SPATIOTEMPORAL ANALYSIS AND PREDICTIVE MODELLING OF CRIME PATTERNS USING GIS AND REMOTE SENSING TECHNIQUES

CASE STUDY: MASAKA DISTRICT

A dissertation presented to

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This dissertation has been produced under my supervision and submitted for examination with my approval as the appointed academic supervisor.

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Signature of Supervisor: ________________

Date of submission: 04/09/2024

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Dedication

This research is dedicated to St. Padre Poi for his intercession and prayers when I reached dead end.

Acknowledgement

I sought the Lord and He answered me. It has been a tag of war completing this research. I praise the Lord for seeing through.

I would like to extend my sincere gratitude to my supervisor for his patience, continuous support, and invaluable guidance throughout this journey. Sir, without your encouragement and expert advice, I would not have been able to complete this course. Thank you very much for everything.

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List of abbreviations

AFIS	Automated Fingerprint Identification System
CCTV	Closed-Circuit Television
CID	Crime Investigation Department
DNA	Deoxyribonucleic Acid
DPC	Division Police Commander
ETM	Enhanced Thematic Mapper
EVC	Environmental Crime
GIS	Geographical Information System
GPS	Global Positioning System
IBIS	Integrated Ballistic Information System
LuLc	Land use landcover
Rs	Remote sensing
OC	Officer-in Charge
QGIS	Quantum Geographical Information System
UBOS	Uganda Bureau of Statistics
USGS	United States Geological Survey
UNODC	United Nations Office on Drugs and Crime
UNTOC	United Nations Convention against Transnational Organised Crime
UNSDG	United National Sustainable Development Goal

ABSTRACT

The rising crime rates have become a critical challenge for communities, causing businesses to close or relocate, leading to loss of life and property, and diverting taxpayer funds from development to crime control. Combating crime is a shared responsibility, not just that of law enforcement. However, police often focus on evidence collection for convictions rather than addressing the root causes of crime, allowing offenders to continue criminal activities.

This study conducted a spatio-temporal analysis and predictive modelling of crime patterns in Masaka district using GIS and remote sensing techniques. A quantitative approach was employed, analysing 4,651 crimes reported from 2022 to 2024 across various police divisions. Satellite imagery was processed through loading bands into the software (ArcMap 10.8), band stacking, training samples, determining sample signature and finally through supervised classification to assess land use/land cover (LULC) features. The relationship between LULC features with crimes such as sexual abuse, theft, robbery, assault, and breakings was got from overlaying the two, LULC and a given crime type at a time.

Crime hotspots and coldspots were identified by Kernel Density Estimation (KDE), and analysis of different hotspots and coldspots was done with Getis-Ord Gi*. Predictive models were created by a space- time cube pattern mining through aggregation of points. They revealed new, persistent, and sporadic hotspots. Findings showed an increase in crime from 1,225 cases in 2022 to 1,788 in 2024, with theft, assault, breakings, sexual abuse, and robbery being the most common. Urban areas, especially Nyendo-Mukungwe, Masaka city, Kimanya-Kabonera, and Masaka rural divisions, reported the highest crime counts. Spatial autocorrelation analysis (Moran's I) indicated significant clustering for sexual abuse, theft, robbery, and assault, but not for breakings which showed dissimilar values were near each other. A strong correlation was found between crimes and LULC features, particularly built-up and agricultural/green areas with all the crimes in the study.

Most hotspots were in urban police divisions, with predictive modelling showing some hotspots becoming sporadic or emerging as new high-crime areas. The study underscores the need for proactive crime-fighting strategies using GIS and remote sensing to identify crime attractors and optimize police resource deployment. Enhanced patrols and focused interventions in identified hotspots and emerging crime areas can improve crime prevention efforts in Masaka district.

CHAPTER ONE

1.0 INTRODUCTION

1.1 Introduction and Background

Crime is a complex and multifaceted phenomenon that encompasses a wide range of illegal acts violating established laws and regulations. It involves not only the commission of these unlawful acts but also the social, psychological, and economic factors that drive criminal behaviour (Oghenevovwero et al., 2024). Crimes occur in every country, whether developed or developing, making crime as enduring as society itself. Consequently, it remains a primary concern for all members of human society (More, 2023).

Crimes involve harming others or damaging their property, either intentionally or unintentionally. Criminal acts cover a wide spectrum, including threats, harassment, domestic violence, larceny, drug trafficking, human trafficking, murder, assault, arson, child abuse, kidnapping, enslavement, genocide, sexual violence, enforced disappearance, and persecution (Statista, 2024).

Crime has numerous adverse effects on society. It leads to loss of productivity as businesses close or relocate due to insecurity and diminished customer trust. Additionally, significant public funds are diverted to cover the costs of running prisons, police investigations, and arrests, placing strain on public budgets and often resulting in higher taxes to support these law enforcement expenses.

Beyond economic impacts, crime takes a psychological toll on victims, causing anxiety, trauma, depression, and pain. This psychological harm often extends to family members and friends of the victims. Moreover, crime negatively affects economic activities by discouraging investment and disrupting key economic factors (Leward, Tafadzwa, and Moyo, 2021). It impedes economic prosperity, increases transaction costs, and destabilizes society as a whole (Okpuvwie et al., 2021; Jonathan et al., 2021).

According to Article 7 of the Elements of Crime, crimes against humanity are among the most serious offenses of concern to the international community. These crimes warrant individual criminal responsibility and involve conduct that is prohibited under universally accepted international law, as recognized by major legal systems worldwide. Amnesty International further describes crimes against humanity as acts that “shock the conscience of humanity itself.” Examples of such crimes include enslavement, genocide, sexual violence, enforced disappearance, and persecution (Rome Statute, Article 7).

Property crimes refer to offenses involving the unlawful destruction of or interference with another person's property. Common examples include property theft, burglary, vandalism, arson, and shoplifting. These crimes are prevalent and occur frequently in societies around the world.

In contrast, crimes against morality, often categorized as victimless crimes, comprise illegal acts that do not result in a directly identifiable victim. Such offenses include prostitution, trespassing, illegal gambling, homelessness, loitering, begging, and recreational drug use (Denendorg, 2021).

Furthermore, other categories of crime include white-collar crimes, which are committed by individuals of high social status within the context of their occupation. Examples of such crimes include insider trading, embezzlement, and related offenses.

Another significant category is organized crime. According to the United Nations Convention against Transnational Organized Crime (UNTOC) the most comprehensive international agreement of its kind, adopted in 2000 organized crime is defined as “a structured group of three or more persons existing for a period of time and acting in concert with the aim of committing one or more serious crimes or offenses established in accordance with this Convention, in order to obtain, directly or indirectly, a financial or other material benefit” (Tsvety, 2024).

Organized crime typically involves illegal acts carried out by structured groups, frequently related to the distribution and sale of illicit goods and services. These criminal enterprises engage in activities such as drug trafficking, human trafficking, money laundering, illicit trafficking of firearms, the circulation of falsified medical products, extortion, and racketeering (UNODC, 2019). Organised crime thrives worldwide, affecting governance and political processes, and weakening the advancement of the rule of law (UNDOC,2019).

Additionally, Rabbi (2024) gives another crime category called Environmental crime (EVC) which is an illegal act against the environment. This crime category affects all countries. Such acts include wildlife crimes (killing and keeping), pollution, illegal mining, illegal fishing. Environmental crime (EVC) is currently ranked as the third-most significant form of criminal activity on a global scale (Rabbi,2024; Linet Lireza & Gentian Koci,2023). It is growing at an annual rate of 5-7%, as mentioned by Kuryo (2024), if we do not diverse means of curbing this crime, humanity is bound to perish.

Crimes are punishable by law and the punishment which Maier and Maier (2021), defined as the application of consequences to individuals who have been found guilty of committing a crime in a legal framework, such as a court of law, and it depends on the country's rank of crimes.

The incident of crime worldwide has risen in recent years from 0.74% between 2019 and 2020 to 5.3% in 2023 (Statista,2023). According to Matereke et al.,(2021), Venezuela and Papua New Guinea are ranked as countries with the highest crime rate of 82.1 and 80.4, measured per 100,000 citizens respectively. This high crime rate made Venezuela get a level 4 travel advisory, indicating that it is unsafe to travel to the country (World population review,2024). In Africa, South Africa was ranked number one with 75.4% crime rate followed by Nigeria with 66.7% (Galal,2024). Regionally in Africa, East Africa is ranked the highest with 5.88% followed by West Africa with 5.44% (Global Initiative; Africa Organised Crime Index 2023).

In Uganda, over 2,000 cases are reported to police annually, for instance, between 2020 and 2024, over one million cases were reported at different police stations and divisions with theft, assaults and domestic violence topping the list (Kamusiime,2024; Amanya,2023; sserugo,2024). These numerous crimes or cases put Uganda in the 29th position in the global ranking and also ranked among the top ten (10) African countries with the highest crime rate as reported by Mbabazi (2023). According to district crime data 2020 released by the Uganda police, Masaka, Rakai, Lyantonde and Bukomansimbi were cited in Greater Masaka region as having high crime rates. This made Greater Masaka one of the regions with high crime rate in the country (Data ug,2023).

Security or law enforcement agencies apply crime-solving techniques to take preventive measures but in many cases, they cannot deliver effective results (Dakalbab et al.,2022) and because of this, crimes continue to go on and increase globally. This can be attributed to the spatial and temporal nature of crime occurrence which relate to when and how crime incidents are distributed across geographic locations, often exhibiting patterns of concentration, clustering, hotspots rather than being randomly distributed.

Crime incidents happen at a particular spatial location and at a point in time and this explains why crime seems to occur more frequently in some locations other than others. Different geographic locations, resource endowments, population density, development types, economic conditions, traditional habits and social control mechanisms lead to the emergence of different criminal phenomena. Crimes happen in different places i.e., town, city, village, church, streets, parks, malls and many other places and it is done by people of all ages: the old, young and the youth, people of all gender: male and female, and at different time: night or day, festive or non-festive period.

Kim et al. (2024) argued that crime and land use landcover are considered to be closely related. Land use acts to shape the types and timing of activities that take place in a given location. In doing so, land uses influence the diurnal and weekly flow in population (Felson and Boivin,2025) where some land uses experience a high flux in population numbers across much of the day, residential areas are subject to far smaller shifts in daily population (Bhaduri et al.,2007). There are many consequences associated with these daily shifts in population, one being crime. As population shifts over the course of a day and across a week, it influences crime opportunity through adjusting the requisite co-presence or absence of offenders, target and guardians in both space and time facilitated by land use landcover features (Cohen and Felson,1979 ; Sutherland & Cressey,1978), cited by (Brunsdon and Corcoran,2021),

The land use and land cover types of a given place contribute greatly to crimes that happen in that location. Brundon & Corcoran (2021) argue that there is an association between crime occurrences and places such as shopping centres;(Phillips and Cochrane,1988), green spaces and urban parks (Taylor et al.,2019), and major sporting venues (Kurland and Johnson,2019). A study by Weisburd et al., (2020) found that crime rates are higher in the central cities such as station districts because of new buildings, most of which are commercial.

According to Brunsdon and Corcoran, (2012), assaults were greatly committed in commercial areas and less in industrial parks, drug crimes happened a lot in parkland, residential, educational and agricultural areas, yet robberies were broadly distributed across agricultural, educational, parkland, industrial and residential places. According to Govindaraju et al.,(2021) crime incidents happened more in commercial and residential areas which was also supported by Block and Block (2000), as cited in (Olajuyible, Adegboyega and Adenigba,2015) saying that particular land uses forexample schools, bars, stores and abandoned buildings have been found to attract more crime in their vicinity and crowded high mobility areas, isolated dark places, parks, shades and vacant plots are the most vulnerable to crime as opined by Gupta (2023).

Kong (2024) temporal analysis highlighted distinct patterns in crime occurrences related to green spaces. He noted that during daylight hours, green spaces were associated with reduced crime rates, likely due to increased public presence and natural surveillance. For instance, parks with regular daytime activities saw a 25% reduction in crime during the day. However, during nighttime, certain green spaces became hotspots for crime. At times crimes are committed basing on time and seasons, for different crimes committed during night and others day.

Since traditional methods of crime detection, monitoring and management have failed to be fully effective in curbing the present crimes (Gupta et al.,2012 cited in Mudassar et al,2022), given that crime is a social and spatial phenomenon, it needs suitable prevention with information technology to decrease the intensity, for example, crime mapping and risk distribution using GIS (Eman et al,2023; Townsley ,2017 cited in Mudassar Khushi et al.,2022). Several studies have cited the exceptional capability of GIS to overlay data from disparate sources such as call for service, arrest reports and spatial and temporal components of crime and displaying the analysis on a digital crime map as an important factor in crime prevention and planning (Kannan *et al.,*2017). This is called crime mapping which facilitate visualisation of the intensity of the crime and where it is distributed all over the region (Khushi et al.,2022).

Crime mapping seeks to answer the question of “where” forexample, where does crime occur?, where is crime highest? (Phiri, Phiri and S.,2020). Crime mapping is an effective technology that has gained wide popularity in the global northern countries because of its utility in solving crime problems (Bewul et al.,2022) and provide direction in understanding crimes. After crime mapping, crime forecasting can also be done. Crime forecasting involves first studying certain environmental factors such as the physical layout of an area, proximity to various services and land use and find out how they affect or influence criminal behaviour during data analysis. Crime prediction or forecasting has the potential to decrease their occurrence in areas with identifiable patterns. This early intervention can serve to prevent people from falling victims to criminal acts.

By leveraging historical crime data, demographic information, socioeconomic factors, predictive policing aims to identify crime hotspots, allocate police resources efficiently, and ultimately prevent crime. This enhances strategic deployment of officers in area of high crime probability, leading to quicker response time and decrease criminal incidents.

This study therefore aims to conduct a spatiotemporal analysis using GIS and Remote sensing techniques. GIS provides crime mapping features, which lets users see the locations of crimes, identify areas with a high crime density (Hotspots) and cold spots. More to that, GIS can be used to detect the severity of the hotspots of crime through studying crime trends to help in the predicting of future crimes. GIS together with Remote sensing offer a study into where different crimes take place and the physical features or landcover land use of a place and how certain land use landcover impact criminal activities.

Crimes that will be considered for this study are crimes against humanity, property and violent crimes. The researcher will be in position to undertake crime mapping, hotspot analysis, analyse crime relationships, trends and patterns and finally do crime prediction or forecast to project future crime occurrences such that they can be mitigated.

1.2 Statement of the problem

The current crime detection and management in Uganda are proving inadequate in addressing the rising crime rates (Kamusiime,2023). Despite the introduction of the parish -model policing which is an initiative designed to decentralise policing services to every sub-county/municipal or Town council (Kamusiime,2025) and, the use of technology like toll free emergency number (999), plus installation of CCTV cameras on major streets and high ways, crimes are still prevalent in many parts of the country including Masaka. Conventional crime data analysis methods often ignore the spatial and environmental dimensions that influence criminal activities. Consequently, law enforcement agencies lack the spatial intelligence required to allocate resources efficiently and respond proactively. Moreover, there is limited use of modern geospatial tools like GIS and remote sensing to map crime patterns, identify hotspots, or predict future risk zones.

Many crimes are influenced by factors such as land use and land cover (LULC) characteristics of an area. However, these factors are often overlooked by the police during investigations and in crime prevention strategies. Although there appears to be a lack of studies examining the relationship between LULC features and crime specifically in Uganda, several studies have been conducted in more developed countries, including the United States, China, India, and Nigeria. Police typically focus primarily on gathering evidence to convict suspects rather than identifying and addressing the underlying environmental factors that attract criminal activity in the first place. As a result, because these factors remain unaddressed, offenders continue to commit crimes in the same or other areas even while investigations are ongoing.

The reliance on manual processes, often result into officers often arriving at crime scenes after incidents have occurred. Having less or no crew where crimes have occurred also results into delay in dispatching response services which increases risk of harm or injury to the victim which sometimes cause death and loss of properties as they wait for assistance or rescue. This hinders the development of effective, targeted crime prevention strategies and therefore, presents a need for a spatiotemporal crime analysis approach that integrates satellite imagery and vector data to uncover trends, recognize patterns, and build predictive models for crime in Masaka District.

To enhance better crime management, the adoption of geospatial technologies such as Remote sensing, GIS and predictive models is indispensable as most crimes are committed at a particular location in relation to land use and land cover features of the place. GIS helps integrate vast amount of location-based data from multiple sources, do crime mapping and hotspot analysis with greater precision. Remote sensing and GIS can aid law enforcement agencies to improve their situational awareness, analyse crime relationships, see crime trends and patterns which can help make quick decisions, have a short response time and properly allocate resources.

1.3 Study objectives

The study objectives are divided into two categories, major/general which is the broad, overall aim of the study, describing the primary goal of the study and specific objectives which are more detailed, giving specific aspects the study will address to meet the overall objective.

1.3.1 Major objective

This study will analyse the spatial and temporal distribution of crime in Masaka District using GIS and remote sensing techniques, and apply predictive modelling to identify future crime hotspots based on environmental and infrastructural factors**.**

1.3.2 Specific objectives

The study was guided by the following objectives:

1. To analyse the spatial distribution and temporal trends of crimes in Masaka District from 2020 to 2024 using geospatial techniques.

2. To classify land use/land cover data and assess their relationship with crime incidences.
3. To identify and map crime hotspots, analyse their spatial relationship with environmental and infrastructural features, and predict potential future crime locations.
4. To recommend interventions and crime prevention measures based on spatial relationships between crimes and environmental/infrastructure elements.

1.4 Study Questions

The study was guided by the following questions:

1. What are the spatial patterns and temporal trends of crimes in Masaka district from 2020 to 2024?

2. How do different land use/land cover types relate to incident and distribution of crime in Masaka district?

3(a) Where are the crime hotspots on Masaka district, and how are they spatially related to environmental and infrastructural feature?

(b) How to predict future crime location in Masaka district?

4. What spatially informed interventions and crime prevention strategies can be proposed based on the relationship between crime and environmental/infrastructural elements?

1.5.0 Scope of the study

This section involves geographical scope, functional and time scope.

1.5.1 Geographical scope

The area selected for the study is Masaka district, because of high criminal activities that happen in the area on a daily basis, which are becoming a threat to socio-economic development and the livelihood of the people in the area.

Masaka District is located in southern Uganda and is bordered by Kalungu District to the north, Kalangala District to the east, and Kyotera District to the south and south-west. The district lies at coordinates approximately 0°30' S latitude and 31°45' E longitude, with an average altitude of 1,150 meters (3,658 feet) above sea level (Wikipedia contributors, 2024; Jeremy, 2023).

According to the most recent census data from 2024, Masaka District has a population of 115,251 (UBOS, 2024) and covers a total area of approximately 1,023.7 square kilometres. Of this area, about 801.5 square kilometres consist of open water, wetlands, and marshlands, while approximately 308.3 hectares are under cultivation. The total gazetted forest estate accounts for roughly 6.38% of the district's land area. In addition, scattered natural forests are found along the lake shores (Masaka District Local Government, 2024).

The district's landscape is generally characterized by rolling hills and valleys, with valley bottom swamps and numerous streams that flow into these wetlands (Masaka District Local Government, 2024).

Masaka District is administered under the jurisdiction of the Greater Masaka Police Command. The district is subdivided into four administrative divisions, namely Masaka City, Masaka Rural, Kimanya-Kabonera, and Nyendo-Mukungwe. Each of these divisions encompasses multiple police stations and police posts, which are responsible for maintaining law and order and providing policing services within their respective areas. The figure below shows the location of the study area.

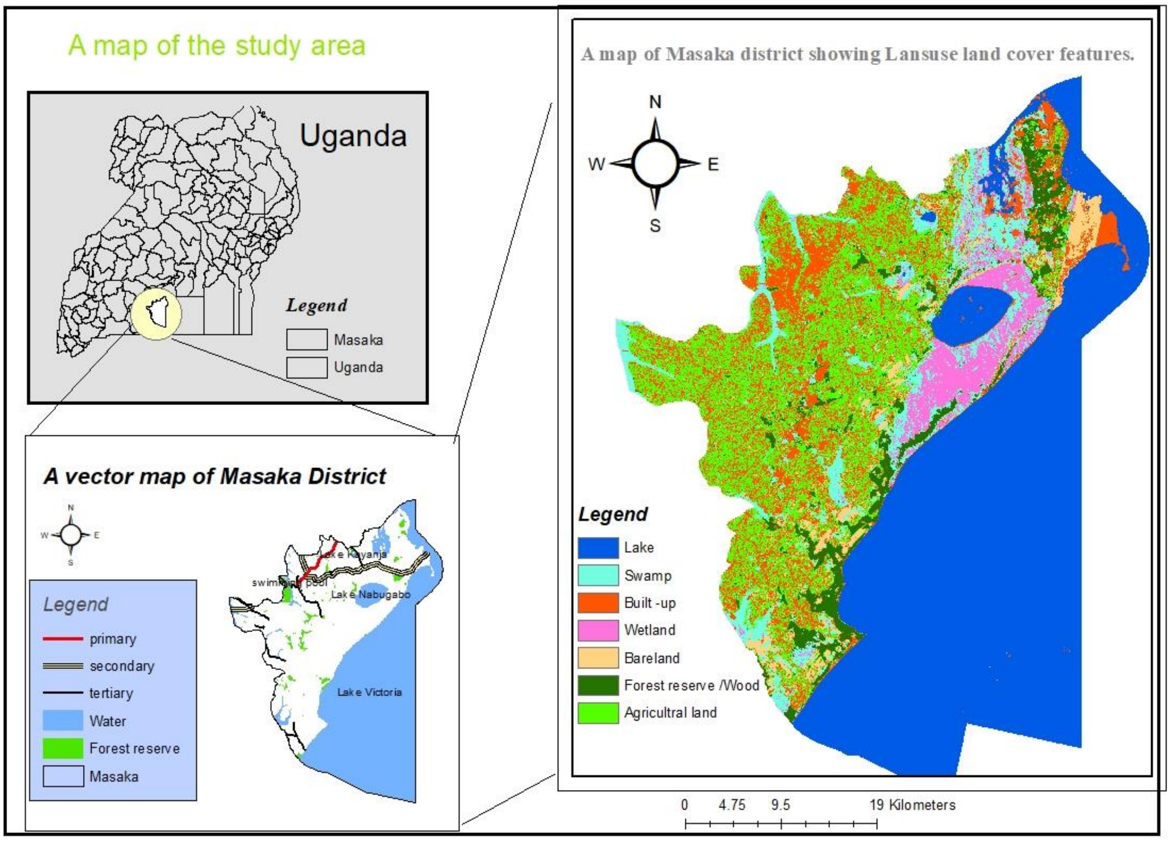

Figure 1:Shows a map of Uganda and Masaka District.

As shown in Figure 1 above, Masaka District in Uganda is characterized by a variety of land uses and land cover features. The district is bordered by numerous water bodies and still contains significant areas of forests and swamps.

1.5.2 Functional or technical scope

This research utilized crime data from the period 2022 to 2024, sourced from various police stations and police posts, and compiled in the Uganda Annual Crime Reports. The data was employed to conduct crime mapping and analysis.

Additionally, the study examined land cover and land use within the district to investigate the relationship between crime occurrences and land cover/land use, particularly in areas exhibiting high crime density. High crime density areas, or hotspots, were identified and analysed using Kernel Density Estimation (KDE). Subsequently, predictive modelling was performed to examine the spatial patterns and temporal trends of the selected crimes. This analysis revealed the emergence of new crime hotspots, as well as the persistence and sporadic nature of others.

1.5.3 Time scope

The research was carried out over an eight-month period, from November 2024 through June 2025. In order to establish a comprehensive theoretical framework and contextual background, the literature review encompassed scholarly works and publications produced between the years 2020 and 2025. This approach ensured that the study was informed by the most recent and relevant findings in the field.

1.6 Justification of the study

This study is in accordance with the United Nations' Sustainable Development Goals (UN SDG), goal 16 "*Promote Peaceful and inclusive societies for sustainable development, provide access to justice for all and build effective, accountable and inclusive institutions at all levels" (United Nations, 2024).*

It is also in line with Africa Agenda 2063 vision," *An integrated, prosperous and peaceful Africa, driven by its own citizens, representing a dynamic force in the international arena*" and in line with Uganda's five year program of Strengthening crime prevention and criminal justice program (2022-2027), "*To contribute to the strengthening of the rule of law through crime prevention and the promotion of effective, fair, humane and accountable criminal justice systems in line with the United Nations standards and norms in crime prevention and criminal justice and other relevant international instruments"*. (Judiciary.go.ug,2022).

Little research has been made on the relationship between land use land cover and crime, so this study comes in to add more information in the field.

1.7 Significance of the study

Law enforcement agencies operate within constructed budgets and resources so, this study is going to help optimize resource allocation by identifying areas with high crime rates, allocating personnel and patrol routes based on demand patterns and prioritising interventions to maximize impact. By deploying resources strategically, security agencies can achieve greater operational efficiency and cost effectiveness (Syed,2024).

