	-1.95	0.05	-1
Ekuasi	0	-2.17	0.03	-2
Butumagyebu	6	-1.84	0.07	-1
Ketan Estates	3	-1.79	0.07	-1
European Town	3	-2.65	0.01	-3
Ngyiresia	1	-2.06	0.04	-2
Essikado	3	-2.69	0.01	-3
Sekondi Ridge	2	-2.42	0.02	-2
Mempeasem	1	-2.36	0.02	-2
Ahinkofikrom	2	-2.47	0.01	-2
Ketan	2	-2.76	0.01	-3
Anoekuma	3	-1.98	0.05	-2
Kojokrom	3	-2.06	0.04	-2
Essaman	6	-2.32	0.02	-2

Source: Fieldwork (2015)

Table 28: Z-score and p-values of Robbery 2009

Suburb	Robbery	Z-Score	P-Value	Bin
New Takoradi	5	1.99	0.05	2
Takoradi	19	2.13	0.03	2
East Tanokrom	4	2.18	0.03	2
Windy Ridge	3	2.52	0.01	2
Airport Ridge	6	3.17	0.00	3
Chapel Hill	9	2.13	0.03	2
Beach Road	2	2.49	0.01	2
Ahinkofikrom	2	-2.14	0.03	-2
Kojokrom	0	-1.95	0.05	-1
Deabenekrom	0	-2.11	0.03	-2
Mampong	3	-1.89	0.06	-1

Source: Fieldwork (2015)

Table 29: Z-score and p-values of Robbery 2010

Suburb	Robbery	Z-Score	P-Value	Bin
Windy Ridge	2	2.37	0.02	2
Kwesimintsim	4	1.69	0.09	1
West Tanokrom	12	1.96	0.05	2
Ngyamuabaka	0	-2.35	0.02	-2

Source: Fieldwork (2015)

Table 30: Z-scores and p-values of Robbery 2011

Suburbs	Robbery	Z-Score	P-Value	Bin
Takoradi	9	1.68	0.09	1
Kwesimintsim	9	1.85	0.06	1
Nkontompo	0	-1.69	0.09	-1
Kwekuma	2	-1.70	0.09	-1
Mempeasem	6	2.34	0.02	2

Source: Fieldwork (2015)

Table 31: Z-scores and P-values of Robbery 2012

Suburb	Robbery	Z-Score	P-Value	Bin
Takoradi	11	2.16	0.03	2
East Tanokrom	6	2.63	0.01	3
Windy Ridge	0	2.63	0.01	3
Kwesimintsim	9	1.65	0.10	1
Airport Ridge	5	2.76	0.01	3
Chapel Hill	3	1.86	0.06	1
West Tanokrom	4	2.99	0.00	3
Effiekuma	9	2.43	0.01	2
Deabenekrom	0	-1.71	0.09	-1
Mampong	0	-2.23	0.03	-2
Bomba	0	-2.68	0.01	-3

Source: Fieldwork (2015)

Table 32: Z-scores and P-values of Robbery 2013

Suburb	Robbery	Z-Score	P-Value	Bin
New Takoradi	1	2.34	0.02	-2
Nkontompo	0	2.08	0.04	-2
Ngyamuabaka	1	1.73	0.08	-1
Kwekuma	2	2.36	0.02	-2
Essaman	4	1.89	0.06	-1

Source: Fieldwork (2015)

Table 33: Z-scores and P-values of Robbery 2014

Suburbs	Robbery	Z-Score	P-Value	Bin
Takoradi	7	3.18	0.00	3
East Tanokrom	10	3.26	0.00	3
Windy Ridge	6	2.85	0.00	3
Kwesimintsim	13	1.96	0.05	1
Chapel Hill	16	2.29	0.02	2
Beach Road	23	2.77	0.01	3
West Tanokrom	7	1.75	0.08	1
Adiembra	3	-2.26	0.02	-2
Bakaekyir	1	-1.66	0.10	-1
Sekondi	15	-2.12	0.03	-2
Bakado	5	-1.98	0.05	-2
Ekuasi	0	-2.62	0.01	-3
Butumagyebu	3	-2.37	0.02	-2
Ketan Estates	4	-1.87	0.06	-1
Ahinkofikrom	6	-1.76	0.08	-1
Ketan Estates	4	-1.79	0.07	-1
Anaji	13	2.27	0.02	2
Essaman	7	-2.15	0.03	-2

Source: Fieldwork (2015)