The goal of law enforcement is to ensure public safety and build trust within communities. By leveraging remote sensing and GIS, security agencies can tailor their interventions to address specific community needs, engage in proactive problem -solving initiatives and foster positive relationships with residents (Kumar et al,2024).

There will be improved decision-making accuracy in law enforcement by harnessing the power of Remote sensing and GIS so that security agencies can analyse large datasets to identify patterns, trends and anomalies so that they gain valuable insight in criminal behaviour, emerging threats and potential areas of concern, allowing them to respond to incidents more effectively and in a timely manner**.**

CHAPTER TWO

2.0 LITERATURE REVIEW

2.1 Introduction

In this section the literature about spatial patterns and temporal trends of crimes, how land use landcover features relate to crime incidences and how crime hotspots are distributed basing on environmental and infrastructural features was discussed.

2.2 Spatial patterns and temporal trends of crimes in urban areas.

Spatial and temporal dimensions of crimes are a key to understanding their distribution and evolution over time. Spatial patterns show how incidences tend to cluster in some places, with other factors such as socioeconomic factors, infrastructural factors, environmental factors among others. Temporal trends on other side, show how crime rates change during different time, days and seasons. Further details are presented below.

Scientific understanding of the spatial dimensions of crime is critical for containing and improving public security, particularly in large cities (Khan and Talukder,2021), as areas with big cities are more prone to harbouring a greater number of offenders than other areas. Using National Crime Records Bureau and National Sample Survey data, to explores the spatial-temporal patterns of different types of crime in India, Kabiraj found that different types of crime have different time consistent spatial clustering of high and low crime regions. The evidence he found was the prevalence of crime in a region that was influenced by the crime rate of its neighbouring regions. This influence was linked to the spatial diffusion of criminal behaviour and harmful social norms that spread across contiguous regions over time (Kabiraj,2022).

Drawing on one year of travel card and police-recorded crime data, Zahnow examined the association between the percentage of regular passengers and crime at 134 train stations, controlling for land use and neighbourhood social demographic characteristics. It was found out that regularity had a buffering impact on theft and property damage at stations but this effect was curvilinear in the case of theft. Regularity was not associated with assault or motor vehicle crime (Zahnow,2023). Whether a person was a regular train user did not mean that they would not be assaulted or his vehicle could not be snatched.

From the above findings, there is need to understand that crimes do not occur uniformly across geographical areas; instead, they tend to cluster in certain locations while being absent in others, depending on environmental change, socio-economic, and infrastructural conditions (Singh,2022). Corcoran et al., (2019) agreed with Singh's research findings when they noted that spatially adjacent precincts (areas) can experience very different crime profiles. Corcoran based his argument on combination of factors including the daily flux in population, opening hours of businesses along with the presence and type of local security and physical design all of which interplay to generate or prevent crime opportunities. Areas with tight security may have few or no crimes and areas a high population influx will have high crimes as claimed by Crimpsy (2024),higher population density often correlates with increased crime rates, as crowded environments provide more opportunities for both violent and property crimes. The opposite can also be true, with a high population coming with a high community vigilance and frequent police patrols.

Tillyer, Acolin and Walter, (2022) study demonstrated that crime concentrates at relatively few micro-places, and changes at a small proportion of locations can have a considerable influence on a city's overall crime level, though there is little research examining what accounts for change in crime at micro-places. Their research (Tillyer, Acolin and Walter) found out that building permits and code enforcement were significantly associated with reductions in crime on street segments across all cities, with spatial diffusion of benefits to nearby segments. This information can be used for planning public safety incentives.

Different researchers found out that many crimes happen in holidays such as school holidays and during festive seasons (Jubit, Masron and Marzuki, 2020), the crimes are mostly property crimes. This was supported by Cohn (2000); Towers et al., (2018) basing on theory of routine which states that shopping activities, school holidays and festival seasons are associated with crime due to residents in urban areas either leaving to go back to their hometown or going on vacation and this lead to the offender taking the opportunity to commit a crime.

Another significant aspect of temporal trend is seasons. Some seasons or months are noted for high crimes. Mairiga et al., (2023) noted an increase in crime from July one year to May the following year. Their argument was anchored to high influx of people from other countries. The findings are almost similar to those reported by Yar and Nasir (2016), in their study of spatial and temporal analysis of crimes in Mardin, Pakistan, Yar and Nasir found out that almost 50% crimes reported in 2009, took place from May-September (summer) compared to 32% in winter (October to February). Meaning in those countries with seasons like summer, winter, spring, crimes change with seasons.

The findings by Yar and Jamal (2016) cited by Jubit et al (2020), found that when the weather gets hot people tend to get mad more easily and would lead them to lose their tempers, hence high crimes. In India, sexual crimes like rape showed clear seasonal patterns, with more incidents reported during summer months, possibly due to more routine activity and social interaction during hot weather according to the recent study by (Mathew and Guddattu,2024). The above research findings confirm that hot times or seasons are contributors to crimes but more research can be done. During winter most people stay home and movements are few limiting the chances of an offender meeting a victim in the absence of a guardian. More research should be made to find the relationship between summer season and crimes other than basing on Yar and Jamal's findings.

In line with the above, Fan, (2014) used kernel density analysis and nearest neighbour hierarchical clustering (NNHC) to predict crime in the city of Houston and found that temporal-spatial analysis showed that crime occurred more frequently (cited by Jubi et al.,(2020) during the summer months that is from September to December, as opined by Yar and Nasir, and occurs mostly during weekends mostly in central and southern Hoston. The above observation was in agreement with what (Hajela, Chawla and Rasool, 2020b) said, crime spatial patterns are sometimes governed by their temporal aspect. For example, in countries with cold winters, pickpockets will go to the beach only during the summer when there are large crowds and not in winter when the beach is empty. Spatiotemporal patterns thus depend on many factors: weather, census parameters, the environment, the points of interest in an area that attract criminals and efforts put in by the security officers.

In the study by Cheng et al. (2022), property crimes were found to occur most frequently during autumn and winter, primarily in the early part of the month, on Wednesdays and Fridays, and in the early morning. Additionally, property crimes also tended to occur during winter and spring, mainly on Mondays and Thursdays, and during nighttime hours. Seasons affect crime patterns differently for example, autumn season often has longer periods of darkness which provide more opportunities for theft and breakings due to lower visibility.

Early mornings and night time are periods when homes and properties are often left unattended, which increase opportunities for property crimes.

From Monday to Friday, they are working days meaning people are out of their homes, allowing motivated offenders to act. Weekends which are Saturday and Sunday, often bring a relaxed mood as many people have time off work and tend to visit entertainment venues. For workers who are paid weekly, Friday marks their payday. As they go out to unwind and enjoy themselves, offenders take advantage of the situation, leading to an increase in crime.

Another group of researchers found that some crimes are more likely to occur during the day, while others are favoured by nighttime. Additionally, certain crimes are interconnected, where the occurrence of one can lead to another. A study conducted in Lagos, Nigeria, revealed that the majority of assaults involving victims under 20 years of age happened during the daytime. In contrast, assaults against adults over 30 were more common at night (Ezechi et al., 2016). This difference may be explained by the fact that individuals under 20 are usually at home at night, whereas adults tend to move around at night without concern about being questioned for their presence outdoors.

In another study by Cowen, Louderback and Roy (2028), the results showed that neighbourhoods (i.e., Census block clusters) with higher levels of walkability had greater levels of aggravated assault. It was also found that the increasing land-use diversity increased both aggravated assault and larceny/stealing. In the same study still, aggravated assault peaked during late night hours, while stealing peaked during daytime hours. This was in agreement with the research done by Ezechi above.

In a study on urban land use planning and its influence on drug-related crimes in high-density areas of the Ampang Jaya District, Malaysia, Ludin et al. (n.d.) reported that both theft and snatch thefts were most frequently committed on weekdays. Over the course of the year, 563 theft cases and 322 snatch theft cases were recorded. In terms of time categories, thefts occurred most commonly between 4:00 a.m. and 9:00 a.m., while snatch thefts were most prevalent between 9:00 a.m. and 5:00 p.m.

Furthermore, in a study by Othman, Mohd Yusoff, and Salleh (2020), 77% of respondents in Taman Gembira reported that the risk of burglary was highest between 1:00 a.m. and 5:00 a.m., while 82% indicated that such incidents typically occurred around midnight. In contrast, the majority of respondents felt safe during the evening hours, with only 2% perceiving a likelihood of burglary at that time. Similarly, Ahmad et al. (2024) conducted an analysis and identified four significant temporal hotspot intervals: midnight (12:00 a.m.–6:59 a.m.), morning (7:00 a.m.–11:59 a.m.), evening (12:00 p.m.–6:59 p.m.), and night (7:00 p.m.–11:59

p.m.). Several of these temporal hotspots had also been noted in earlier research by Ludin et al. (n.d.).

From the conducted analysis by Li et al, (2022), standard deviation ellipse indicated that crime patterns were more concentrated where burglary during daylight and night has a wider area coverage. Similarly, distributions of drug abuse were located near theft and snatch thieves' locations and this supported the prediction that there is a relationship between drug abuse, crimes and land use planning.

In a detailed study made, it was concluded that public disorder which constitutes gambling, criminal mischief, threaten to injure, harassment, disturbing peace were some subtypes of public disorder occurred consistently in all weekdays, but were at peek during June to August months, traffic accidents were at peek between June–August and quiet low in March and April. Clear weather may be one of the reasons for less accident cases in March–April. Larceny cases were consistent in weekdays, and more on weekends. Burglary crimes were more in April and consistent on all weekdays (Gayathri et al., 2021). For crimes that peek at weekends, there are many entertainments going on and many people are out to relax and sometimes the lose vigilance.

2.3 Relationship between land use and landcover features and crimes.

Brantingham et al. (2017) introduced the concepts of attractor and Repeller factors, which either encourage or deter criminal behaviour in specific areas. Based on the dynamisms in the nature of crime, evidence have shown that there is a strong correlation between criminal activities and the geographical areas where they occur (Omobayo, Olusegun and Chimbo,2025), for example, Abubakar Bashir, Belongeb and Musa, (2024) claimed that areas at lower elevations, such as valleys or urban centres, may exhibit higher crime incidence due to higher population density and accessibility. The following part moves on to describe in greater detail how land use landcover of a place relate to crime incidents.

Vegetation in different shapes such as parks, forests, trees influence various aspects of urban environment which directly or indirectly impact crime opportunities as argued by Ceccato et al.(2020). In another study in support of Ceccato et al, using LiDAR data, Lin et al., (2021) found out that tree canopy cover, streetscape greenery, and species diversity were associated with various crime rates. More specifically, small-sized trees were associated with increased crime rates, while tree canopy cover and streetscape greenery showed a reduction in more severe crimes such as violent crimes after controlling for another criminogenic factor.

More studies were done to prove Ceccato’s argument, to clearly show how vegetation in form of green spaces parks attract or detract crimes. In his seminal study of the relationship between crimes and land use land cover features, Kong (2024) showed that, areas with well-maintained and actively used green spaces exhibited lower crime rates, particularly for minor crimes such as vandalism and petty theft and in another important study it was found that green space in a city is linked with lower risk of crime against property such as burglary, arson and vandalism and less risk of violent offences (Ogletree et al.,2022). This could be due to the natural surveillance taking place since it is used and criminals find it hard to hide there and do criminal acts.

He continued to say that green spaces that were neglected or poorly maintained tended to have higher crime rates. Specifically, his data showed that areas within 500 meters of well-maintained parks experienced a 20% reduction in petty theft and a 15% reduction in vandalism compared to areas farther away.

Another study reported, larger green spaces with diverse amenities and recreational facilities were associated with lower crime rates. For example, parks over 10 hectares in size with sports facilities and community events saw a 40% reduction in overall crime rates (Kong, 2024). The study by Sukartini also claimed that excessively large green spaces with a lack of visitors can contribute to increased crime rates by providing ample space for criminals to hide and carry out illicit activities (Sukartini et al., 2021). The difference is, green spaces that are not well kept, not guarded breed crimes as they become grounds for criminal activities or hiding places for offenders. Well-kept green spaces within parameters or enclosed have little or no crimes.

Some results are similar to those reported by (kondo et al.,2017; Liu et al.,2017) as cited by Akiner, Akiner and Akiner (2023), when they showed that people living in cities with dense green spaces tend to have less aggression and violent tendencies than in places with inadequate green spaces. Akiner, Akiner and Akiner mentioned that, the relationship between the green texture and the crime frequency showed that crime intensity was high in the counties where the land cover type turns intensely from the forest and wild areas to urban areas. The study clarifies that living in lucky regions with woodland and green texture is safer (Akiner, Akiner and Akiner,2023). What they did not say was that city green spaces are guarded and entry is restricted and so it becomes hard for criminals to use such places.

The above argument was supported by Sypion-Dutkowswa and Leither (2017) with their detailed survey that concluded, grandstands, cemeteries, green areas, allotment gardens, and depots and transport base as land use types strongly detract crime. For crime to take place, three things must be in place; the motivated offender, a suitable target and the absence of a capable guardian (Cohen and Felson,1979), a routine activities theory.

Absence of crimes in some land use landcover feature areas means there is a component missing from the crime triangulation. Myhill and Allen, (cited by Lu et al.,2024), found out that public outdoor spaces such as parks, alleys provide hiding venues for sexual offenders, allowing them to carryout actions without being seen or heard by others. This still show the contribution of open spaces and green spaces on crimes.

Turning now to the general built-up, Naidu and Priya (2025), suggested that the built environment influences criminal behaviour by shaping opportunities for crime. This was better explained by Mao et al. (2025); Sharma and Tailor (2023) when they noted that residential, industrial and recreational land uses have a significant correlation with crime rates, forexample shopping malls, parks, schools, liquor stores may attract criminals to commit crimes because these places generate high level of crime opportunities.

Another study on the same plane claimed that residential and commercial land-use had been discovered with the highest crime rates in the study area. Stealing, robbery, and gambling were found as the most common crime types (Chukwudi Nwaogu,2019)**.** Ceccato and Ioannidis (2024), opined that urban structure, transportation systems can impact criminal activities. Areas with tightly spaced buildings might have more hiding spots and obstructed views that can facilitate criminal activities (Merry,1981; Minnery & Lim,2005 cited by Ceccato &Ioannidis,2024) and on other hand, unfinished or semi finished buildings also tend to hide criminals most as supported by Dube (2024). 'Most of the uncompleted stands have now become hiding places for thieves and those conducting illegal activities which have had a negative impact on the growth of our community, reported Ward 6 councillor Nkosinathi Hove Mpofu, (New Ziana (2024).

Such building can be found in slum areas, in busy areas such as commercial building. Robberies and thefts were concentrated in residential areas according to Dutkowska and Leither (2017) in the study of land use influencing the spatial distribution of urban crime in Szczecin, Poland and multi-residential buildings exhibit higher crime rates as opined by (Bacer et al.,2025). Even with a security guard it becomes hard to differentiate criminals from non-criminals.

Some crime incidents are frequently associated with urban area which are more at risk as compared to other areas. Main roads, overpass, commercial areas such as banks, shopping complexes, bus stands, and restaurants appear to be the preferred locations for criminals to find their victims (Ludin et al., no date).

This was clarified by Mao et al.,(2025) when they found out that residential and industrial areas have a positive impact, whereas recreational spaces have a negative impact on crime rates. Recreational areas or spaces are places specially designed for leisure activities, physical excises and social interactions. Such places include playgrounds, walking trails, sports fields, parks, night clubs, bars and many others. Dutkoswa and Leitner (2017) remarked that alcohol outlets, clubs and discos, cultural facilities, municipal housing, strongly attract crime. The above places are under recreational places or spaces. These places bring criminals closer to their victims and avail an opportunity for attack forexample after one has become drank or after one has taken some drugs.

According to a study done by Mafumbatete et al (2019), places holding liquor, public transit areas like bus stops, vacant and abandoned residential and other commercial areas seemed to influence crime's spatial distribution. This is similar to Dutkoswa and Leitners study above. In their detailed analysis of crimes, Lersch and Hart (2023), found out results that showed hot spot areas for sexual assaults were more concentrated during the COVID timeframe (2020-2021), compared to the Pre-COVID timeframe (2019). While blight complaints public transport stops, points of sale for liquor, and the locations of drug arrests were consistent risk factors for sexual assaults before and after COVID restrictions, other factors, such as casinos and demolitions, were only influential in the COVID period. It is hard to believe that such crimes were prevalent during the pandemic with the very serious restrictions and security that were put up by different governments.

There are crimes facilitated by road network i.e. nature and type of the road as remarked by Sharma and Tailor (2023), increased road connectivity has a positive correlation with crime rates. This study suggests that the crime rate varies with different land uses and road networks. In their detailed analysis of crimes and land use landcover features, Fazzami et al., showed that the nearer the house to the main road, the more vulnerable toward the occurrence of the crime of burglary.

The road can give criminals a quick escape route and can easily mix with other road users. Regions with higher road densities generally experience increased human traffic, which can include both potential crime victims and perpetrators. Other Studies have indicated a correlation between road network density and crime rates, especially in public settings (Naidu and Priya,2025).

Collector or distributor and arterial roads are well-travelled, but in comparison to freeways and highways, they provide many opportunities to stop, start, identify, and access potential targets (Wuschke, Andresen and Brantingham,2021). In their study, collector roads recorded 15% and arterial roads had 35.5% of all criminal events reported on roads.

Along the same lines, Fadhil and Alifa (2025) subsequently argued that, street crimes are notably more frequent on roads with medium- high integration values (above 1000), where activity levels are substantial but still allow opportunities for criminal behaviour due to a greater number of potential targets. Although high-integration roads generally reduce crime through increased natural surveillance and activity, medium-high integration roads appear to strike a balance that facilitates criminal opportunities. They give a chance to the motivated offender to meet the target without a guardian.

Fadhiland and Alifa continued to point out that vulnerable areas are characterized by high vehicular traffic, easy accessibility, limited pedestrian activity, and minimal direct surveillance. Roads with higher connectivity have fewer crime cases, likely due to increased activity and better surveillance. In Uganda's city traffic officers are put at a point (on the road) with higher connectivity to help direct traffic. It becomes hard for criminals to act which give roads (well-maintained) a negative correlation with crime incidences.

In support of the above, Jen (2025) also argued that areas with high street connectivity and roads wider than 10m are associated with a lower probability of residential burglary. This is because of the continuous flow of vehicles and people or public presence.

A unique study by Abubakar Bashir, Belongeb and Musa (2024) reported that criminal activities might be more prevalent near water bodies due to their strategic importance for transportation or access to resources. Many studies have talked about transportation in terms of roads. This brought to light how water bodies relate with crimes. For this study, crimes that happen on water are handled by a different police unit called Marine police, so crimes related to water need to be analysed with information got from Marine police.

2.4.1 Hotspots, infrastructure and environment

Xie, Shekhar and Li, (2023), discussed that spatial hotspot mapping is important in many areas like public health, public safety, transportation, and environmental science. It helps to identify areas with high rates of certain events like disease or crime, but traditional clustering techniques can give false results, which can be costly.

Numerous types of crimes can occur in an area with different frequencies. An area may be flagged for higher pick-pocketing events while the other for a particular type of crime as claimed by (Butt et al., 2020). Crimes cluster because of certain favourable factors such as environment, infrastructure and others. Physical environmental factors include spatial variables of the crime. It is very important to determine the relationship of crimes with land use and the environment design in order to reduce crime events (Bediroglu and Colak, 2024).

According to Butt et al. (2020), mapping of crime hotspots can help understand the reasons behind the frequent occurrence of crimes in those areas. They continued to say that certain types of criminal incidents such as larceny, identity theft, or even pick-pocketing can cause disturbance and stress in an individual’s life and affect his mental peace. Wolfe and Mennis (2012), suggested that well-developed public infrastructure (such as roads) had a positive impact on law enforcement activities, another research made claim that, consistent with the law of crime concentration at place, burglary in Taipei City is significantly concentrated. Specifically, 51.3% of burglaries occurred in just 5% of micro-place units and 25.9% in only 1.7% of units. Over 80% of spatial units were burglary-free, the concentration of burglary incidents within Taipei City's was on street segments, (Jen, 2025).

After knowing that certain land use landcover features attract crimes, there is a need to start predicting crimes as this is an important function in developing more effective crime prevention strategies or developing investigative efforts based on the availability of prior data such as case information, location, date, and time (Singh, Bhandari and Khatwani, 2025).

2.4.2 Crime prediction methods used by others researchers.

Crime hotspot identification and prediction is an essential area of research to oversee criminal activities for the law and enforcement agencies. A vast amount of literature has been cited to identify and predict criminal hotspots in Spatio-temporal context as reported by (Butt et al., 2020).

Crime prediction has become very important in recent years to both security officers and researchers in different countries. There are different types of tools adopted by police departments for analysing crime data and predictive policing. There are technologies that use machine learning (ML) algorithms and statistical analysis methods to predict criminal activities, their location, date and time, type of crime, and victims of future crimes based on both historical and real-time crime data as epitomised by (Yang,2019).

There are two common crime prediction approaches that is location-based and person-based approach. Crimes prediction that involves location-based approaches predict where and when a crime is likely to be committed, with a focus on relevant factors of criminal activities and environmental features. On the other hand, person-based approach or offender-based models predicts the next person to commit a crime or to be crime victims based on their personal information assessment or their history of criminal behaviour as claimed by (Bertovskiy, Novogonskaya and Fedorov, 2022). For any selected method or tool what is important is the accuracy of the results got because accurate crime prediction results are vital for the beforehand decision-making of government to alleviate the increasing concern about the public safety (Liu et al.,2022).

Liu et al., (2022) developed a spatial- temporal hypergraph self- supervised learning model that was based on self-supervised methods to model complex spatial- temporal relationships. For one to use it, it required retraining on crime types in different regions and it is a machine learning model. The inclusion of spatial and temporal information in the crime datasets using GIS has revolutionized the crime prediction systems (Deshmukh et al., 2020).

Another research by Wang et al. (2022) designed a hierarchical graph convolutional recurrent network (Hagen) that could jointly capture the crime correlation between regions and the temporal crime dynamics by combining an adaptive region graph learning module with the Diffusion Convolution Gated Recurrent Unit (DCGRU). It also incorporated crime embedding to model the interdependencies between regions and crime categories with the only regret that wang et al used machine learning algorithm without GIS.

A study by Hashim et al. (2019) used emerging hotspot analysis for crime pattern recognition and ordinary least squares regression, finding that 53% of neighbourhood locations showed a 99% confidence level with Z-scores exceeding +2.58. However, this method cannot be applied in certain studies because the primary causes of crime are related to land cover and land use features, for which relevant data are not available from authorized agencies. Additionally, economic factor data lack precise location information and are recorded on different dates, making them unsuitable for this type of spatial analysis.

Dubey et al. (2024) proposed a clustering-based method for crime hotspot recognition and forecasting, using historical crime data from San Francisco. They employed ensemble learning techniques—including stacking, voting, and bagging—to improve prediction accuracy. This approach successfully identified crime hotspots and yielded promising results. However, the methodology did not incorporate Geographic Information Systems (GIS), limiting its spatial analysis capabilities.

In the process of obtaining crime data from the database of crime statistics for South Africa's nine provinces, Obagbuwa and Abidoye (2021) used data mining tools. They then used a supervised learning technique (a linear regression algorithm) to build a crime prediction model, which produced accurate predictions with an R-squared accuracy metric of 84.7%. This model was generated from sex crimes, population, population density and area. The approach used is good for showing linear relationship but not where next crime will occur and at what time.

In another study, Sukhija et al. (2020) performed a linear regression analysis to determine the correlation between traits linked to rape incidents in Haryana and to indicate pertinent variables that can better assist police personnel in crime prevention. When building predictive models with data analytics, linear regression and decision trees work well (Obagbuwa & Abidoye, 2021).

In their wide-ranging study of crime prediction with historical crime and movement data of potential offenders using a spatio-temporal cokriging method, Yu et al., (2020) used the movement data of past offenders collected in routine police stop-and-question operations to infer the movement of future offenders. The offender movement data compensated historical crime data in a Spatio-Temporal Cokriging (ST-Cokriging) model for crime prediction. The models were implemented to predict crime on weekly, biweekly, and quad-weekly intervals in the XT police district of ZG city, China. Incorporating offender movement data consistently improved prediction accuracy, with the greatest improvement seen in the weekly model, followed by the biweekly and quad-weekly models. Although the results were promising, offender movement data are difficult to obtain from police stations because they are classified information. Therefore, this spatial-temporal cokriging method cannot be applied in studies that rely on aggregated data.

All in all, some researchers have mentioned the best techniques among the ones they implemented and compared. However, they are according to the dataset being used, performance measures being used, and in a particular scope. The majority of reported datasets do not have space and time information, so it is challenging to compare techniques based on this fact that crime detection approaches improve a lot after the usage of Spatio-temporal information. Spatial and temporal information addition in datasets found to be more effective for crime prediction (Butt et al., 2020).

2.5 Possible interventions to mitigate crime occurrences

The spatially informed interventions to mitigate crime occurrences play a very crucial role in designing crime detection, prevention and prediction measures. This can be done through analysing patterns, infrastructural factors and environmental factors that bring about crime. The possible spatial interventions are discussed below in details.

In their historic study, MacDonald et al.(2024) suggested place-based approach that focus on changing the environmental features of places, offer some guidance for intervening in the hot spots that generate the majority of serious crime and violence in cities. Place-based studies of crime invoke elements of environmental criminology in that they focus on how changes to the physical and social environment of places may impact criminal opportunities and offending decision-making (Wilcox & Cullen, 2018).

MacDonald et al, suggested remediating abandoned property and vacant land as the most consistent evidence in helping reduce serious violence**.** From several studies, abandoned houses or buildings hide criminals and vacant lots do the same. The best solution for abandoned property like buildings would be to renovate and have occupants in it other than demolition for demolition still cause problems as Han and Helm (2020) reported in their "*Does Demolition Lead to a Reduction in Nearby Crime Associated With Abandoned Properties?"*. The findings show that demolition of abandoned homes did not reduce nearby crime, which Han said indicates policymakers should consider holistic approaches to improve neighbourhood safety. Han further suggested that the very first thing that should happen is to get these houses and properties occupied. So someone is at least living there and paying taxes, and so the city can provide more services.

Designing a proper layout is believed in cutting fear of crime. Any space with high visualisation and natural surveillance can raise a confidence level to survive so, public space needs to maximise visibility and natural surveillance for limiting the crime event (Othman, Mohd Yusuff and Salleh,2020).

In line with the above, Kaplan and Chalfin (2022) analysed the extent to which street lighting improvements affected daily night-time activities and concluded that enhancing public lighting could help control crime and improve community well-being. In Chalfin et al. (2022), also a study on street lighting in New York, the results suggested that a tactical deployment of lighting could control crime through a deterrent effect that leads to a reduction in outdoor night-time crimes. Criminals avoid lights fearing observation by another person or a possibility that there could be a camera installed in lights.

There are studies that point out crime prevention through environmental design (CPTED) as a spatial intervention strategy to mitigate crimes. Muhamad Ludin et al., (2013) noted that CPTED basically emphasises on the idea that proper design and effective use of the built environment can lead to a reduction of crime incidence. Isolated, abandoned, and derelict houses, as well as public spaces with no protection, are hotbeds of crime because they provide assailants with the anonymity, they need to commit heinous crimes while avoiding detection. There are various types of dead spaces such as abandoned & derelict buildings and sites, mono-functional zones such as industrial parks and commercial districts typically occupied during fixed hours only, and public spaces with little visual connectivity.(Adel et al., 2016, cited by (Waleed, FaroukandHamdy,2021).
The first pillar of Crime Prevention Through Environmental Design (CPTED) is surveillance, which can be categorized into natural and artificial surveillance. Natural surveillance involves strategically designing the environment to increase the perception that individuals can be observed, thereby limiting opportunities for crime. This is achieved by maximizing visibility through thoughtful landscaping and urban design. For example, overgrown bushes, dense trees, and tall fences can create hidden areas or blind spots that shield criminals from view, increasing the risk of illicit activities (docmckee.com).

Proper maintenance of trees and shrubs is essential to ensure clear sightlines while avoiding the creation of potential hiding places. Effective natural surveillance encourages informal social control by increasing the number of "eyes on the street," which deters criminal behaviour by raising the likelihood of offenders being noticed and reported. Additionally, artificial surveillance, such as security cameras and lighting, can supplement natural surveillance to further enhance visibility and safety in an area.

By integrating these principles into environmental design, communities can proactively reduce crime and increase the perception of safety among residents and visitors (CPTED International, 2020; Crowe, 2000).

When offenders are aware that they could be observed, they perceive a higher risk of being caught, which acts as an effective deterrent to criminal behaviour (essexdesignguide.co.uk). This concept is central to natural surveillance, where the environment is designed to maximize visibility and increase the chances that potential offenders are seen by residents, passersby, or users of the space. Natural surveillance relies on factors such as strategic placement of windows, open sightlines, active street use, and well-maintained landscaping to create an environment where people feel watched and, consequently, less likely to commit crimes.

On the other hand, artificial surveillance involves the deployment of technology to monitor activities and enhance security. This includes tools such as CCTV cameras positioned to cover vulnerable or high-risk areas, GPS tracking systems for monitoring the movements of individuals or vehicles, and drones or aerial surveillance that provide broader, real-time coverage of larger spaces. These technologies supplement natural surveillance by providing continuous monitoring capabilities that can act as a deterrent and assist in rapid response and evidence collection when crimes occur.

Together, natural and artificial surveillance form a comprehensive approach within the Crime Prevention Through Environmental Design (CPTED) framework, effectively increasing the perceived and actual risk of detection for offenders, thereby discouraging criminal activity and enhancing community safety.

Focused deterrence strategies or pulling lever was pointed out as a spatial intervention towards reducing crimes by (Moore and Pease, 2023; Braga, Weisburd and Turchan, 2019). Deterrence relates primarily to the use of the criminal justice system to reduce offending through the prospect of punishment. Deterrence is either by punishment aimed to make a would-be opponent view a conflict as potentially too painful to endure. Or deterrence by denial sought to deny an aggressor the benefits of any aggression (Moore and Pease, 2023).

The available empirical evidence suggests these strategies generate noteworthy crime reduction impacts and should be part of a broader portfolio of crime reduction strategies available to policy makers and practitioners (Braga, Weisburd and Turchan, 2019).

Kong(2024) urged that enhancing community engagement through the thoughtful development and maintenance of green spaces had proven to be a crucial strategy in reducing crime rates. Green spaces that actively foster a sense of community, by hosting events and providing recreational activities, significantly contribute to lowering crime rates. He continued to say that community gardens and parks that regularly hosted events like local farmers' markets, fitness classes, and cultural festivals had reported up to a 35% reduction in petty crimes, such as vandalism and theft. The engaging of the community increases a sense of ownership and this increases community's vigilance hence a reduction in crimes.

CHAPTER THREE

3.0 METHODOLOGY

3.1 Introduction

This chapter presents the research methodology, detailing the research design, approach, and the specific methods employed for data collection and analysis. It explains the rationale behind choosing these methods, outlines the procedures followed to ensure data reliability and validity, and describes how the collected data were processed and interpreted to address the research objectives comprehensively.

3.2 Research Design

This research adopted a mixed-methods design, incorporating both qualitative and quantitative approaches for data collection, analysis, and presentation. While qualitative methods provided in-depth insights and contextual understanding, the study predominantly relied on quantitative techniques to generate measurable and statistically significant results. This combination allowed for a comprehensive examination of the research problem, enhancing the validity and reliability of the findings.

3.3 Research Approach

The approach used was inductive, beginning with the collection of specific observations or data, followed by the identification of patterns and trends within the dataset. This method allowed for the development of broader generalizations and theories based on empirical evidence. By systematically analysing the data, the study was able to uncover underlying relationships and insights that informed the overall conclusions and recommendations

3.4 Data Collection.

The study used both primary and secondary data.

3.4.1Primary Data

This study used satellite images as the primary data source, obtained from Earth Explorer (https://earthexplorer.usgs.gov). Earth Explorer is a platform developed by the United States Geological Survey (USGS) that provides free access to a wide range of satellite imagery and remote sensing data**.**

These images offer valuable information on land cover, land use, and environmental features over large geographic areas and extended time periods. Using satellite imagery allows researchers to analyse spatial and temporal patterns in the study area, supporting assessments such as environmental changes, urban development, and crime-related factors linked to land use. The high resolution and frequent updates of satellite data make Earth Explorer an essential tool for acquiring reliable, up-to-date, and comprehensive geospatial information that can underpin spatial analyses and decision-making in various research fields.

3.4.2 Secondary Data

This was got from the reports or documents such as Uganda annual crime reports for the last five years (2020-2024). It was expected that this period (2020-2024), would be sufficient in drawing a solid conclusion as well as present a define picture of the spatial distribution of crime within Masaka district. Crimes under study include: Sex abuse, theft, robbery, assault and breakings among others.

Theft which is defined by legal dictionary as a term used to describe a crime that involves taking a person's property without his consent (Legal dictionary) or as the taking of someone's property without permission. Theft cases include larceny, pickpocketing, shoplifting and others. This is a common occurrence that is hard to prevent.

Robbery refers to the felony crime of taking something of value from another person through force or threat of violence (Legal dictionary). Breakings is sometimes called burglary. This refers to entry into a building or structure without permission from the owner with the intent to commit a crime. A breaking or burglary which involve an offender entering a home or living space is considered residential burglary while entering a shop, store, office building or other structure used for business purposes with the intent to steal is commercial burglary (Cyndi,2014).

Assault is typically defined as an act which gives an individual reason to believe that they are in danger of being physically harmed by an aggressor (Legalserviceslink.com, 2022). Assaults range from simple physical harm acts like slapping, kicking, pushing to aggravated assault which involve serious bodily harm of use of a deadly weapon, such as a knife or firearm, assault with a deadly weapon among others (www.schmidtandclark.com).

The study also used vector data such as shapefiles for Uganda districts and divisions.

3.5.0 Data Collection Methods And Tools.

3.5.1 Data Collection Form

This study utilized a data collection form to systematically gather information from various annual crime reports, as direct access to detailed crime incident point data was not available. The use of data collection forms allowed for the extraction and organization of relevant crime statistics and spatial information reported in these documents. Although crime incident point data which provide exact geographic locations of individual crimes are ideal for detailed spatial analysis, their unavailability necessitated relying on aggregated data from official reports. This approach ensured that the study could still analyse crime trends and patterns over time, though at a broader spatial scale. The collected data (from Uganda police annual crime reports) were carefully tabulated to maintain consistency and accuracy, enabling meaningful interpretation of crime distribution and facilitating the identification of hotspots within the study area. A copy is appended (appendix C).

3.5.2 Observation

The researcher conducted visits to various locations for ground truthing, a process that involves comparing physical features and conditions observed directly on the ground with the information obtained from remotely sensed data, such as satellite images. Ground truthing is a crucial step in validating and assessing the accuracy of remotely sensed data, ensuring that the interpretations made from imagery accurately represent real-world conditions.

By verifying features such as land cover, vegetation, and built environments in the field, the researcher could identify and correct any discrepancies or errors in the remotely sensed datasets. This validation enhanced the reliability of subsequent spatial analyses and helped to refine data classification and mapping efforts.

Ground truthing is widely recognized as an essential practice in remote sensing and geographic information science to improve data quality and support credible research conclusions (Campbell & Wynne, 2011; Jensen, 2015). Without such field verification, interpretations based solely on remote sensing may be prone to inaccuracies due to factors like image resolution, atmospheric conditions, and sensor limitations.

3.6 Data Analysis

The study employed various analytical methods including temporal-statistical analysis, spatial analysis (such as crime mapping, crime pattern and clustering analysis), and predictive analysis to better understand and examine crime data trends and patterns over a three-year period. For the temporal-statistical analysis, crime data from Uganda's police annual crime reports were analysed and presented using data visualization tools such as tables and graphs, created with Microsoft Excel. Time series analyses were conducted for different locations, with calculations of crime averages, totals, density.

Spatial analysis involved use of Software like ArcMap (10.8.3) and QGIS to produce maps for crime distribution (average), crime densities and crime hotspots.

For predictive analysis, a space time cube pattern mining by aggregating points was used in ArcMap software. This was used to determine future crime hotspots, persistent, consecutive and sporadic hotspots.

Kernel density estimation (KDE) is useful in detecting crime hotspots due to a series of estimations sone over a grid placed on the entire study area. The user has to specify appropriate bandwidth for estimation, where if the bandwidth is set too large, important information may be lost.

The output of a KDE is a raster with different classifications showing the pattern of the phenomenon under study. A suitable number of classes is picked basing on methods like, Natural breaks, Equal breaks and others for better visualisation. The crime zones were identified basing on low values to high values which were got after integration.

Results of a KDE were further analysed to get the statistical significance of the hotspot got. Hotspot analysis was done where clusters of low and high values were detected in data with a confidence level. Those were used to tell how significant identified clusters were basing on z-scores and p-values attained. A high z-score and small p-value for a feature indicate a spatial clustering of high values. A low negative z-score and small p-value indicate a spatial clustering of low values. The higher (or lower) the z-score, the more intense the clustering. A z-score near zero indicates no apparent spatial clustering

(*ArcGIS tool reference*).

3.7 Methodological Approach For The Study.

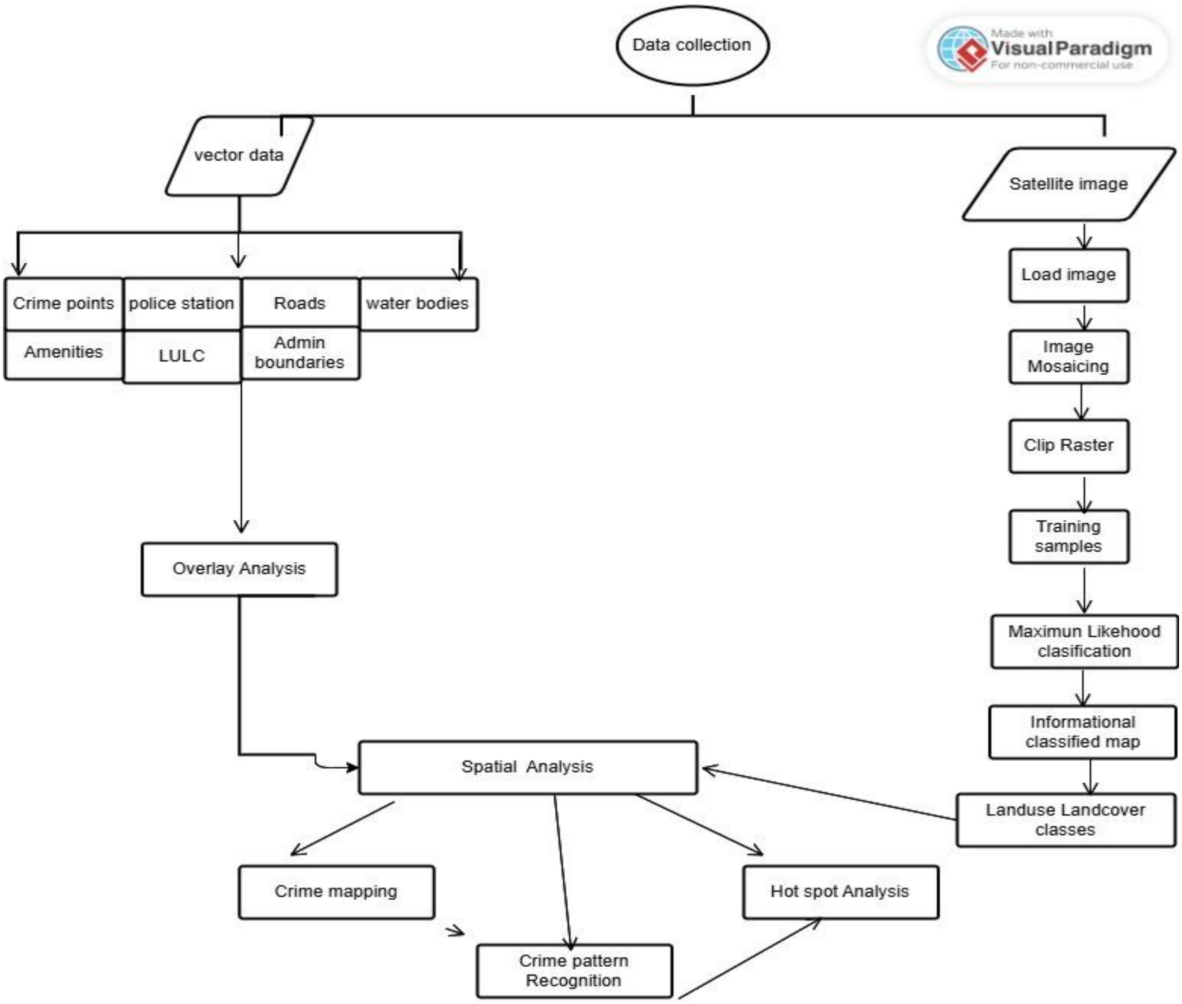

Figure 2: Methodological approach used in the study.

Data collected included Vector and Raster (Satellite imagery) for Masaka district. Raster data collected included satellite images for Masaka from 2020 to 2024. These were got from USGS-EarthExplorer (https://earthexplorer.usgs.gov) using Landsat 7 ETM+CL1 and Landsat 8-9. Uganda shapefiles or polygons were got from the Uganda GeoPortal (https://uganda-Africa.hub.argis.com) and the parish boundaries shapefile for Uganda (openAFRICA, 2010) was used in this study to define administrative areas that were used in predictive modelling.

With the help of GIS software like ArcMap, Satellite image spectral bands were loaded into the program, one year at a time. Bands were combined to form one complete image; a process called band stacking and administrative boundaries were added into the software. Vector data like crime data points, banks, schools, roads, police station's location, water bodies were overlaid to aid crime analysis.

Analysis was done and major information classes identified. Training samples for different information classes were picked from different places and extracted using supervised classification (Maximum likelihood).

Crime mapping and crime pattern recognition were done; hotspots were identified and more analysis done to deeply understand the relationship between a given information class and a type of crime in that area using Kernel density estimation (KDE). Prediction of future crimes and crime locations was done using Space time cube mining pattern by aggregating points.

3.8 Ethical Considerations

Before going into the field to collect data, the researcher obtained an introduction letter from the university. This letter helped assure respondents that the research was legitimate and a valuable use of time and resources.

During the interviews, the researcher clearly explained the purpose of the study and the specific information required from the respondents. Confidentiality was strictly maintained; respondents' names were either hidden or removed from the data collection tools, and their information was not disclosed outside the scope of this research. Additionally, photos and videos taken during ground truthing were only captured after obtaining permission and consent from the relevant authorities.

3.9 Research Dissemination Strategy.

After completing the research, the findings will be disseminated through several channels;

A copy of the research will be placed in the Uganda Martyrs University library, specifically within the Institutional Repository, to allow other students, researchers, and the wider academic community to access and use it as a valuable resource for knowledge. By making the research publicly accessible, it contributes to the university's commitment to knowledge sharing, supports further studies, and fosters a culture of academic collaboration and innovation. Additionally, this enhances the research's visibility and impact both within and beyond the university community.

Presentations will be made at various workshops and conferences to highlight the application and benefits of geospatial technologies in crime prevention. These events will provide opportunities to engage with stakeholders, including law enforcement agencies, urban planners, community leaders, and researchers, fostering collaboration and knowledge exchange. Demonstrating practical examples and case studies will help to illustrate how geospatial analysis can effectively identify crime hotspots, support resource allocation, and inform targeted interventions.

In addition to workshops, the research and its findings will be published in reputable academic journals to undergo rigorous peer review. Publishing in open access journals will ensure that the knowledge is widely disseminated and accessible to researchers, practitioners, policymakers, and the wider public globally. This will promote transparency, facilitate replication of the study, and encourage further investigations in the field of crime prevention through geospatial technologies.

Additionally, copies of the research findings will be provided to the Uganda Police Research Department to support and promote the adoption of geospatial technologies in crime prevention and law enforcement efforts. This collaboration will facilitate the integration of advanced spatial analysis tools into policing strategies, enabling more effective identification of crime patterns and hotspots. By equipping the police with actionable geospatial insights, the research aims to enhance decision-making processes, optimize resource deployment, and strengthen overall crime-fighting capabilities. Furthermore, ongoing dialogue and training sessions will be proposed to build capacity within the department, ensuring sustainable use and continuous improvement of geospatial methods in operational contexts.

Finally, the research findings will be published in newspapers and other mainstream media outlets to raise public awareness about the role and benefits of geospatial technologies in crime prevention. This dissemination will be conducted subject to obtaining the necessary permissions and approvals from the Uganda Police Force's Research Unit to ensure that sensitive information is handled appropriately and in line with official protocols.

Publicizing the findings through widely accessible channels will help inform and engage the community, fostering greater understanding and support for innovative crime-fighting approaches. Additionally, increased public awareness can encourage community participation in crime prevention efforts and strengthen trust between law enforcement agencies and the public they serve.

CHAPTER FOUR

4.0 PRESENTATION OF RESULTS AND FINDINGS

4.1 Introduction

Understanding the evolving relationship between land use and land cover patterns and crime occurrences is essential for effective urban planning, resource management, and the promotion of public safety. This chapter focuses on the methods of data acquisition, processing, and analysis using Geographic Information Systems (GIS) and Remote Sensing (RS), and presents the results derived from these approaches. By leveraging these geospatial technologies, the study aims to reveal insights into how changes in land use influence crime distribution and patterns over time.

4.2 Crime distribution in Masaka district

Crime data used for this study was obtained from Uganda annual crime reports since crime incident data (location, time and crime type, offender gender) could not be got from the different Uganda police stations within Masaka district. The table 1 below shows how crimes were reclassified, giving the category and other crimes within a major crime selected for study.

Table 1 : Major and minor classes of selected crimes.

S.no	Different crimes	Major class	Category
1	Theft of all kinds (vehicles, properties, cash, cattle, phones and pickpocketing	Theft	Property crime
2	Aggregated rape, rape, defilement, incest, unnatural offences and indecent assaults	Sexual abuse	Human/violent crime
3	Aggravated and common assaults.	Assaults	Human/violent
4	Aggravated, general, simple robberies.	Robberies	Property

5	Burglaries, house breakings, shop breakings, office, garage breakings	Breakings	Property

The data sets have the temporal crime data of theft, robbery, assaults and sexual abuse from 2022 to 2024. A total of 4651 cases were selected for this study as shown in the table 2 below:

Table 2: Temporal distribution of crimes from 2022-2024 in Masaka district.

Crime type	**2022**	**2023**	**2024**	**Total**
Sex abuse	157	171	198	**526**
Theft	642	909	972	**2523**
Robberies	67	85	111	**263**
Assaults	183	248	353	**784**
Breakings	176	196	154	**526**
Total	**1225**	**1609**	**1788**	

Since 2022, crime rates in Masaka have been increasing. For example, the number of crimes reported in 2023 was higher than in 2022, with 2024 experiencing the highest crime levels during the study period. Theft is the most frequently occurring crime, followed closely by assaults, sexual abuse, and robberies, respectively.

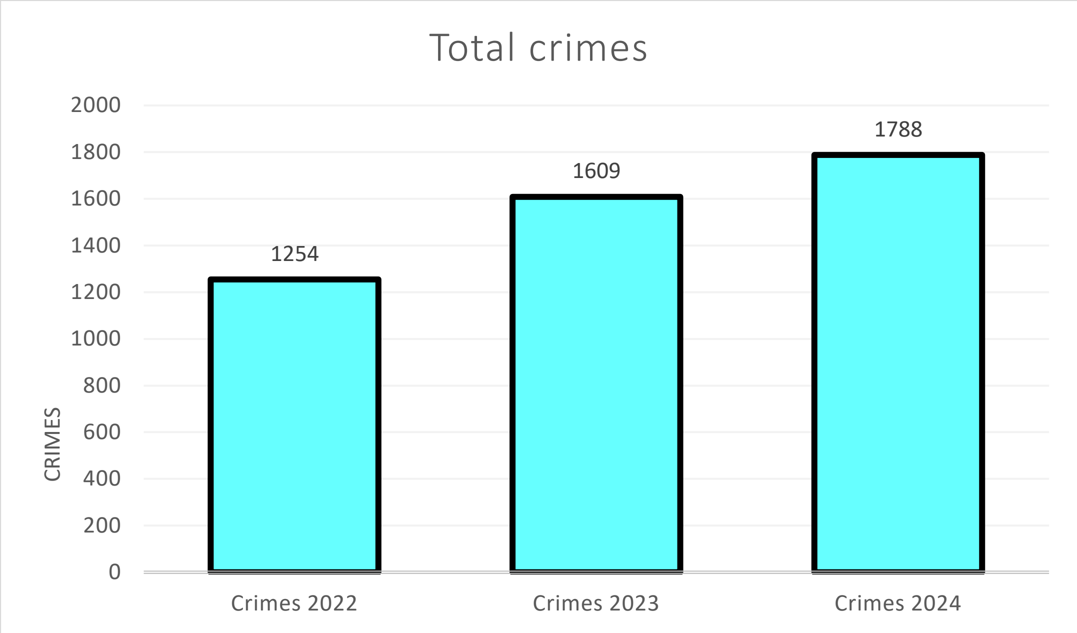

Figure 3: Total crimes trend from 2022 – 2024

Table 3 above illustrates the increasing trend of crimes in Masaka district, with the total number rising from 1,254 in 2022 to 1,788 in 2024, representing an increase of 534 cases. This upward trend has contributed to a growing sense of insecurity among the residents of Masaka, as the rise in crime contradicts the expectation of a decline during this period.