Table 34: Z-scores and P-values of Robbery 2015

Suburb	Robbery	Z-Score	P-Value	Bin
New Takoradi	7	1.91	0.06	-1
Takoradi	27	2.06	0.04	2
Chapel Hill	6	2.74	0.01	3
Beach Road	8	3.52	0.00	3
Ngyamuabaka	0	1.77	0.08	-1

Source: Fieldwork (2015)

Table 35: Z-scores and P-values of Stealing 2007

Suburb	Stealing	Z-Score	P-Value	Bin
Takoradi	17	1.75	0.08	1
Windy Ridge	3	1.92	0.06	1
Airport Ridge	7	1.98	0.05	2
Deabenekrom	2	-1.91	0.06	-1

Source: Fieldwork (2015)

Table 36: Z-scores and P-values of Stealing 2008

Suburbs	Stealing	Z-Score	P-Value	Bin
Takoradi	16	1.80	0.07	1
Windy Ridge	4	2.07	0.04	2
Airport Ridge	8	2.15	0.03	2
Ntankoful	1	-1.65	0.10	-1

Source: Fieldwork (2015)

Table 37: Z-scores and P-values of Stealing 2009

Suburbs	Stealing	Z-Score	P-Value	Bin
New Takoradi	11	2.31	0.02	2
Takoradi	18	3.51	0.00	3
East Tanokrom	5	3.76	0.00	3
Windy Ridge	6	3.80	0.00	3
Kwesimintsim	15	2.86	0.00	3
Airport Ridge	15	2.57	0.01	2
Chapel Hill	22	2.18	0.03	2
Beach Road	13	2.10	0.04	2
West Tanokrom	24	2.44	0.01	2
Effiekuma	23	2.25	0.02	2
Adiembra	6	-1.82	0.07	-1
Bakaekyir	6	-1.91	0.06	-1
Bakado	13	-1.77	0.08	-1
Butumagyebu	7	-2.35	0.02	-2
Ahinkofikrom	3	-2.18	0.03	-2
Ketan	8	-2.13	0.03	-2
Anoe	2	-1.83	0.07	-1
Anoekuma	5	-1.73	0.08	-1
Twabewu	3	-1.76	0.08	-1
Kojokrom	7	-1.87	0.06	-1
Deabenekrom	6	-1.77	0.08	-1
Anaji	12	1.90	0.06	1

Source: Fieldwork (2015)

Table 38: Z-scores and P-values of Stealing 2010

Suburb	Stealing	Z-Score	P-Value	Bin
Takoradi	18	2.11	0.03	2
Airport Ridge	9	2.45	0.01	2
Chapel Hill	7	1.66	0.10	1
Beach Road	6	2.44	0.01	2

Source: Fieldwork (2015)

Table 39: Z-scores and P-values of Stealing 2011

Suburb	Stealing	Z-Score	P-Value	Bin
New Takoradi	11	3.12	0.00	3
Takoradi	45	3.49	0.00	3
East Tanokrom	9	3.74	0.00	3
Windy Ridge	9	3.73	0.00	3
Airport Ridge	9	4.01	0.00	3
Chapel Hill	12	3.47	0.00	3
Beach Road	8	3.48	0.00	3
West Tanokrom	15	1.96	0.05	2
Effiekuma	12	3.08	0.00	3
Nkroful	9	-1.84	0.07	-1

Source: Fieldwork (2015)

Table 40: Z-scores and P-values of Stealing 2012

Suburb	Stealing	Z-Score	P-Value	Bin
Takoradi	24	3.28	0.00	3
East Tanokrom	19	3.59	0.00	3
Windy Ridge	6	3.63	0.00	3
Kwesimintsim	19	2.50	0.01	2
Airport Ridge	11	3.94	0.00	3
Chapel Hill	8	2.76	0.01	3
Beach Road	5	2.72	0.01	3
West Tanokrom	7	2.68	0.01	3
Effiekuma	12	2.73	0.01	3
Adiembra	6	-2.65	0.01	-3
Bakaekyir	7	-2.65	0.01	-3
Sekondi	9	-2.07	0.04	-2
Bakado	0	-2.46	0.01	-2
Ekuasi	2	-2.56	0.01	-2
Butumagyebu	0	-2.71	0.01	-3
Ngyamuabaka	1	-1.80	0.07	-1
Kwekuma	4	-2.08	0.04	-2
Ketan Estates	6	-2.60	0.01	-3
Essikado	6	-1.70	0.09	-1
Sekondi Ridge	3	-2.15	0.03	-2
Ahinkofikrom	4	-1.81	0.07	-1
Ketan	7	-1.75	0.08	-1
Nkroful	9	-2.00	0.05	-2
Essaman	2	-2.54	0.01	-2

Source: Fieldwork (2015)