4.2.1 Average spatial crime distribution

To accurately map the crime data, the average number of a particular crime for each division was calculated by summing the total crimes recorded from 2022 to 2024 and then dividing by the three-year period. These averages were subsequently used to illustrate the spatial distribution of each crime type across the divisions, providing a clear picture of crime prevalence over time. This method helped smooth out anomalies and seasonal fluctuations, allowing for more reliable comparisons between divisions.

4.2.2 Sex abuse average

Analysing average crime figures rather than raw totals allow for more accurate comparison between divisions of differing sizes and population densities. It also aids in identifying divisions with consistently high or increasing incidences of sex abuse, which are crucial for targeted intervention and resource allocation. By mapping these averages, stakeholders including law enforcement agencies, policymakers, and community organizations can pinpoint hotspots and prioritize crime prevention efforts effectively.

Overall, the use of averaged crime data over multiple years strengthens the reliability of spatial crime analysis and supports comprehensive planning for crime reduction and community protection**.**

Table 3: Average spatial distribution of Sex abuse crimes

	Sex abuse crimes				
Divisions	**2024**	**2023**	**2022**	**Total**	**Average**
Masaka city	47	33	68	148	**49**
Masaka rural	59	45	35	139	**46**
Kimanya- Kabonera	29	25	17	71	**24**
Nyendo- Mukungwe	63	68	37	168	**56**

For the year 2024 and 2023, Nyendo-Mukungwe division received the highest cases of sex abuse, followed closely by Masaka rural, Masaka city and Kimanya- Kabonera respectively. In 2022, there was a decrease in sex abuse crimes in Nyendo-Mukungwe, Kimanya- Kabonera and Masaka rural, however, Masaka city crimes increased tremendously. The data above is illustrated in the chart below to facilitate better analysis and visualization.

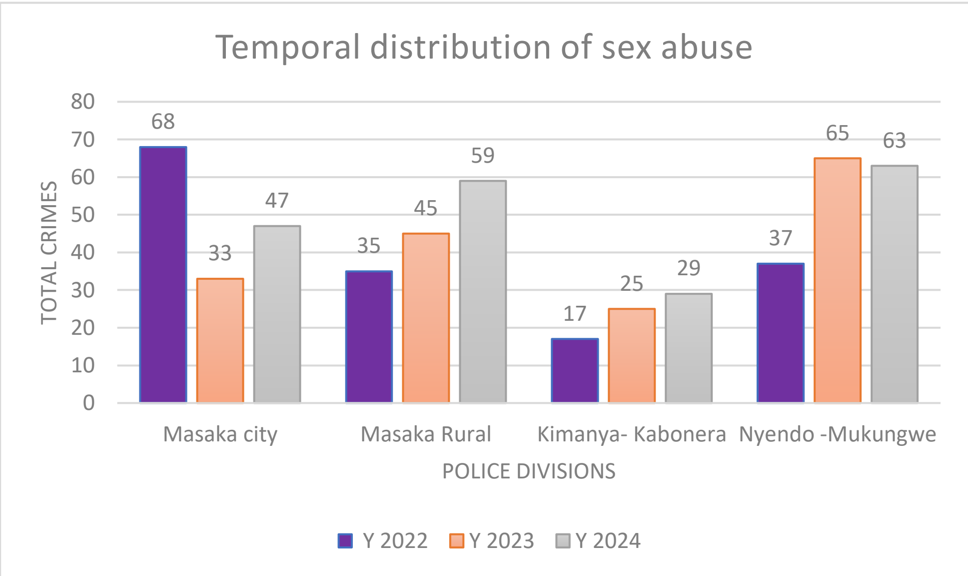

Figure 4: Temporal distribution of sex abuse

Figure 4 above illustrates the trend of sex abuse crimes in Masaka City, showing a decrease from 68 cases in 2022 to 33 cases in 2023, followed by an upward trend in 2024. In contrast, sex abuse crimes in Masaka Rural increased steadily over the years, a trend that was similarly observed in Kimanya-Kabonera. For Nyendo-Mukungwe, the number of sex abuse cases sharply increased from 37 in 2022 to 65 in 2023, then slightly declined to 63 in 2024.

A map showing spatial distribution for sex abuse crimes is shown below.

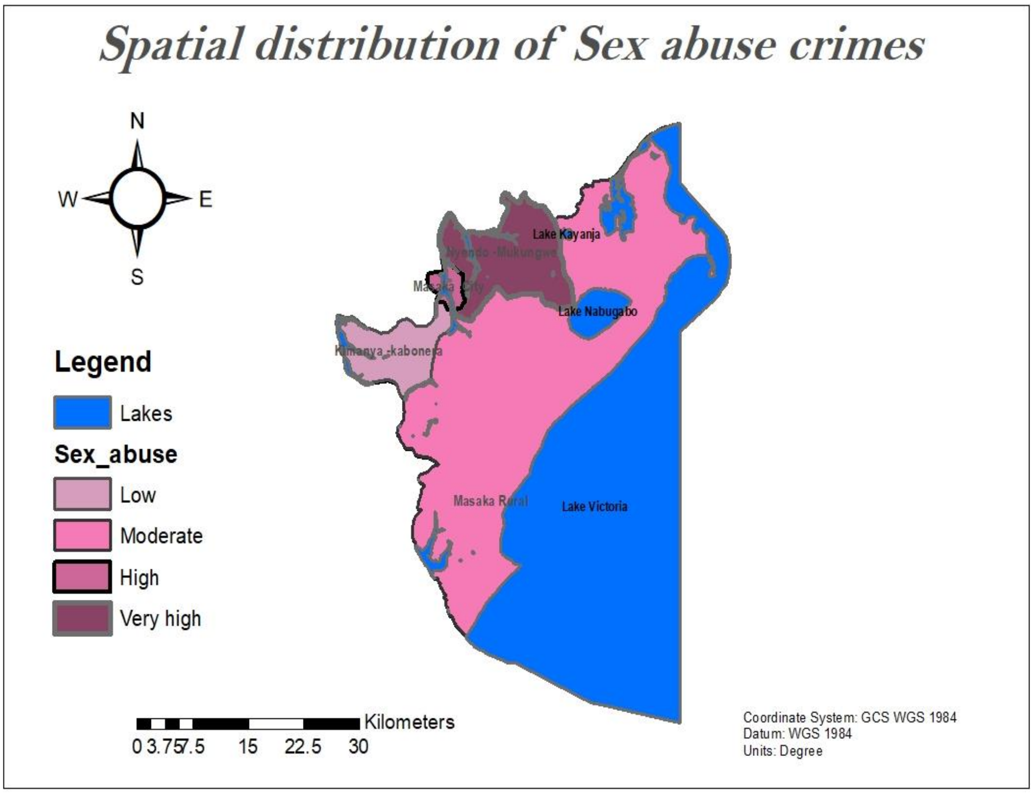

Figure 5: Spatial distribution of Sex abuse crimes

Based on the collected and mapped data, Nyendo-Mukungwe division recorded the highest number of sex abuse crimes, resulting in the highest average for the study period. Masaka City and Kimanya-Kabonera exhibited nearly similar average crime rates, while Masaka Rural showed a moderate level of sex abuse crime distribution.

4.2.3 Theft crimes

The table below shows averages got for different crimes in different divisions.

Table 4: Spatial distribution of Theft cases and their average

	Theft crimes				
Divisions	**2024**	**2023**	**2022**	**Total**	**Average**

Masaka city	231	193	265	689	**230**
Masaka rural	278	299	105	682	**227**
Kimanya- Kabonera	140	185	126	451	**150**
Nyendo - Mukungwe	323	232	146	701	**234**

Table 5 above shows that Nyendo-Mukungwe had the highest average number of crimes per year (234), followed closely by Masaka City. Masaka Rural recorded a lower average, while Kimanya-Kabonera had the lowest average number of crimes. The yearly crime reports for the different divisions are further illustrated in the figure below.

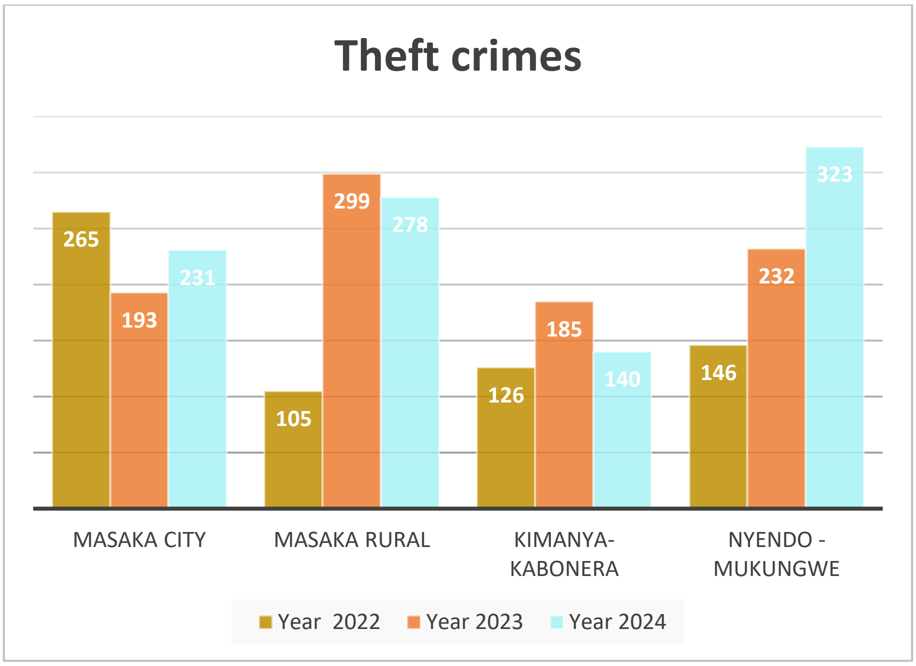

Figure 6: Temporal distribution of theft crimes

Figure 6 above shows that Masaka City experienced a fluctuating trend in crime rates, with a high level in 2022, a moderate decline in 2023, followed by an increase in 2024. Masaka Rural saw a sharp rise in crime from 2022 to 2023, followed by a slight decline in 2024. Kimanya-Kabonera exhibited a trend of a slight increase initially, then a slight decrease thereafter. In contrast, Nyendo-Mukungwe's crime rate steadily increased throughout the period from 2022 to 2024. The theft crimes distribution was mapped as shown in the 5 below.

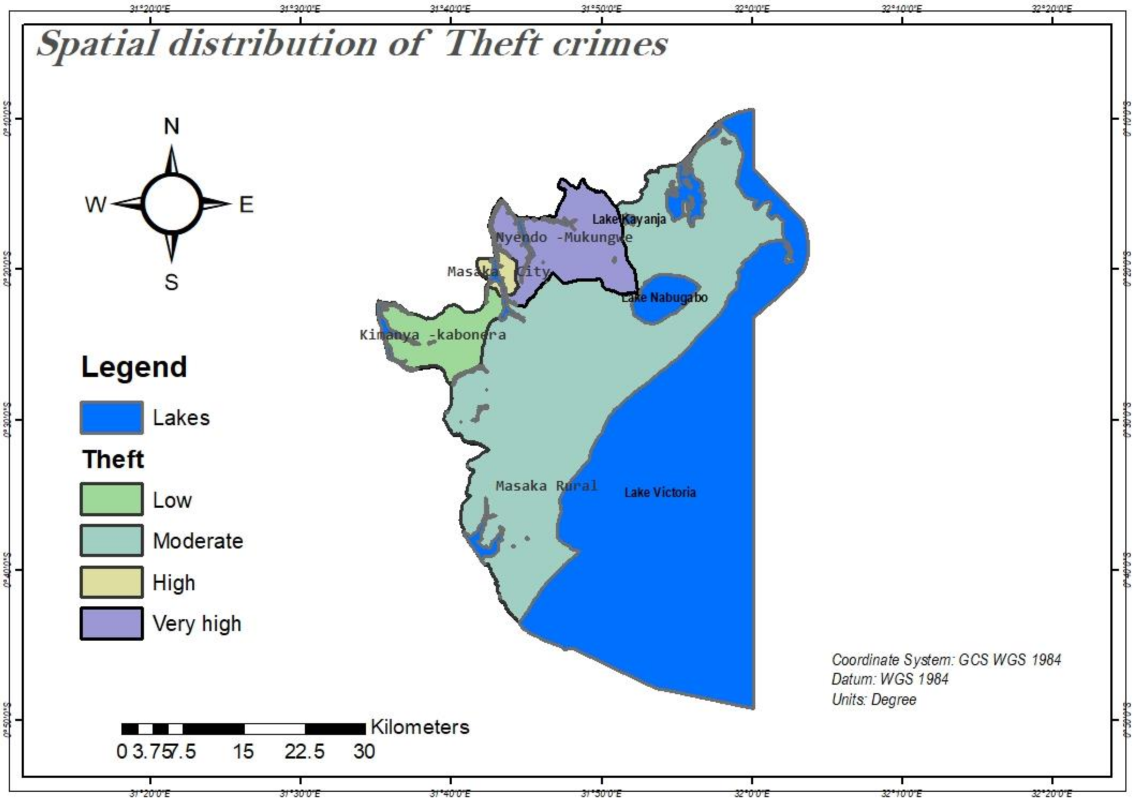

Figure 7: Spatial distribution of Theft crimes.

Theft crimes were widespread across almost all divisions, except for Kimanya-Kabonera. The highest average number of theft crimes was recorded as 230, closely followed by another division with the same average of 230. Theft ranks consistently among the top five crimes annually in Uganda and remains an everyday occurrence affecting communities nationwide.

4.2.4. Robbery crimes

Between 2022 and 2024, Masaka district reported a total of 263 robbery cases. Among the divisions, Nyendo-Mukungwe recorded the highest number of robbery incidents, resulting in the highest average annual cases during the study period. This was followed by Masaka City, Masaka Rural, and Kimanya-Kabonera, in that order. The average number of robbery cases for each division is detailed in Table 6 below.

Table 5: Spatial distribution of Robbery cases.

	Robberies				
Divisions	**2024**	**2023**	**2022**	**Total**	**Average**
Masaka city	29	25	21	75	**25**

Masaka rural	20	22	09	51	**17**
Kimanya- Kabonera	13	14	19	46	**15**
Nyendo- Mukungwe	49	24	18	91	**30**

The figure below illustrates the spatial distribution of robbery crimes from year 2022 to 2024. Overall, the number of robbery cases was relatively low across all divisions. Nyendo-Mukungwe recorded the highest number of robbery incidents, totalling 91 cases, followed by Masaka City, Masaka Rural, and Kimanya-Kabonera, respectively. Figure 8 further depicts the annual number of robbery cases reported in each division during the study period.

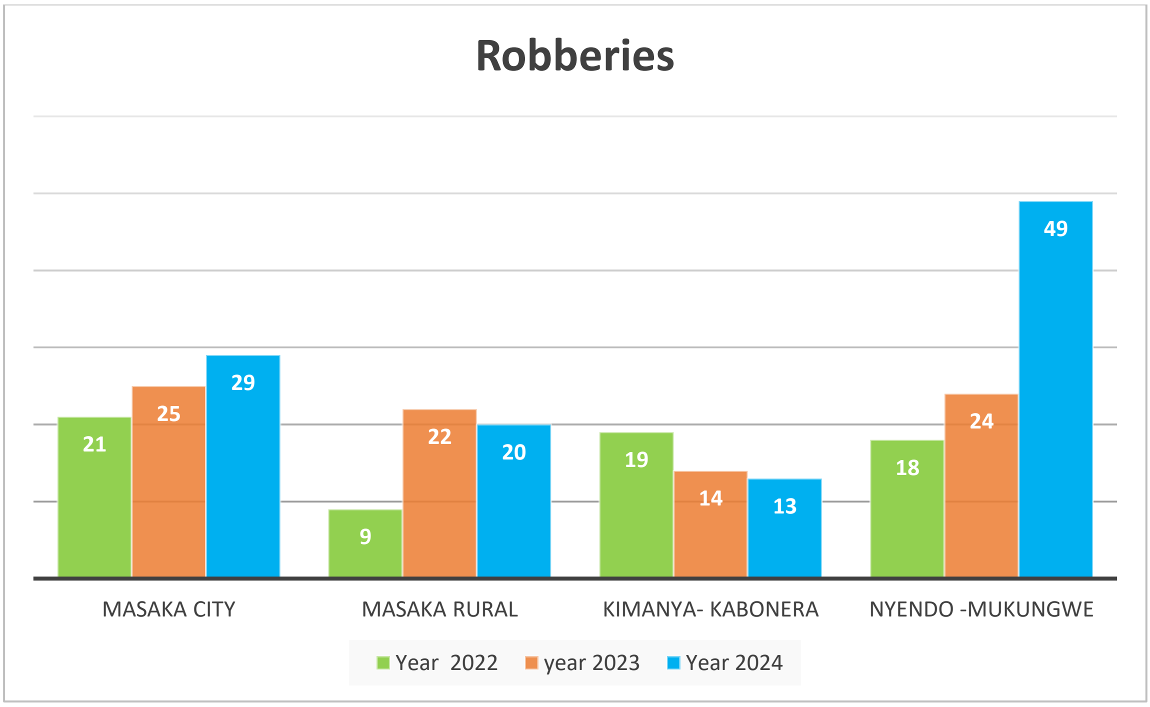

Figure 8: Temporal trend of Robbery cases.

Masaka City experienced an increase in robbery crimes, rising from 21 cases in 2022 to 29 cases in 2024. Masaka Rural initially showed an upward trend in robbery incidents, followed by a slight decline towards the end of the study period. In contrast, Kimanya-Kabonera exhibited a consistent downward trend in robbery cases over these years. Meanwhile, Nyendo-Mukungwe saw a steady increase in robbery crimes throughout the study period.

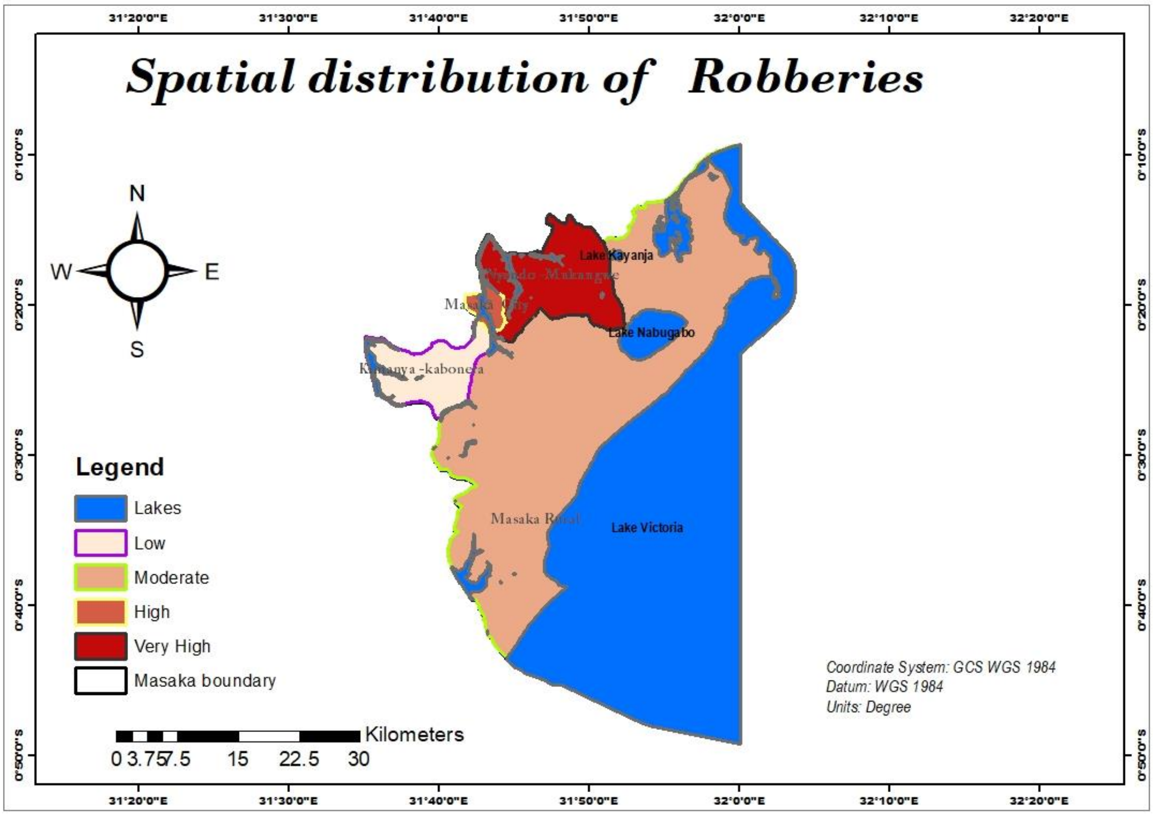

Figure 9: Spatial distribution of Robbery crimes.

According to the figure 9 above, Nyendo-Mukungwe recorded the highest average number of robbery cases, with approximately 30 incidents per year. Masaka City followed with an average of 25 cases annually, while Masaka Rural and Kimanya-Kabonera had lower averages of 17 and 15 cases per year, respectively.

4.2.5. Assault crimes

Since 2022, Masaka district has had a total of 814 reported assault incidents, their distribution is presented below in table 7.

Table 6: Spatial distribution of Assault crimes

	Assault crimes				
Divisions	**2022**	**2023**	**2024**	**Total**	**Average**
Masaka city	97	56	54	**207**	69
Masaka rural	40	04	25	**69**	23
Kimanya- Kabonera	58	94	142	**294**	98

Nyendo -Mukungwe	18	94	132	**244**	81

.

Assault crimes were most prevalent in Kimanya-Kabonera, followed by Nyendo-Mukungwe, Masaka City, and Masaka Rural, respectively. The temporal distribution of these crimes is illustrated in Figure 10 below.

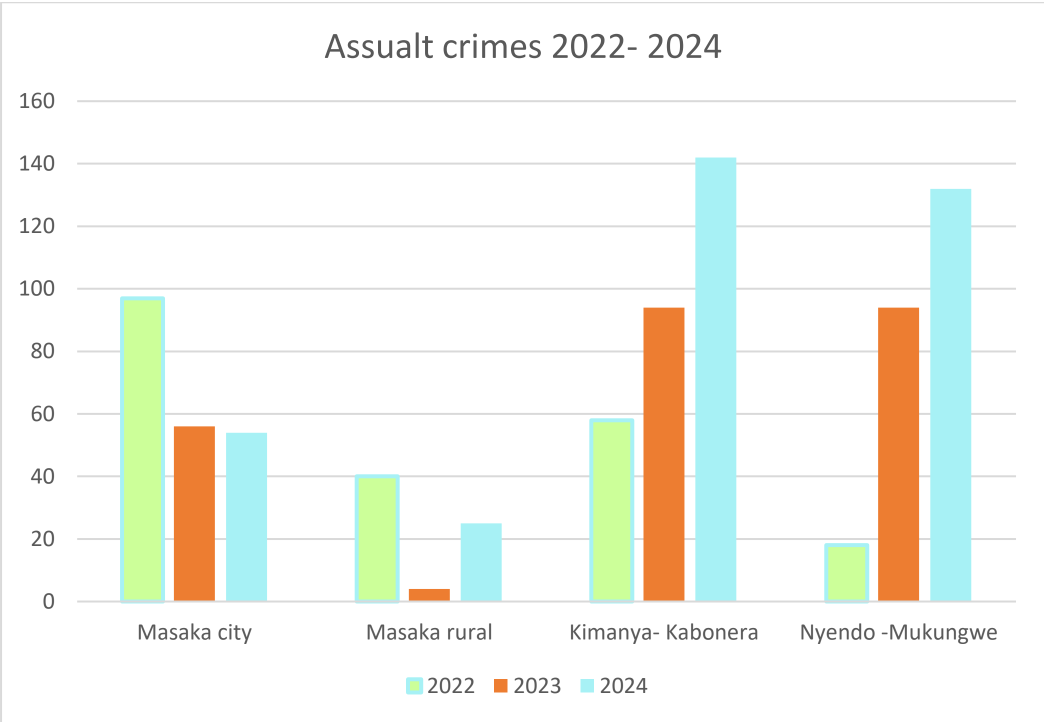

Figure 10: Spatial distribution of Assault crimes

The trend of assault cases in Masaka City was initially high, followed by a nearly uniform decline over the subsequent years. In Masaka Rural, assault cases decreased in 2023 but increased again in 2024. Both Kimanya-Kabonera and Nyendo-Mukungwe exhibited a steady increase in reported assault cases over the years.

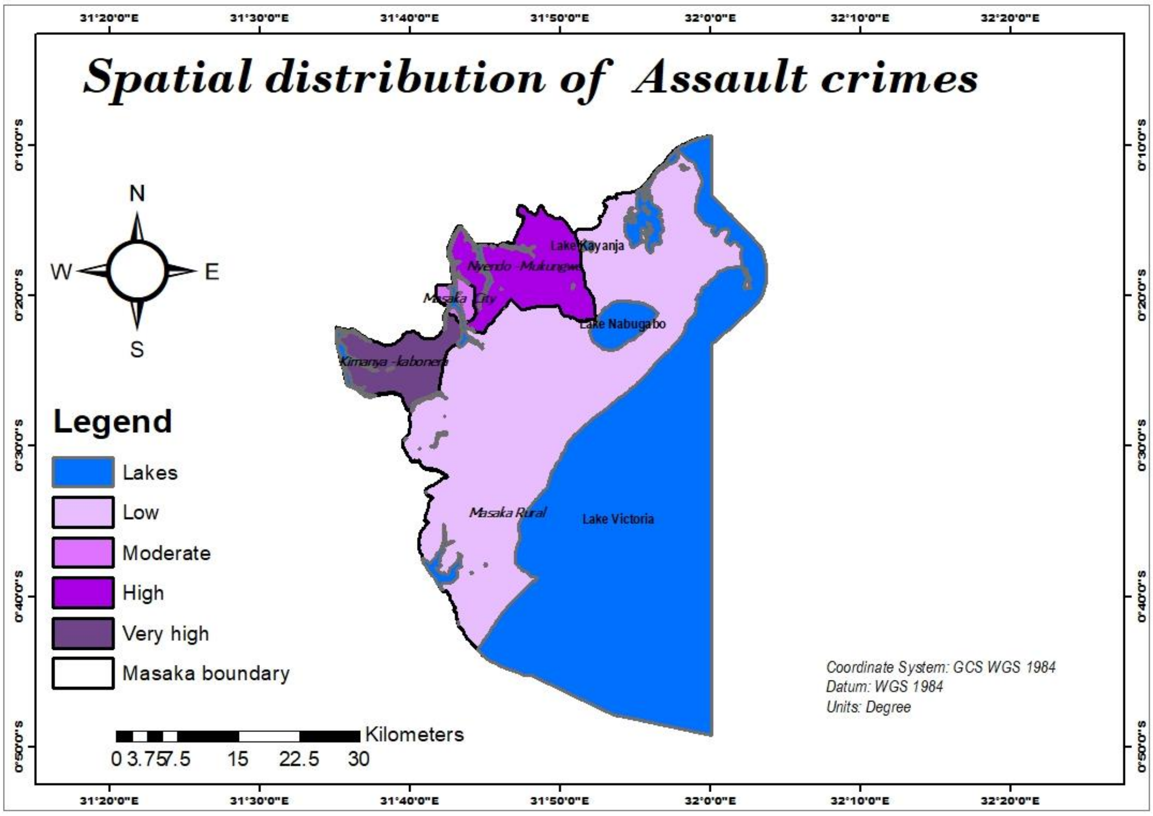

Figure 11: Distribution of Assault crimes in the study area.

Kimanya-Kabonera recorded the highest number of assault crimes, followed by Nyendo-Mukungwe with a high count of 81 cases. Masaka City had a moderate number of assaults at 60, while Masaka Rural reported the lowest number of assault cases.

4.2.6 Breakings spatial and temporal distribution

A total of 526 breaking and burglary crimes were recorded, with their distribution presented in Table 7 below**.**

Table 7: Spatial distribution of Breakings.

	Breakings				
Divisions	**2022**	**2023**	**2024**	**Total**	**Average**
Masaka city	74	55	35	**164**	55
Masaka rural	28	49	52	**129**	43
Kimanya- Kabonera	33	28	28	**89**	30
Nyendo -Mukungwe	41	65	39	**145**	48

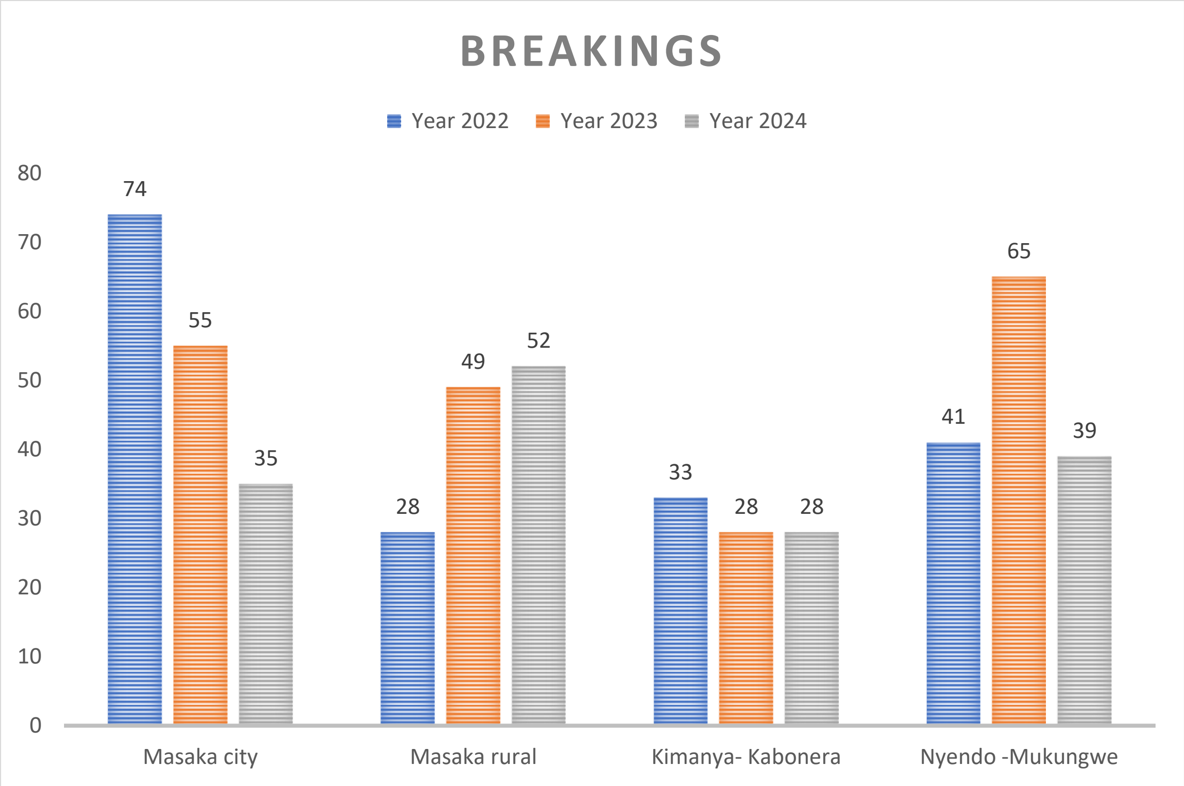

Figure 12: Temporal trend of Breakings.

According to the figure above, Masaka City experienced a steady increase in breaking cases over the study period. In contrast, Masaka Rural showed a declining trend over the years. Kimanya-Kabonera maintained a relatively consistent trend, while Nyendo-Mukungwe initially saw an increase in cases followed by a significant decrease.

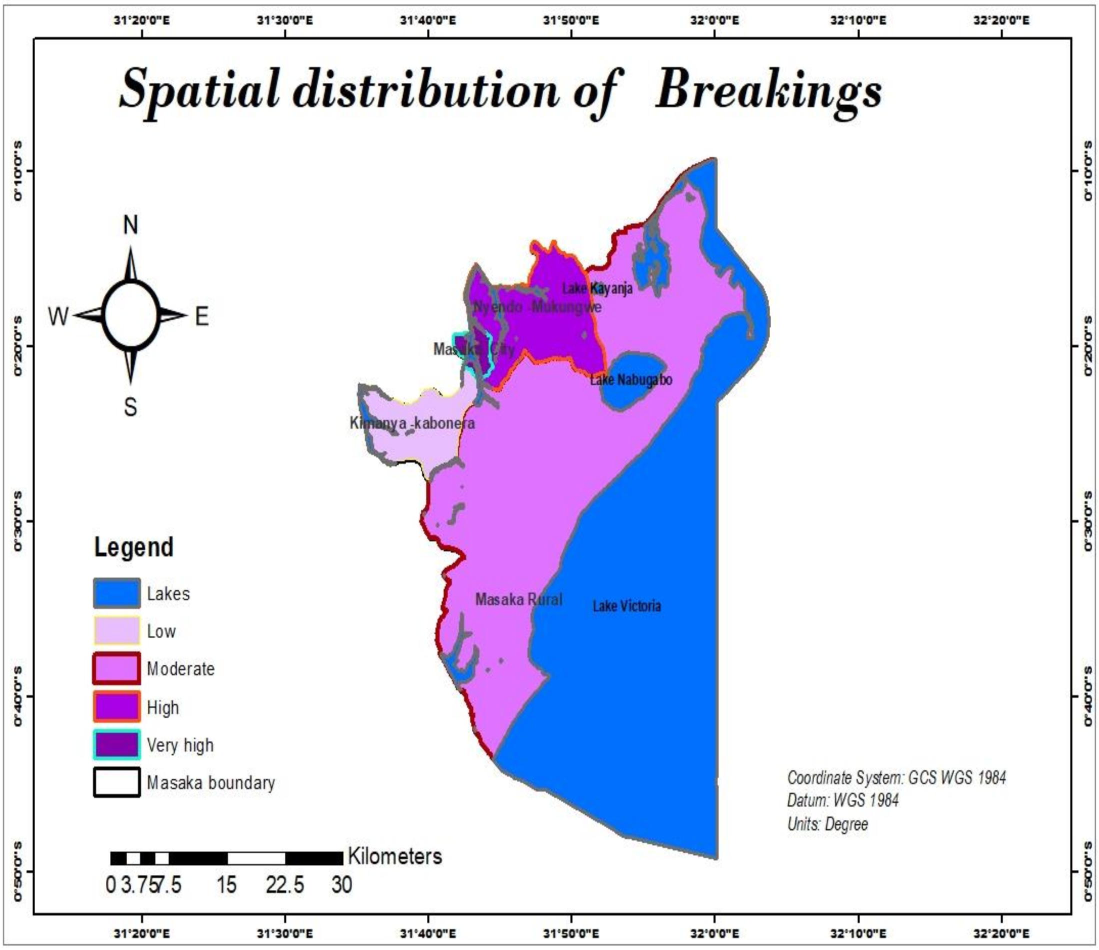

Figure 13: Breakings - spatial distribution.

Masaka City recorded the highest number of crimes with 55 cases, followed by Nyendo-Mukungwe with 48. Masaka Rural experienced a moderate number of crimes, while Kimanya-Kabonera reported the lowest. Breakings appeared to occur more frequently in urban areas than in rural ones.

4.3 Crime Density Analysis

Crime density measures the spatial concentration of criminal incidents, such as property crimes (e.g., burglary, theft) and violent crimes (e.g., assault, robbery), within a defined geographic area, usually a neighbourhood, census tract, or city block (Opulands.com, 2024). Analysing crime density provides a basis for assessing crime risk, support strategic planning for crime reduction and common safety initiatives.

High crime density can negatively impact residents' sense of safety, property values, and overall quality of life. Neighbourhoods with lower crime densities are generally perceived as more desirable.

For crime density analysis, year crimes for a particular crime type were summed up to represent total crime. Division area was got from https://www.citypopulation.de/en/Uganda/central/admin . For Masaka rural area, Buwunga, Bukakata, Kyanamukaka and Kyesiiga were added to together. Crime density was got by, $\frac{Total\ crime}{Area\ of\ a\ place}$ for every crime used in the study. The table below represents figures got. The figures were added into Masaka division attribute table and density computed.

Table 8: Crime density results

Divisions	**Area (km2)**	**Sex abuse**	**Theft**	**Robberies**	**Assault**	**Breakings**
Masaka City	25.6	5.78125	26.91406	2.929688	8.085938	6.40625
Masaka rural	869	0.15995	0.78481	0.058688	0.079402	0.148446
Kimanya-Kabonera	154.1	0.46074	2.926671	0.298507	1.907852	0.577547
Nyendo-Mukungwe	211.5	0.7943	3.314421	0.43026	1.153664	0.685579

4.3.1 Sex abuse crime density

Masaka City had the highest crime density, with approximately 5.78 crimes per km². In comparison, the other divisions experienced significantly lower crime densities. For example, Nyendo-Mukungwe recorded around 1 crime per km², while the remaining divisions had crime densities of less than 1 crime per km². Additionally, the distribution of sexual abuse cases is clearly illustrated in Figure 14 below.

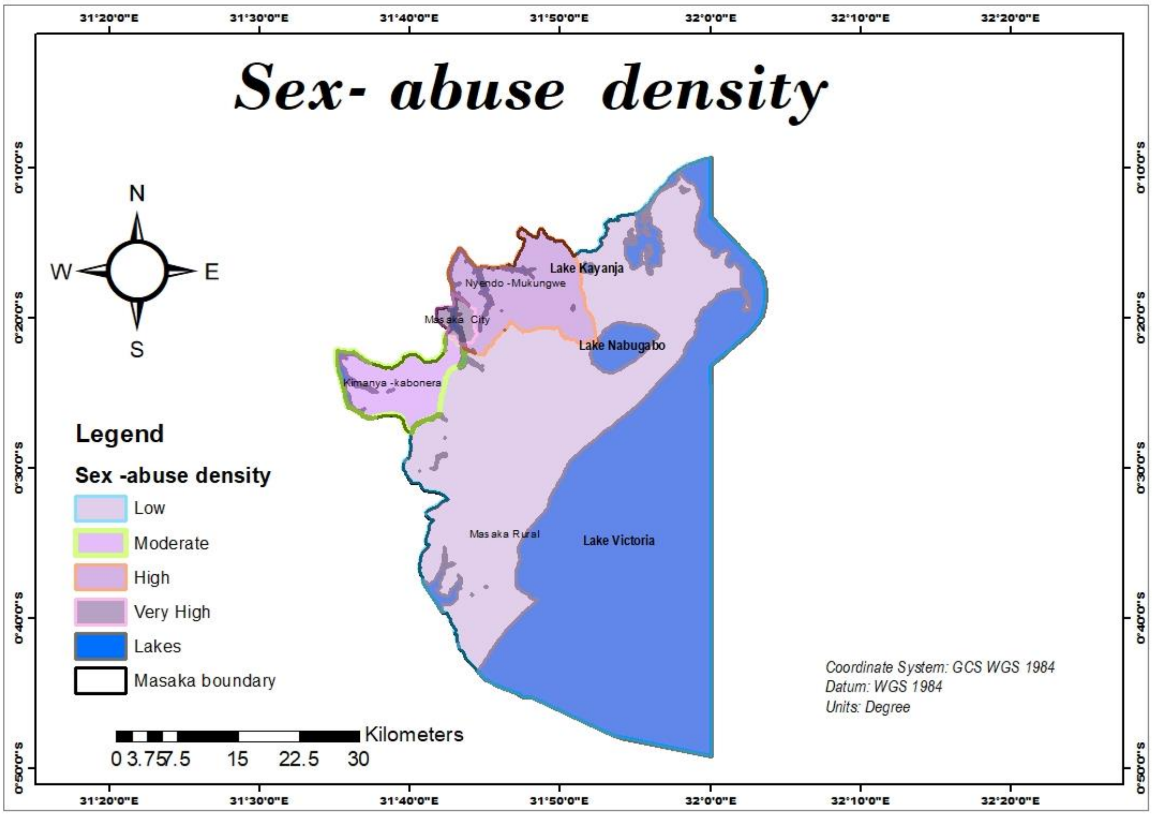

Figure 14: Sex abuse crime density

From the figure above, sex abuse crime density indicates that Masaka City is the most dangerous division, followed closely by Nyendo, Kimanya, and Masaka Rural. Generally, higher crime density corresponds to greater risk and indicates a less safe area. Therefore, divisions with lower crime densities, such as Masaka Rural, are comparatively safer than Masaka City.

4.3.2 Theft crimes density

Masaka District experienced a high number of theft crimes throughout the study period, resulting in certain areas being more at risk than others. The density or concentration of theft incidents is illustrated in Figure 15 below.

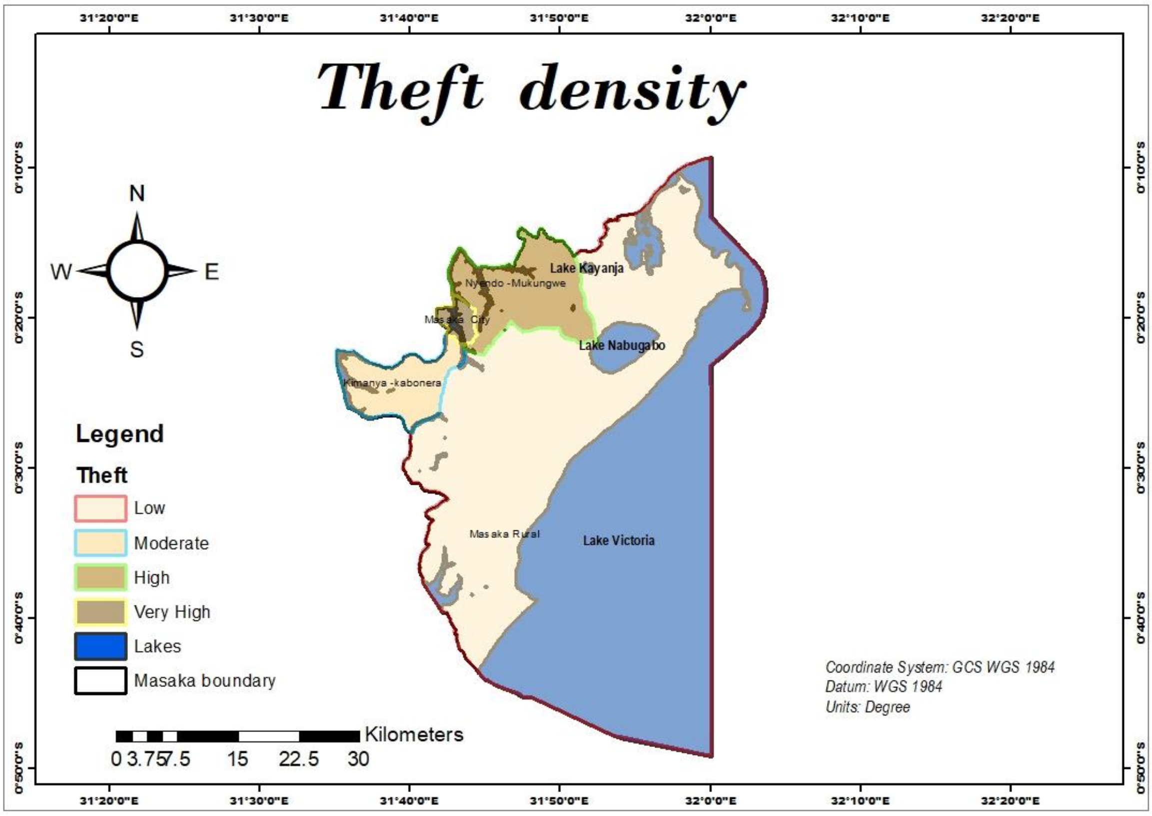

Figure 15: Theft crime density

Total crimes per year for each division were summed to calculate the overall number of crimes. This total was then divided by the area of the respective division to determine the crime density. For example, in Nyendo-Mukungwe division, there were 701 recorded theft crimes, and the area covered 211.5 km². This results in a crime density of approximately 3.31 crimes per km² per year.

Masaka City recorded a higher number of theft crimes, making it a less safe area according to the data. In contrast, Masaka Rural is the safest division, with a significantly lower crime density of 0.78 crimes per km² per year.

4.3.3 Robberies crime density

The robbery density for different divisions was as follows: Masaka city had 2.929688 (≈ 3 crimes/km^2), Masaka rural had 0.058688 crimes/km2, Kimanya- Kabonera had 0.298507 and Nyendo-Mukungwe had 0.43026crimes/km^2. Figure 16 below represents robbery crime density.

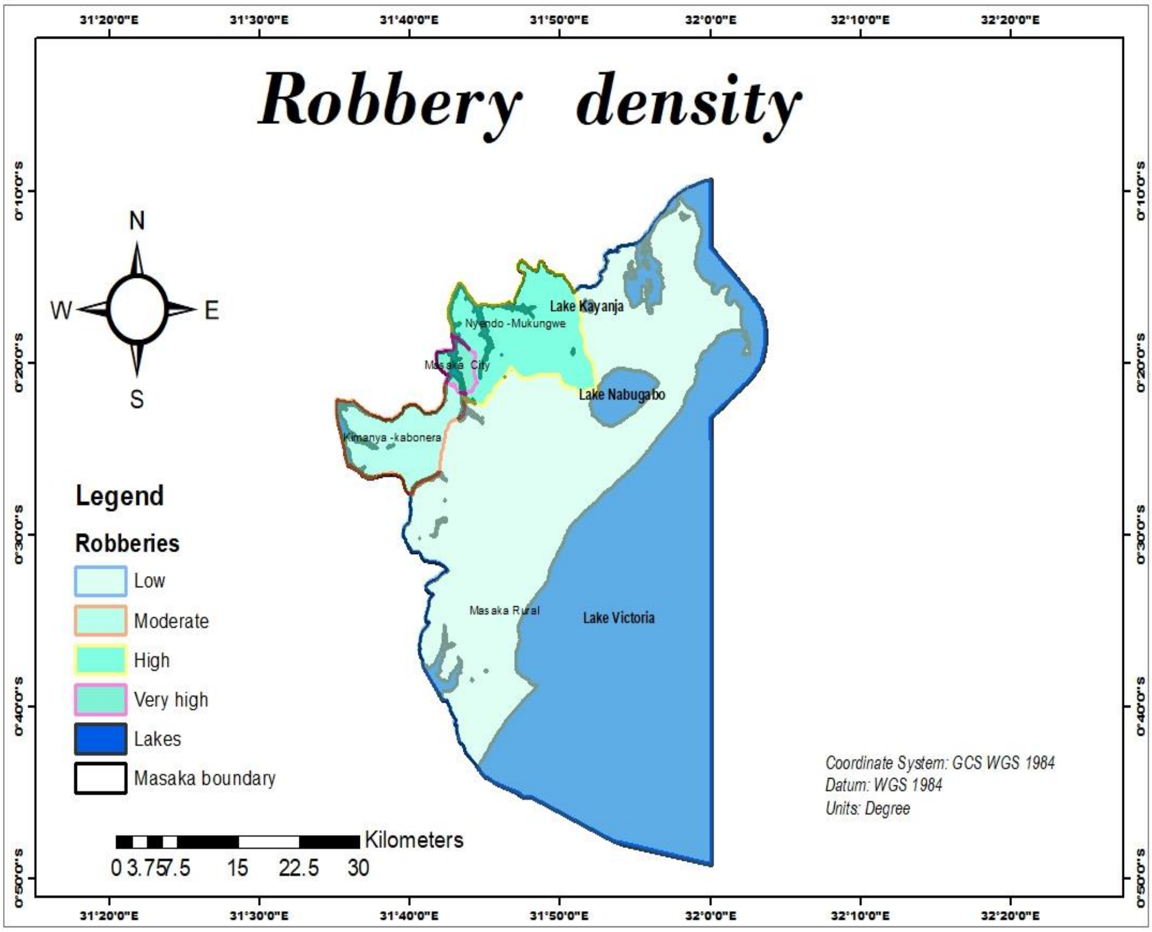

Figure16: Crime density for Robberies

4.3.4 Crime density for assaults

Assault crimes are common in societies and rank second after theft cases. In the study area, the assault crime densities were as follows: Masaka City had the highest density at approximately 8.09 crimes per km² per year, followed by Kimanya-Kabonera with about 1.91 crimes per km² per year, Nyendo-Mukungwe with roughly 1.15 crimes per km² per year, and Masaka Rural with the lowest density of 0.08 crimes per km² per year. Figure 17 illustrates the assault crime densities across the different divisions within the study area.