Table 41: Z-scores and P-values of Stealing 2013

Suburb	Stealing	Z-Score	P-Value	Bin
Takoradi	27	1.85	0.06	1
East Tanokrom	16	1.72	0.09	1
Windy Ridge	4	2.34	0.02	2

Source: Fieldwork (2015)

Table 42: Z-scores and P-values of Stealing 2014

Suburb	Stealing	Z-Score	P-Value	Bin
New Takoradi	9	2.10	0.04	2
Takoradi	28	2.27	0.02	2
East Tanokrom	3	2.52	0.01	2
Windy Ridge	12	2.72	0.01	3
Airport Ridge	4	1.80	0.07	1
Chapel Hill	13	2.10	0.04	2
Beach Road	10	2.21	0.03	2
Race Course	4	-1.65	0.10	-1
Assakae	3	-1.97	0.05	-2
Effiekuma	18	2.46	0.01	2
Bakado	15	-1.03	0.30	0

Source: Fieldwork (2015)

Table 43: Z-scores and P-values of Stealing 2015

Suburb	Stealing	Z-Score	P-Value	Bin
New Takoradi	6	2.13	0.03	2
Takoradi	30	3.42	0.00	3
Effia	19	1.75	0.08	1
East Tanokrom	9	2.59	0.01	3
Windy Ridge	6	3.02	0.00	3
Airport Ridge	10	1.92	0.06	1
Chapel Hill	8	2.72	0.01	3
Beach Road	11	2.29	0.02	2
Effiekuma	19	2.39	0.02	2
Osofokrom	2	-1.71	0.09	-1

Source: Fieldwork (2015)

Table 44: Total Defrauding by False Pretence Cases (2007 to 2015)

Suburbs	Defrauding	Z-Score	P-Value	Bin
New Takoradi	27	1.65	0.10	1
Takoradi	103	3.43	0.00	3
Effia	19	2.19	0.03	2
East Tanokrom	17	3.12	0.00	3
Windy Ridge	17	3.11	0.00	3
Kwesimintsim	61	2.85	0.00	3
Airport Ridge	48	3.22	0.00	3
Chapel Hill	29	2.81	0.00	3
Beach Road	24	2.86	0.00	3
West Tanokrom	51	3.14	0.00	3
Effiekuma	44	2.66	0.01	3
Butumagyebu	33	-1.93	0.05	-1
Essikado	24	-2.38	0.02	-2
Sekondi Ridge	23	-1.69	0.09	-1
Mempeasem	8	-1.90	0.06	-1
Ahinkofikrom	13	-1.67	0.09	-1
Mpintsin	3	-1.84	0.07	-1
Ketan	11	-2.13	0.03	-2
Nkroful	8	-2.02	0.04	-2
Anoe	8	-1.81	0.07	-1
Anoekuma	9	-2.04	0.04	-2
Twabewu	8	-1.71	0.09	-1
Deabenekrom	19	-1.84	0.07	-1

Source: Fieldwork (2015)

Table 45: Total Stealing Cases (2007 to 2015)

Suburb	Stealing	Z-Score	P-Value	Bin
New Takoradi	77	2.33	0.02	2
Takoradi	223	3.94	0.00	3
East Tanokrom	73	3.69	0.00	3
Windy Ridge	64	3.82	0.00	3
Kwesimintsim	104	1.83	0.07	1
Airport Ridge	81	3.24	0.00	3
Chapel Hill	96	2.77	0.01	3
Beach Road	77	3.08	0.00	3
West Tanokrom	94	1.80	0.07	1
Effiekuma	155	2.47	0.01	2
Butumagyebu	71	-2.14	0.03	-2
Kansaworado	45	-1.67	0.10	-1

Source: Fieldwork (2015)

Table 46: Total Assault Cases (2007 to 2015)

Suburb	Assault	Z-Score	P-Value	Bin
East Tanokrom	37	2.10	0.04	2
Windy Ridge	61	1.72	0.09	1
Chapel Hill	83	1.97	0.05	2
Beach Road	42	1.97	0.05	2

Source: Fieldwork (2015)

Table 47: Total Robbery Cases (2007 to 2015*)*

Suburb	Robberies	Z-Score	P-Value	Bin
Takoradi	120	3.39	0.00	3
East Tanokrom	34	2.95	0.00	3
Windy Ridge	27	3.19	0.00	3
Kwesimintsim	62	2.30	0.02	2
Airport Ridge	77	2.37	0.02	2
Chapel Hill	81	1.95	0.05	1
Beach Road	66	2.26	0.02	2
Ekuasi	10	-1.69	0.09	-1

Source: Fieldwork (2015)