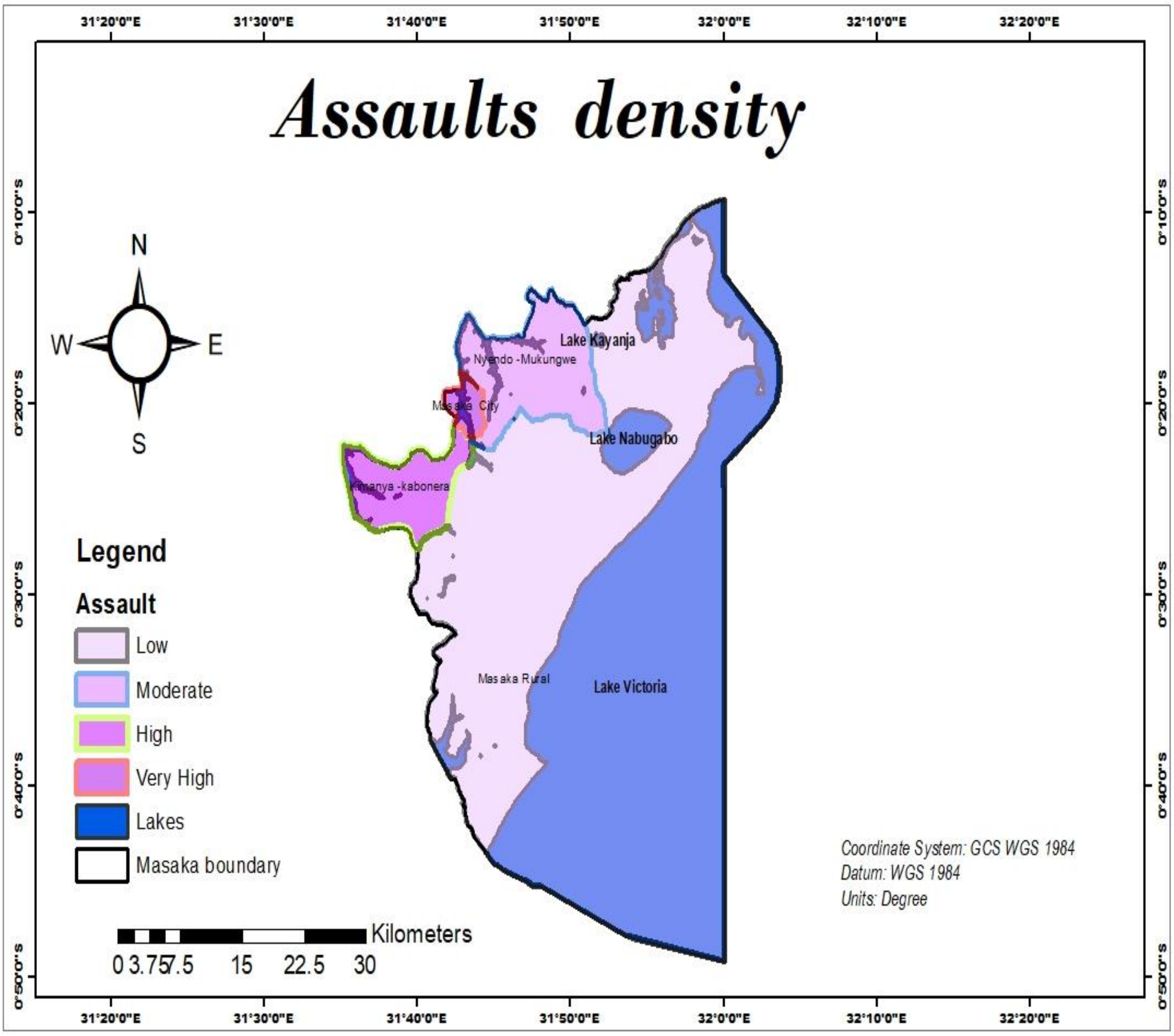

Figure17: Crime density for Assaults

Assaults like other crimes had a higher concentration in Masaka city followed by Kimanya-Kabonera, Nyendo -Mukungwe and lastly Masaka rural.

4.3.5 Breakings density.

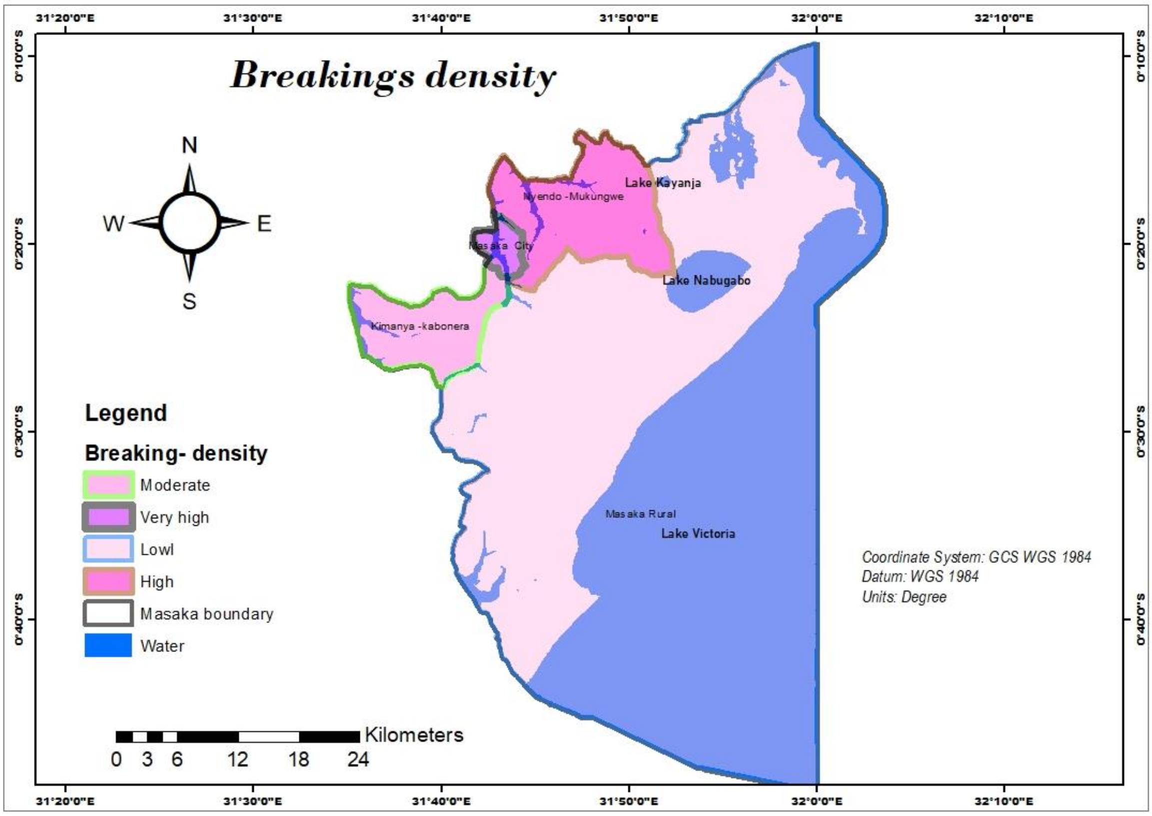

Figure 18: Breakings crime density

From the figure above, Masaka city has the highest concentration of crimes and Masaka rural has the lowest which makes Masaka city unsafe and Masaka rural safe for both living and business.

4.4. 0 Classification of LULC features using Remote sensing techniques.

In this section, a satellite image was analysed for different information classes are regards land use and land cover of the study area. It is very crucial to understand the changing relationship between land use land cover feature patterns and crime occurrences for proper planning, resource management and general public safety. This facilitates a better understanding of criminogenic environments by operationalising influence of land use landcover features with crime events. More about data acquisition, processing and analysis with GIS and RS were discussed in this section and their results presented.

4.4.1 Preparation of Satellite Image

The satellite imagery for Masaka district was downloaded from EarthExplorer (https://earth exploler.usgs.gov) using Landsat 8-9, collection 2 level 2. Different images with similar bands were loaded in the GIS software (ArcMap 10.8) to form Masaka district complete satellite image. The images' spectral bands were combined into a single band raster and later joined as one new raster image through a tool called, Merge to new raster. The band combination was set to 6,5,4 which is a reflective colour as shown in the figure 19 below.

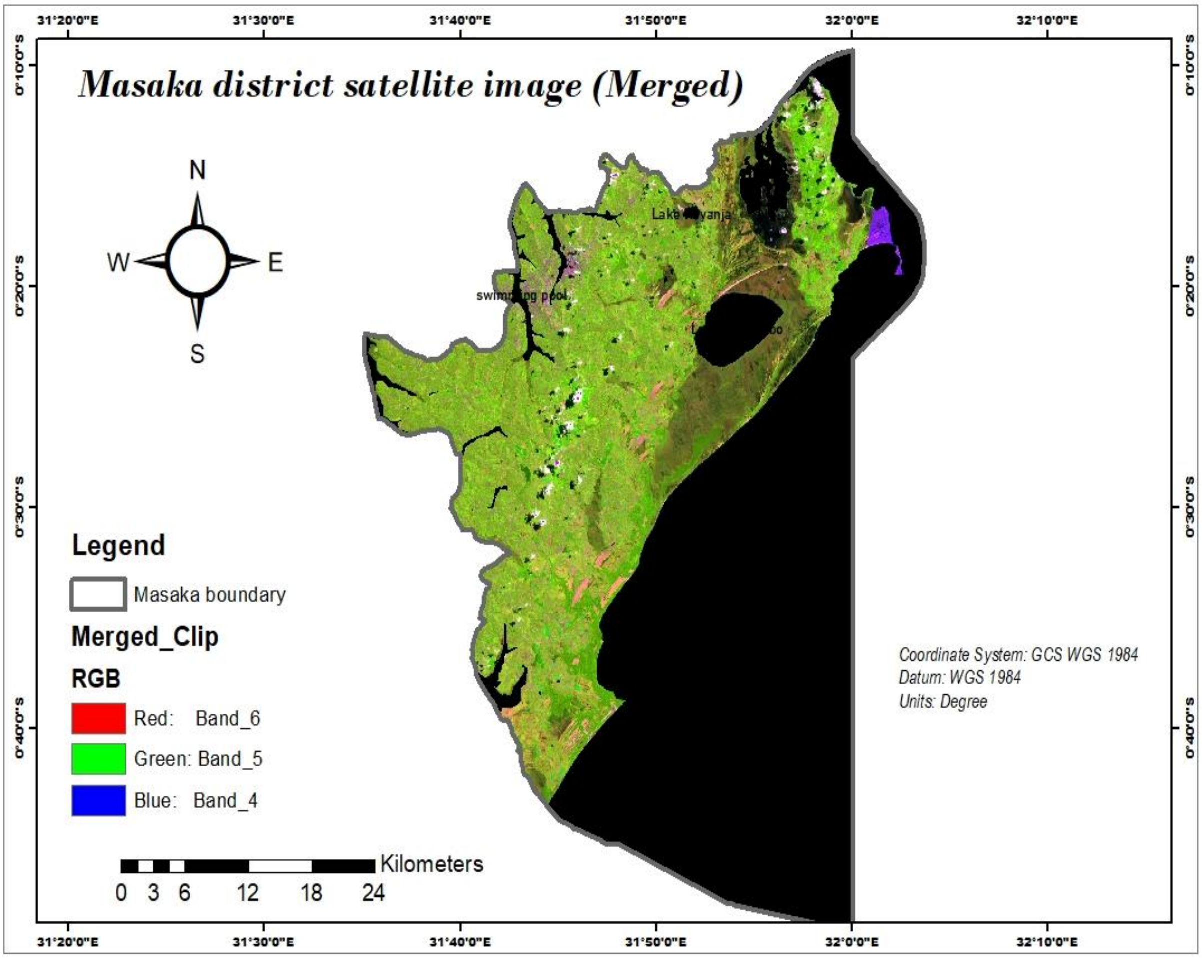

Figure 19: A satellite image for the study area.

To provide supplementary details, land cover refers to the observed physical and biological cover of the earth's land. Land is covered by various forms of vegetation, grasslands, scrubs, water bodies, bare soil etc. All the naturally occurring vegetation cover is called land cover.

Land use is defined as "the total of arrangements, activities, and inputs that people undertake in a certain land cover type", according to Food and Agriculture Organization (Inflibnet.ac.in, 2025). The table below shows the land use landcover features used in this study based on classification levels, I and II as set by USGS (*land use and landcover classification – resource geography* 2025b; James et al, 1976) and Kilamu Luwa et al., (2022), review of Land Use Land Cover Change (LULCC) studies in Uganda, which indicated agriculture, forest, grassland, and woodland as the major land use and land cover types.

Table 09: Land cover and land use feature classes.

Feature(landcover) (level I)	**Components (level II)**	**Examples**
Lake /water	Streams and canal Reservoirs Bays and estuaries	Lake Victoria Nabugabo lake Lake Kayanja (Birinzi)
Built-up/ Urban	• Residential • Commercial • Industrial • Transportation, • communication and utilities	Homes Schools Banks Bars Hotels and guest houses Roads Office buildings
Forest land/Forest reserves	Deciduous forest land Evergreen forest land Mixed forest land	Eucalyptus forests Pine forests Woodland Plantations
Agricultural land	• Cropland and pasture • Orchards • Groves • Vineyards • Tree Nurseries • Horticultural land	Gardens Compounds Playgrounds Roadside trees/ flowers

Bare land	Dry salt flats Beaches Sandy areas Bare expose rock Strip mines quarries, gravel pits Mixed barren land	Areas with extensive brick making, Quarry sites Rocky area.
Wetland	Forested wetland Non forested wetland	Swamps like Namajjuzi

Training samples for land use land cover features were picked from different parts, stored and classified using a supervised classification method of Maximum likelihood.

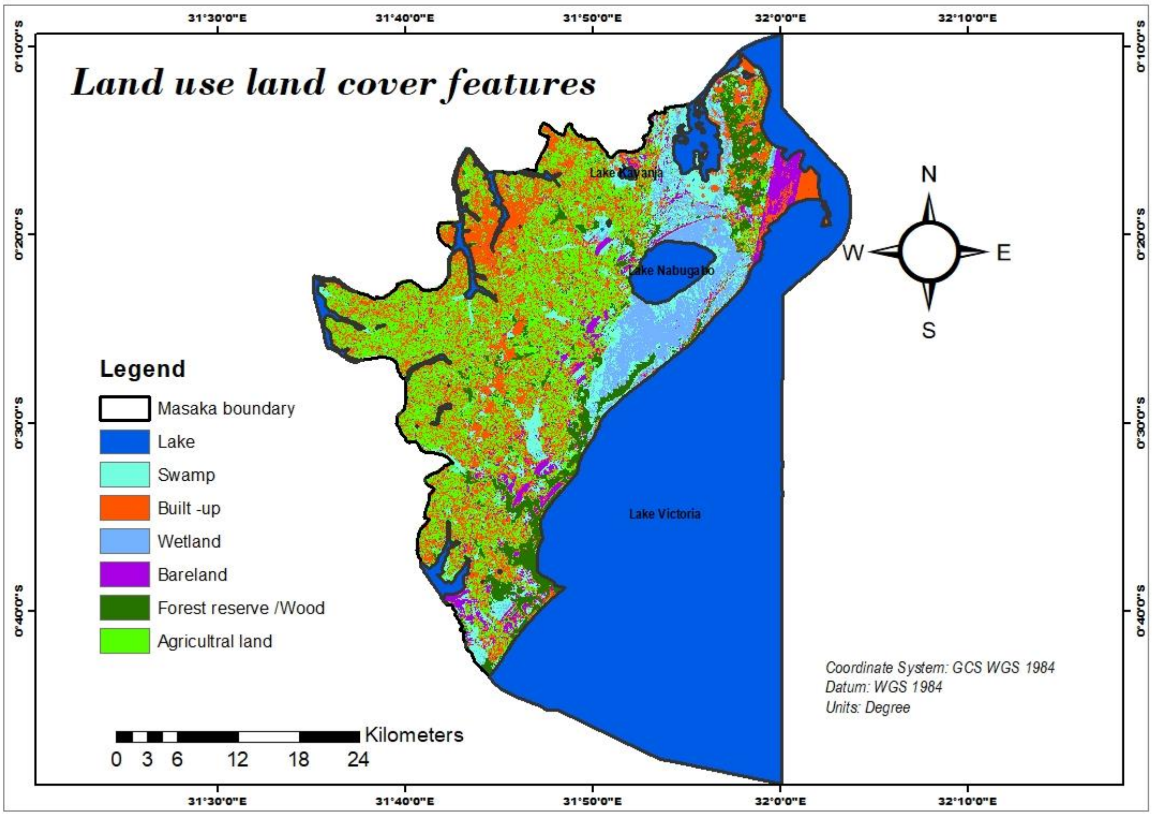

Figure 20: Land use landcover features.

Figure 20 above shows the land use and land cover features as indicated in the map legend. Large lakes, such as Victoria and Nabugabo, occupy a significant portion of the study area. Areas with a high concentration of built-up land include Nyendo-Mukungwe and Masaka City. In contrast, Kimanya-Kabonera and Masaka Rural are predominantly covered by cropland and plantations. Masaka Rural, in particular, is dominated by agricultural land with some forest reserves scattered throughout.

4.4.2 Overlay of LULC Features and Crimes

At this stage, different average crime-type maps were overlaid with the land use and land cover map to visualize potential correlations or relationships. This approach is supported by various studies showing that crime patterns are influenced by the land use and land cover characteristics of an area. Overlaying these maps helps to identify how different land uses, such as built-up areas, agricultural land, or water bodies, may attract or deter specific types of crimes, providing valuable insights for crime analysis and prevention planning.

4.4.3 Sex abuse crimes distribution and land use land cover features

To create the map shown in Figure 21 below, the average sexual abuse data was calculated and then overlaid onto the land use and land cover map to visualize spatial patterns. The crime data layer was set to 50% transparency, allowing for the underlying land use features to remain visible. This approach facilitates a clearer understanding of how sexual abuse incidents are distributed in relation to different land cover types, providing valuable insights for targeted interventions and resource allocation.

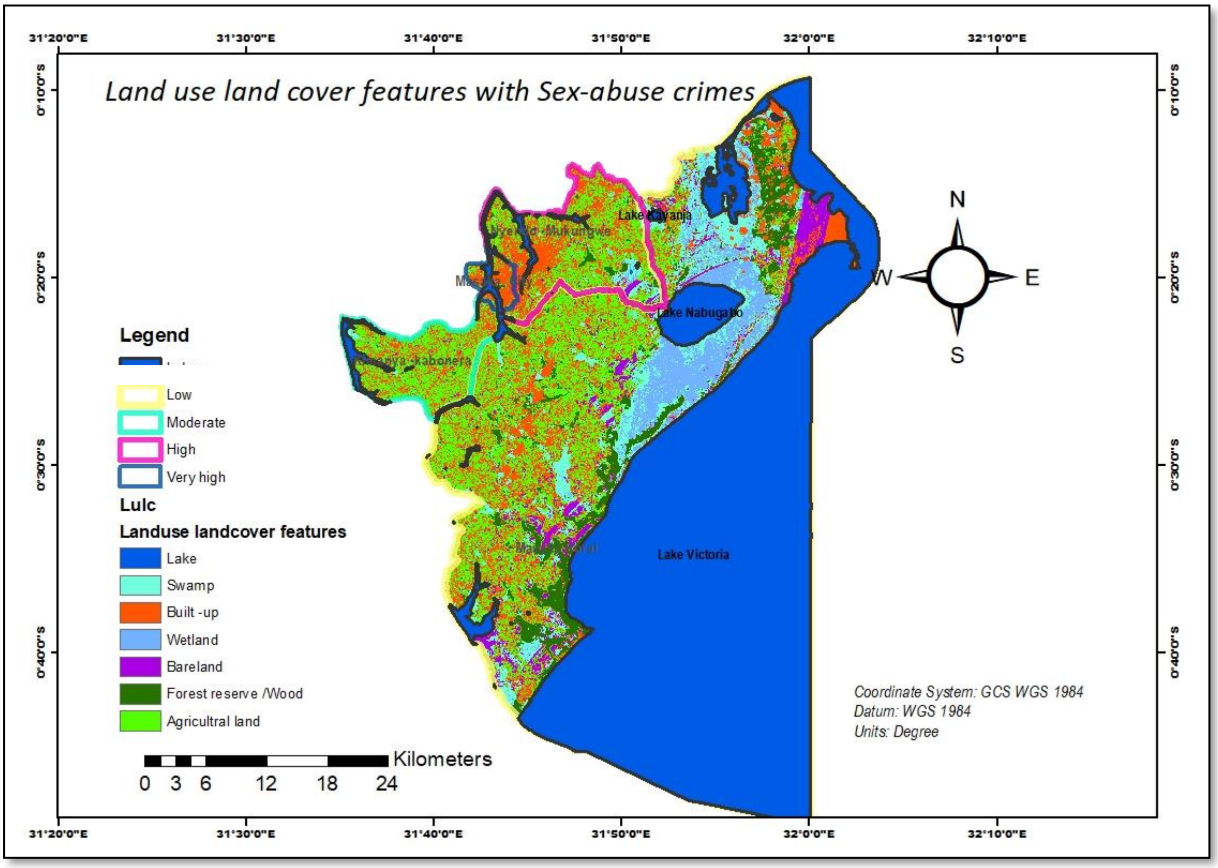

Figure 21: LuLc and Sex abuse crimes

The figure reveals that sexual abuse crimes were more prevalent in Masaka city which is characterized by built-up land cover and road networks, high sexual crimes were in Nyendo, Kimanya-Kabonera with moderate and Masaka rural low. There is a clear indication that sexual crimes are attributed to landcover land use of the place forexample, Masaka rural that has a lot of agricultural and bare land has low cases of sexual crimes yet Masaka city that had a lot of built-up spaces has the highest cases.

4.4.4 Distribution of theft crimes in different land use land cover

From the figure below, Masaka rural is showed by cyan, Masaka city by yellow, Kimanya-Kabonera by green and Nyendo- Mukungwe by purple. Nyendo-Mukungwe and Masaka city are dominated by built-up, Kimanya-Kabonera and Masaka rural have more agricultural land, bare land and forest reserves. The theft crimes were overlaid with land use landcover in the figure 22 below.

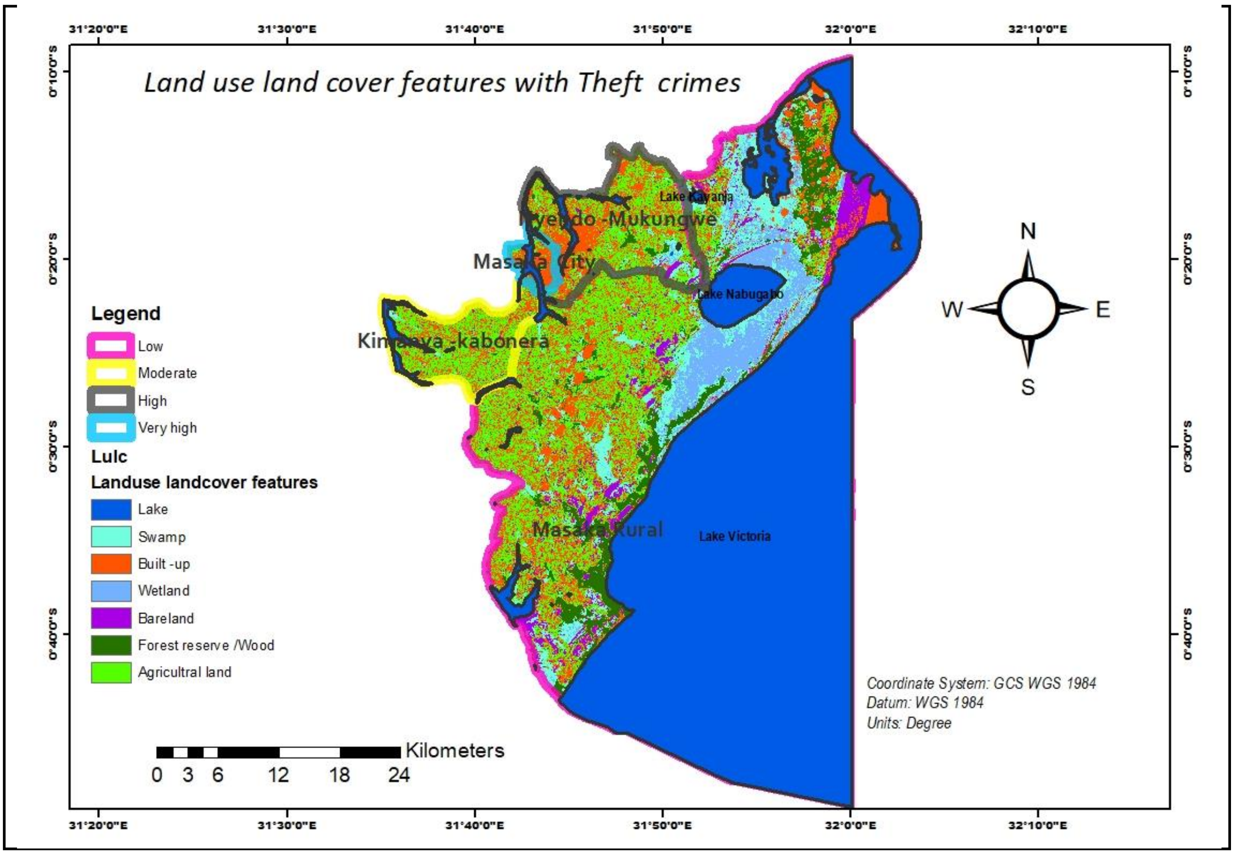

Figure 22: LuLc and Theft crimes

According to figure 22 above, theft crimes are widespread in the community and involve the stealing of various types of property, including phones, vehicles, livestock, crops, and other valuables. These incidents were most prevalent in Nyendo and Masaka City Division, moderately reported in Kimanya-Kabonera, and least common in Masaka Rural. The frequency of theft was notably higher in areas with dense built-up environments, which are typically urban in nature. These urban settings provide more opportunities for theft due to high population density, increased economic activity, and a greater concentration of valuable property.

4.4.5 Robbery crimes and land use landcover features

In Figure 23 below, the divisions are represented with the following colours at 50% transparency: Nyendo-Mukungwe in yellow, Masaka City in purple/pink, Kimanya-Kabonera in brown, and Masaka Rural in green.

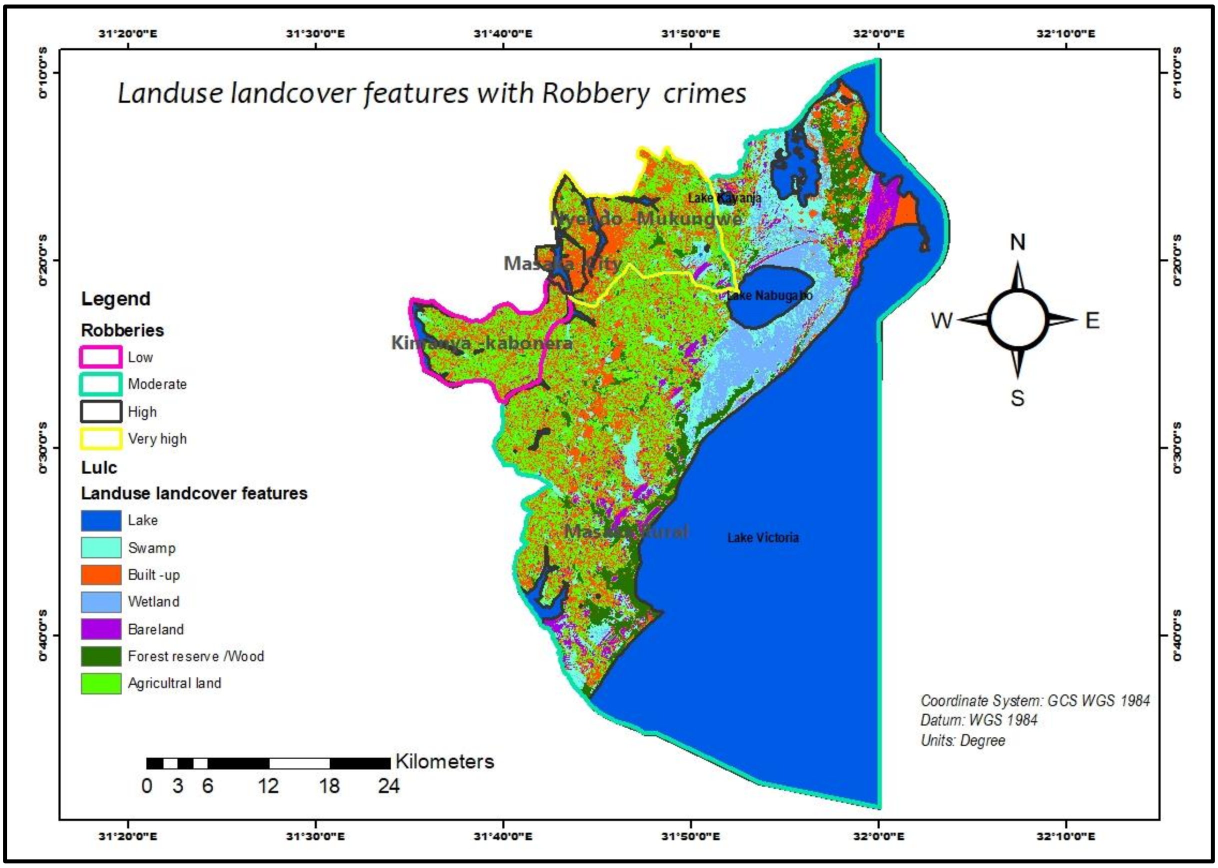

Figure 23: LuLc and Robberies

Robberies are concentrated in areas with a high density of built-up environments and are less common in agricultural land, bare land, and forested areas. This pattern can be explained by the nature of robbery as a violent crime that requires human targets rather than trees or uninhabited spaces like swamps.

According to crime theory, for a crime to occur, three elements must be present: an offender, a suitable target, and the absence of a capable guardian. In places such as forests, these three elements rarely coincide, making robberies unlikely in such environments.

4.4.6 Assault crimes and land use land cover features.

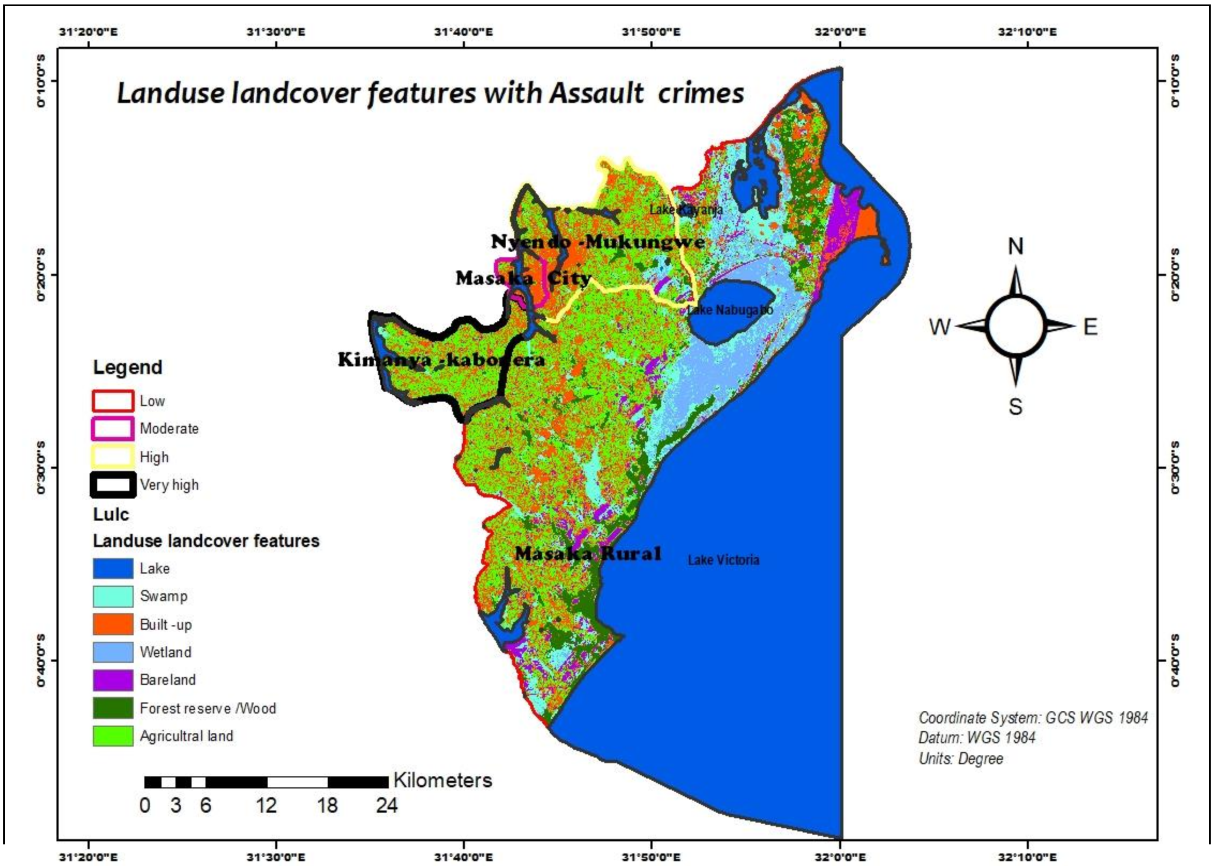

Figure 24: LuLc and Assault crimes

Assault crimes were very high in Kimanya-Kabonera, high in Nyendo-Mukungwe, moderate in Masaka city and low in Masaka rural as shown in figure 22. This pattern of crime distribution is not common. Kimaya- Kabonera is boarded by swamps/wetlands or locally ‘rivers’. There is one after Masaka city and another as you complete Kimanya- Kabonera proceeding to kinoni. These swamps/wetlands have away they attract assault criminals.

4.4.7 Breakings and land use landcover

According to the figure below, Kimanya -Kabonera had the highest concentration of breakings and is shown by pale yellow, Nyendo_ Mukungwe had 48 and is shown by blue, Masaka city is deep yellow, and Masaka rural is purple.

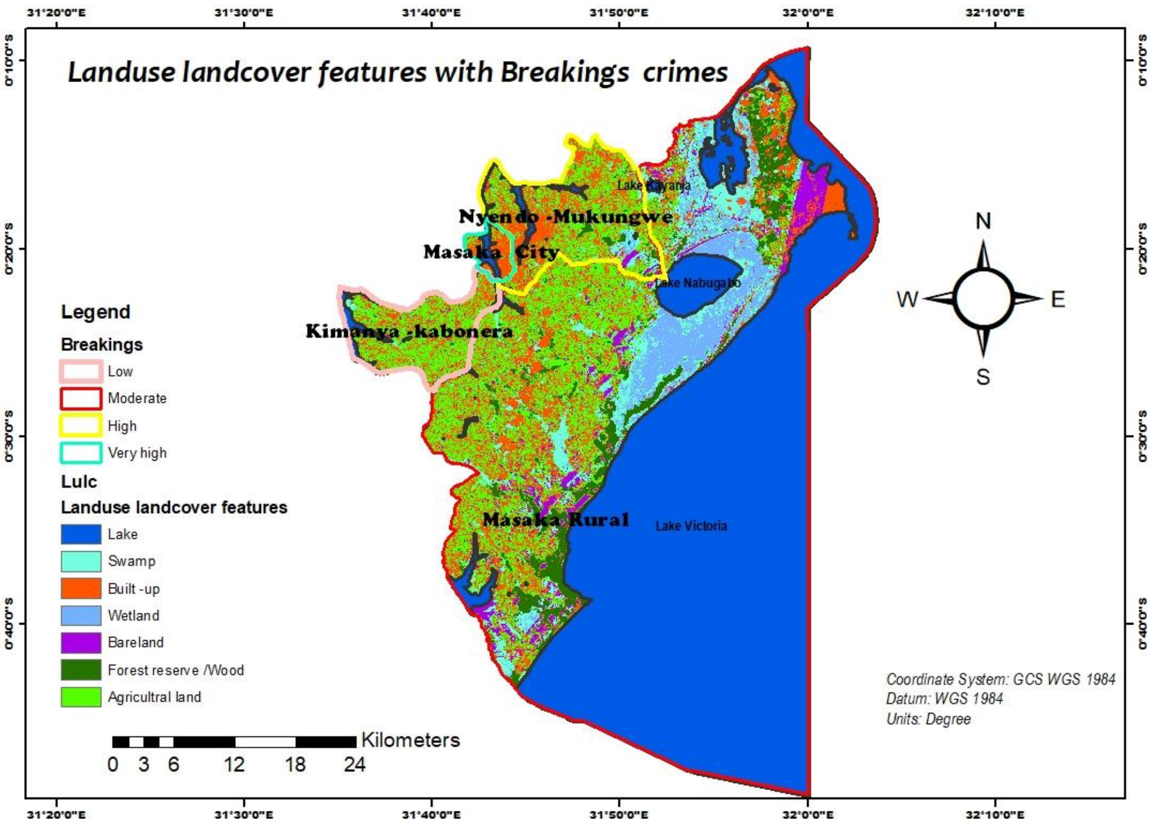

Figure 25: LuLc and Breakings

Breakings typically involve unauthorized entry into homes, businesses, and other premises. As shown in Figure 25, the highest number of break-in incidents occurred in Masaka City, followed by a high concentration in Nyendo-Mukungwe, moderate levels in Masaka Rural, and the lowest in Kimanya-Kabonera**.**

4.5.0 Detection and analysis of crime hotspots and cold spots.

Uganda police force couldn't share the incident-level data that include the details of the crimes such as location, time or date of occurrence and type. The denial was due to their official regulations and so aggregate -level data from various Uganda annual crime reports was got during data collection. This aggregate -level data involved a summary information about the crimes committed in Masaka district police divisions from 2022 to 2024. The crime information was grouped by incident in different years.

Due to the difficult in obtaining correct and accurate crime data for proper analysis, Poisson distribution was used to simulate incident-level point location of the selected crimes in the study area, to enable a better analysis with the primary focus on incident- level functionalities such as finding spatial correlation between crimes and land use land cover features. The points were simulated randomly basing on the average number of crimes (crime type) and the number of years for the study.

The Poisson distribution is found appropriate for applications that involve counting and predicting the number of times a random event occurs in a given amount of time, distance, area, etc, (Wayne,2000).

4.5.1 Assumptions adopted for Poisson distribution

- Crimes can occur randomly at any location.
- Multiple crimes can occur simultaneously at the same place.
- Crimes can be counted as discrete events: 1, 2, 3, 4, and so on.
- Crimes are independent of one another.
- Crime counts are always positive whole numbers (integers).

Poisson distribution takes a nonnegative integer value (λ) which is both the mean and the variance of the distribution (Saleh and Mashee,2013).

4.5.2. Steps taken in the Simulation of crime events using Poisson distribution.

(i) Creation of maps. The geographical map for the study area (polygon) was created from Uganda district shapefile.

(ii) Creation of a random raster allows the generation of values following a specified statistical distribution. For this study, a Poisson distribution was chosen. The mean value of the distribution is adjusted according to the number of points required in the study area. Specifically, the mean was set to the average number of crimes for a particular crime type over the study period from 2022 to 2024. This approach ensures that the simulated spatial data accurately reflects the expected frequency of crimes within the area of interest.

(iii) Clip Raster. After running the above tools, a raster is created and extends outside the extent. To select raster for the study area only, clipping is done as to the extent or same as the study area.

(iv) Raster to points. The data got from the raster created is turned into point using conversion tool, (Raster to points). The points are randomly distributed across the study area. These simulated points were then given XY coordinates from data management tool for proper identification. With the help of editing tool, some points were moved to other places for better analysis. Some points were randomly distributed in Lakes, in the middle of swamps etc and so they were copied and pasted in other places.

4.5.3 Spatial autocorrelation for different crimes

For any hotspot to occur, data must be clustered, dispersed data gives cold spots only. The created random points were first projected to align them with the study area projection. From (*Data management tool > projections and transformations > project)*. The projection coordination for the study was WGS-1984-UTM-Zone- 36N, Project: Traverse- Mercator.

The next step was to copy the feature (crime point feature) and create another copy. *(Data management tool > features > Copy features).* With a second copy, the integrate tool was used to set the XY tolerance in metres. This helps to stack points on top of others. (Data management tool > feature class > Integrate). XY tolerance was set to 90m (ninety metres) for every crime type.

The stacked points were then merged to coincide them and make a count of how many were merged to others. *(Spatial statistics > Utilities > collect events).* Data was added to the map with graduated symbols such that correction could be done. The tool collect events adds a new field in the attribute table, ICOUNT which is useful during correlation. The ICOUNT holds count of coincident points from the integrate layer.

For spatial autocorrelation, (*Spatial statistics > Analysing patterns > Spatial autocorrelation (Moran's I*). The input feature class was the aggregated output feature, Input field was ICOUNT field, generate a report was *checked*, conceptualised of spatial relation set at Inverse- *distance* (here nearby neighbouring features have a large influence on the computation of the target feature than features that are far away, (ArcGIS help). The distance method was left to *Euclidean- distance*, standardisation set to *none* and distance band or threshold and weigh matrix file left as *default*. The output was a map and a summary for different Moran index parameters. Moran's I index parameter values for different crimes is presented in the table 10 below.

Table 10: Moran's' I results for different crimes.

Moran's parameters	**Sex abuse**	**Theft**	**Robberies**	**Assaults**	**Breakings**

Moran's Index	0.411121	0.08468	0.040344	0.014384	-0.028991
variance	0.000049	0.000935	0.000442	0.000348	0.00091
Z-score	59.202358	2.9176524	2.193729	0.889384	-0.731928
P-value	0.000000	0.003527	0.028255	0.373797	0.464213

For Sex abuse, with Morons' Index positive and close to one (1) means there is a positive spatial autocorrelation, which indicates that values cluster together. The high Z-score means that clustering exists within data with high values.

Theft crimes showed a similar pattern like sex abuse: a positive Moran's index that is close to one (1) and positive. Theft crimes were clustered and the Z-score means clustering exist within high values.

For breakings, the Moran index is negative which means a negative spatial correlation which implies that dissimilar values tend to cluster together. The negative Z-score indicates a dispersion of values and the p-valve is not statically significant, so the null hypotheses cannot be rejected (Esri,n.d). This means that basing on the data and statical results got, there is not enough evidence to conclude that all hypotheses is true.

4.5.4 Hotspots and cold spots for different crimes

Crime hotspot detection is essential for law enforcement agencies to allocate resources effectively, predict potential criminal activities, and ensure public safety (Ahmad et al., 2024b).

4.5.5 Sex abuses hot and coldspots

To get sex abuse crimes for mapping, their average was got from a total of all sex crimes (526) and divided by the number of years, three (3). The average got was 175 and it is the number of points generated for sex crimes. It was hard to map all the 526 crime points.

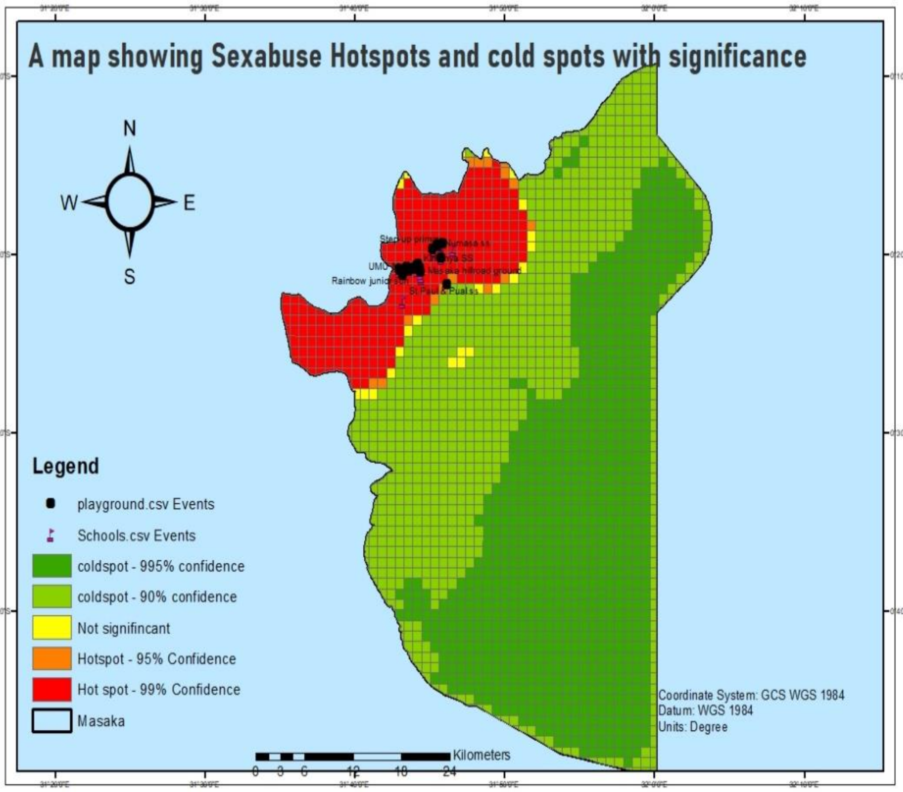

Figure 26: Sex abuse hotspots and cold spots

Like Roy and Chowdhury (2023) said, understanding the spatio-temporal dynamics of sexual crimes is essential for policy development, prevention strategies and resource allocation. From the fig. 23 above, Masaka city, Nyendo-Mukungwe and Kimanya- Kabonera were showed as hotspots with confidence of 99% and 90%. Areas that are covered by Lake Victoria are coldspot 95% confidence and the biggest part of Masaka rural is a cold spot with a confidence of 90%.

4.5.6 Theft crime coldspot and Hotspot

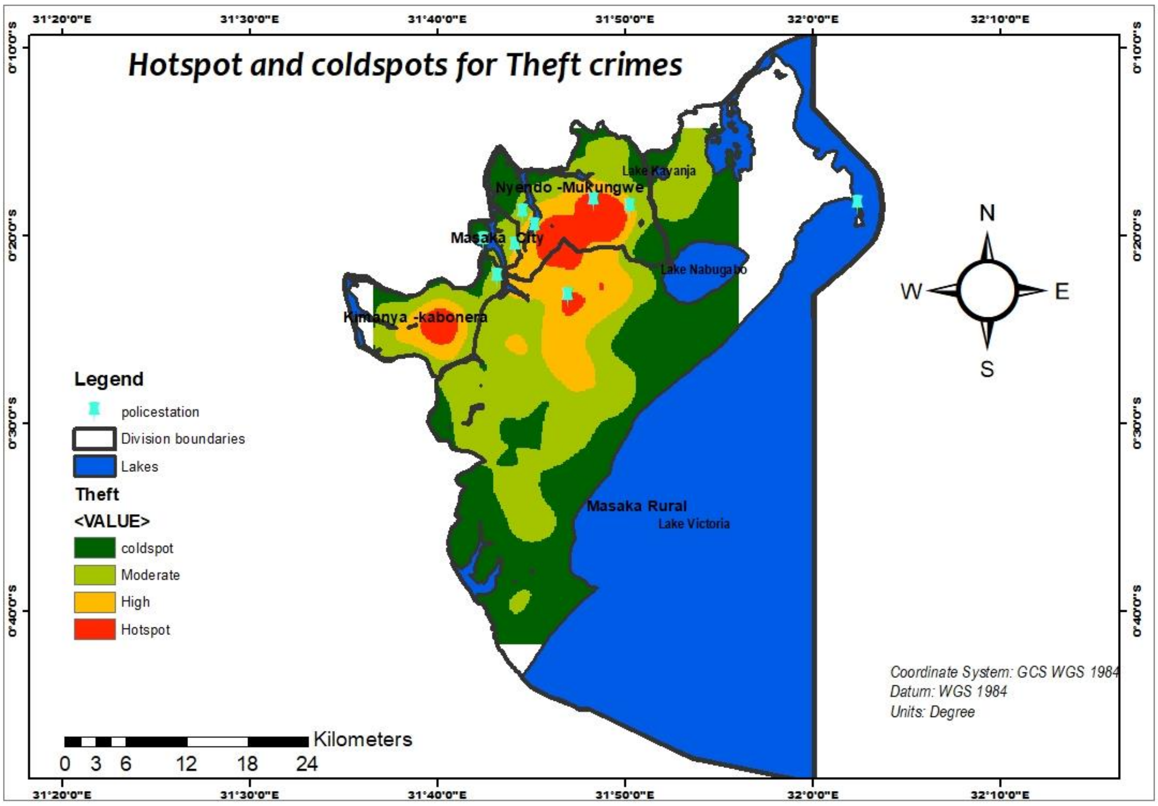

Figure 27: Theft coldspots and hotspots

Figure 27 illustrates the clustering of theft crimes, highlighting areas with high and low incidences. Hotspots are evident in divisions such as Nyendo-Mukungwe, Kimanya-Kabonera, and Masaka Rural. Among these, Nyendo-Mukungwe exhibits the largest hotspot, while Masaka Rural has the smallest. Notably, Masaka Rural has the highest overall percentage of high crime occurrences, making it a particularly risky area.

4.5.7 Robbery coldspot and Hotspot

Robbery detection of coldspot and Hotspot was done by kernel density *(spatial analyst > density > Kernel density)* and analysis was done with Geri-Ord-Gi* to get the real significance of the coldspot and hotspot showed on the map.

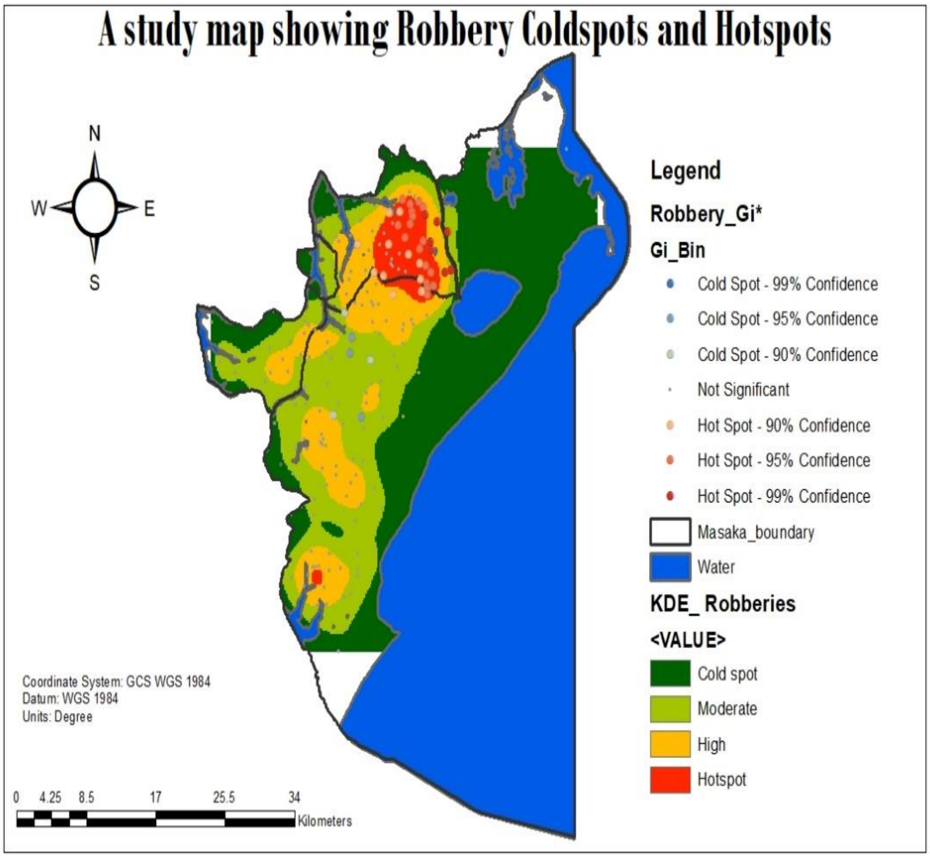

Figure 28: Robbery coldspot and hotspot.

Figure 28 shows that robbery cases are concentrated primarily in the Nyendo-Mukungwe division, identifying it as a significant hotspot. The second, smaller hotspot appears in Masaka Rural. These patterns of concentrated hotspots align with the "law of crime concentration" proposed by Weisburd (2015), which states that crime tends to cluster consistently in a small percentage of places. To further verify the significance of these hotspots and coldspots, the Geri-Ord Gi* statistic was applied. This analysis revealed areas with strong clustering, where some locations are coldspots with 99% confidence, while others are hotspots also at the 99% confidence level.

4.5.8 Assault coldspot and hotspot

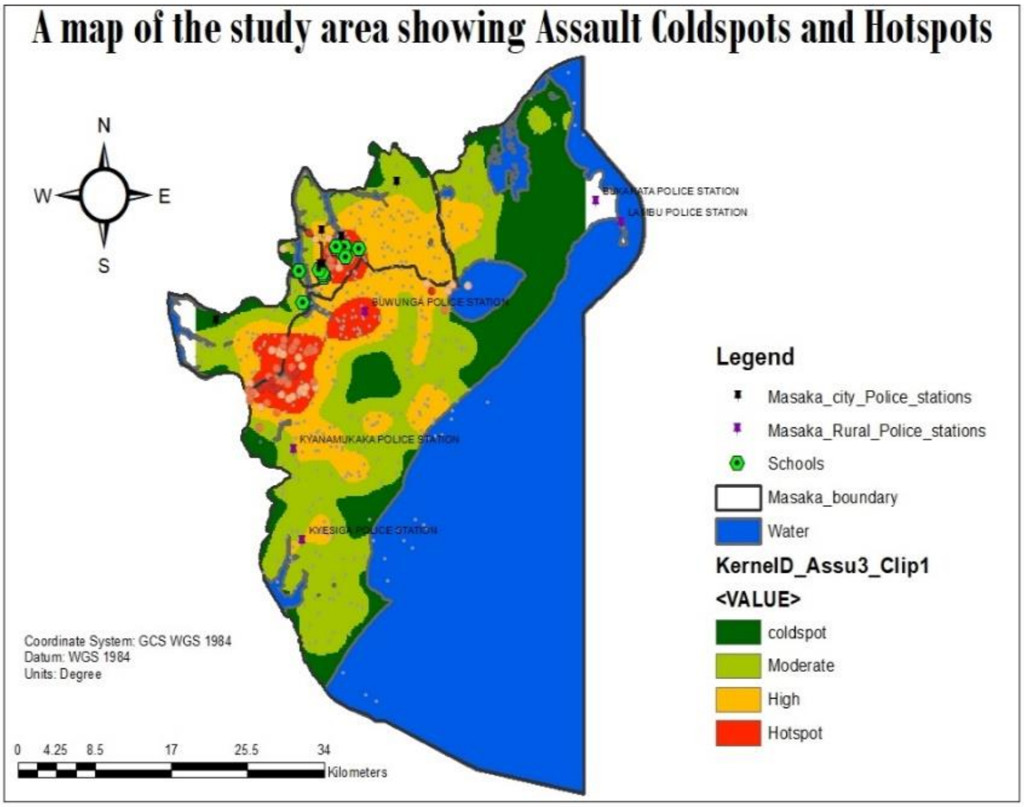

Figure 29: Assault coldspots and Hotspots.

There are three hotspots identified for assault incidences in Masaka district. The biggest falls in Kimanya- Kabonera and Masaka rural, the other two are almost of the same size, one in Masaka rural and the other in Nyendo-Mukungwe and Masaka rural. Nyendo-Mukungwe has no coldspot and Kimanya- Kabonera has very little space as a coldspot. Some schools are identified in hotspot regions which puts them at a high risk of suffering from crimes and their recaptions.

4.5.9 Breakings coldspot and hotspot

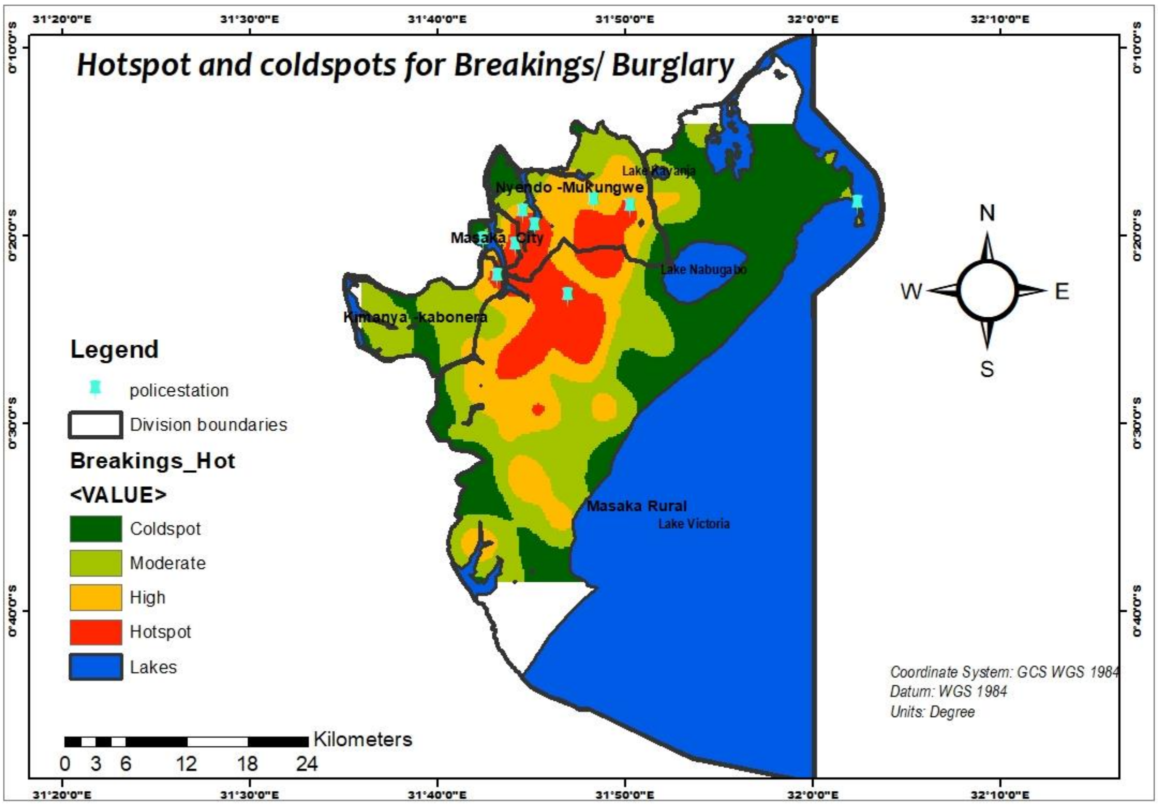

Figure 30: Breakings Hotspot and coldspot

Break-in hotspots in the study area are extensive and often span across multiple administrative divisions. The largest and most prominent hotspot stretches across Masaka City, extends into parts of Nyendo-Mukungwe, and further reaches Masaka Rural. This pattern suggests that break-ins are not confined to isolated zones but instead form a broad corridor of criminal activity cutting across urban and peri-urban boundaries.

This cross-divisional spread of breakings may be attributed to the seamless connectivity between these areas, the presence of major roads, and the mixture of commercial and residential properties that provide numerous opportunities for burglary. Built-up environments with minimal surveillance and a high density of properties tend to attract offenders who can move quickly between zones with limited risk of detection.

Importantly, many of the police stations in these areas are either located within the identified hotspots or very close to high-crime zones. While their presence is critical for crime response, their location within high-crime areas may indicate reactive rather than preventive policing, or in some cases, inadequate staffing or resources to effectively deter breakings.

4.6 Prediction of future crime locations using Space- time pattern mining

According to the literature reviewed the best prediction method for this study was analysis and prediction through space time cube pattern mining- emergency hotspot analysis and outlier analysis. Spatio- temporal analysis of crimes for the study area can be best analysed by a space time cube.

The prediction of crimes was done in different steps starting from creating of a space -time cube – Emergency hotspot analysis and the correlation of the new hotspots got as the spatiotemporal framework of the study.

The space -time cube summarizes a set of points into a netCDF data structure by aggregating them (points) into space-time bins. Within each bin, the points are counted, and specified attributes are aggregated. For all bin locations, the trend for counts and summary field values are evaluated (ArcGIS Pro documentation).

Since ArcMap only has '*create a space time cube pattern by aggregating points'*, a shape file for Uganda parishes (political) 2010 was used. The police divisions were few, a space time cube need at least 60 bins, so that is the reason why political wards or parishes were selected. The process of preparing Parish point was as follows:

(i) Loading parish polygon data into ArcMap, adding X,Y coordinates since they were missing.

(ii) The parish polygon file was projected to the same projection system as the main polygon for Masaka district. *(Data management* > *Projections and transformations* > *Project).* It is a major requirement for working with a space time cube to have projected polygons.

(iii) Feature to points. The projected polygon file was changed to a point layer since creating a space time cube in ArcMap is only possible with point layer as the input feature. This creates a point in the middle of every parish such that it will be taken as the point layer during creation of a space time cube.

(iv) A parish polygon (projected) was exported to excel to assign crimes to different parishes and different dates.

A space time cube works with date and time, so dates were assigned randomly basing on the different years of crime data. For date, an assumption was made that crimes happen any day, be it a working day or a weekend.

The parish data file was then added to the software as a .csv file. This file could not be joined with the original point parish polygon until OIDs (Object Identifications) were added. This was done through, exporting this file through data export, the add a copy of the exported data to the map as a layer.

The new exported layer with OIDS was joined with a point layer (parish points) and attributes of a csv file were added in the point layer.

The point data layer was used as an input for creation of space-time cube, saved as .cn (NetCDF data – Network common data Form). Columns with same region (x,y) and have the same ID (location-ID/Point- ID) were integrated *(Data management tool > feature class > Integrate)* to represent bin time series. For creation of space- time cube, the settings were as follows:

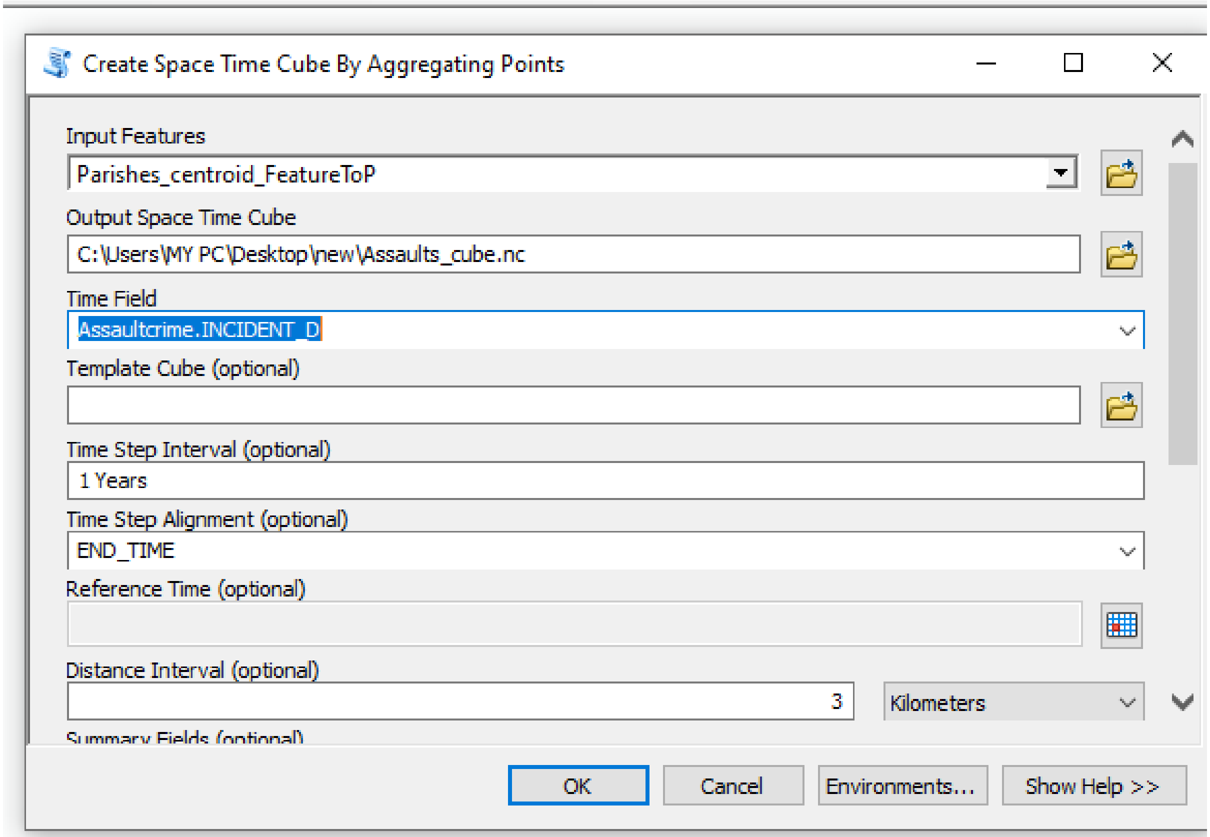

Figure 31: An extract for creating a Space -Time cube.

The input features consisted of crime incident points obtained from the parish point layer (Parishes_centroid_featureTop). The output, named "Assault-cube," refers to the filename designated for the generated cube. The time field used was Date (representing the date of each crime occurrence) from the attribute table. The time step interval was set to one year to analyse changes in crime occurrences on an annual basis, enabling the prediction of hotspots over a 12-month period.

The distance interval was set to 3 km after testing other intervals such as 5 km, 1 km, and 500 m. We found that a large distance interval tends to obscure spatial patterns, while a very small distance interval results in numerous bins with zero crime points, complicating cluster detection. The 3 km interval provided a balanced spatial resolution for meaningful analysis.

For spatial binning, the aggregation method was set to a fishnet grid for all crime types. Although hexagonal binning was also tested, it produced very large hexagons that extended beyond individual parish boundaries, which was not desirable for this analysis. An example of the binning output is attached.

After creating a space-time cube for each crime type, the visualization was presented in 3D. When ArcGIS generates the space-time cube, it independently calculates the Mann-Kendall statistic for each spatial location. The Mann-Kendall test is a non-parametric rank correlation method used to identify whether there is an increasing or decreasing trend in the time series data. The observed trend is then compared against the null hypothesis of no trend to determine if the trend is statistically significant (Arcgis.com, 2025; Element 84, 2017). Below is the visualisation of a space time cube.

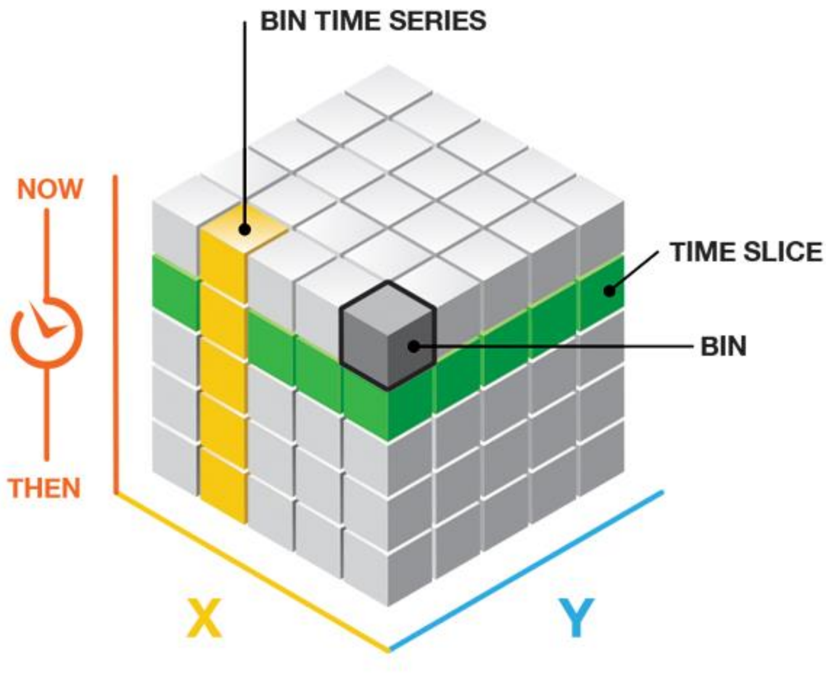

Figure 32 : Visualizing the space time cube (source: Esri)

The cube created for different crimes shows time, places and number of crimes. On the top are the very recent crime counts for example those of 2024 and at the bottom are the old crime counts (2022). Each bin represents a place or location of a crime with a value (crime count) and summary field (sum). Time slices are the time intervals such as1 year, 3 months, set for the study.

4.6.1. Emerging hotspot analysis

This was used to calculate the statistical significance of the crimes in different regions in the study area, to find out the spatial patterns and temporal trends of hotspots over a period of four years (2021- 2024).

The time slice was set as end -time analysis based on yearly data. The output for Space-time cube was used as input for the emerging hotspots. The parameters used are explained below.

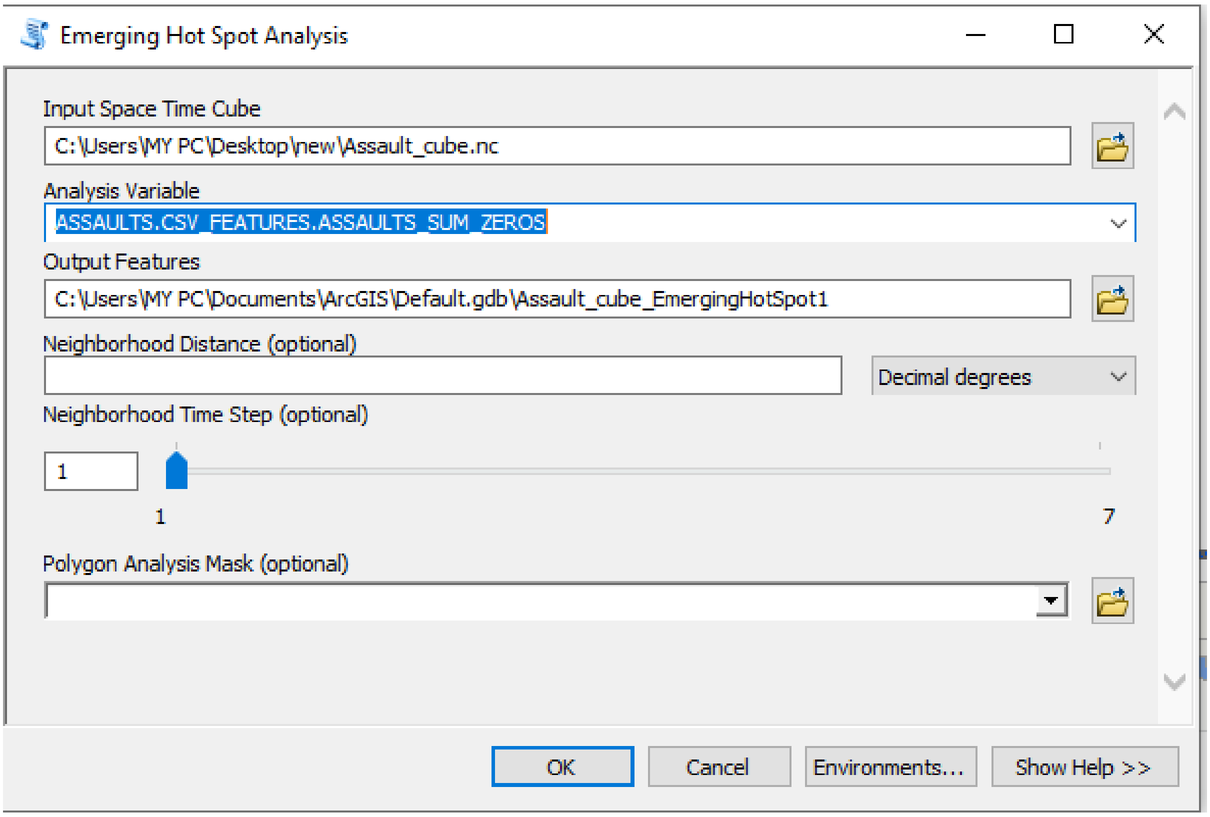

Figure 33: Emerging hotspot analysis

Input space time cube, the cube that was created in the above step (create a space time cube – assault-cube) was loaded. Analysis variable requires the crime under study and its statistics for example sum, mean, standard deviation, max among others. Other settings were left as defaults.

The out for emerging hotspot is a map with different categories of places such as a new hotspot, consecutive, intensifying, persistent, diminishing, sporadic, oscillating and historical hotspot and cold spots.

The patterns created were explained according to (Arcgis.com, 2021):

Persistent Hot Spot

A location that has been a statistically significant hot spot for ninety percent of the time-step intervals with no discernible trend indicating an increase or decrease in the intensity of clustering over time.

Diminishing Hot Spot

A location that has been a statistically significant hot spot for (90%) ninety percent of the time-step intervals, including the final time step. In addition, the intensity of clustering in each time step is decreasing overall and that decrease is statistically significant.

Sporadic Hot Spot

A location that is an on-again then off-again hot spot. Less than ninety percent of the time-step intervals have been statistically significant hot spots and none of the time-step intervals have been statistically significant cold spots.

Oscillating Hot Spot

A statistically significant hot spot for the final time-step interval that has a history of also being a statistically significant cold spot during a prior time step. Less than ninety percent of the time-step intervals have been statistically significant hot spots.

Historical Hot Spot

The most recent time period is not hot, but at least ninety percent of the time-step intervals have been statistically significant hot spots.

New Cold Spot

A location that is a statistically significant cold spot for the final time step and has never been a statistically significant cold spot before.

Consecutive Cold Spot

A location with a single uninterrupted run of statistically significant cold spot bins in the final time-step intervals. The location has never been a statistically significant cold spot prior to the final cold spot run and less than ninety percent of all bins are statistically significant cold.

Intensifying Cold Spot

A location that has been a statistically significant cold spot for ninety percent of the time-step intervals, including the final time step. In addition, the intensity of clustering of low counts in each time step is increasing overall and that increase is statistically significant.

Persistent Cold Spot

A location that has been a statistically significant cold spot for ninety percent of the time-step intervals with no discernible trend, indicating an increase or decrease in the intensity of clustering of counts over time.

Diminishing Cold Spot

A location that has been a statistically significant cold spot for ninety percent of the time-step intervals, including the final time step. In addition, the intensity of clustering of low counts in each time step is decreasing overall and that decrease is statistically significant.

Sporadic Cold Spot

A location that is an on-again then off-again cold spot. Less than ninety percent of the time-step intervals have been statistically significant cold spots and none of the time-step intervals have been statistically significant hot spots.

Oscillating Cold Spot

A statistically significant cold spot for the final time-step interval that has a history of also being a statistically significant hot spot during a prior time step. Less than ninety percent of the time-step intervals have been statistically significant cold spots.

Historical Cold Spot

The most recent time period is not cold, but at least ninety percent of the time-step intervals have. (Arcgis.com, 2021).

Below are the different output maps generated.

4.6.2 Sex abuse prediction

A sex abuse prediction map was created with the following settings: Cube was Sex abuse.cn, the time interval was one year, distance was set to 3 kilometres.

From the overall trend analysis from crime count, trend direction was increasing, trend statistic was 4.4115 and the trend p-Value was 0.0000.

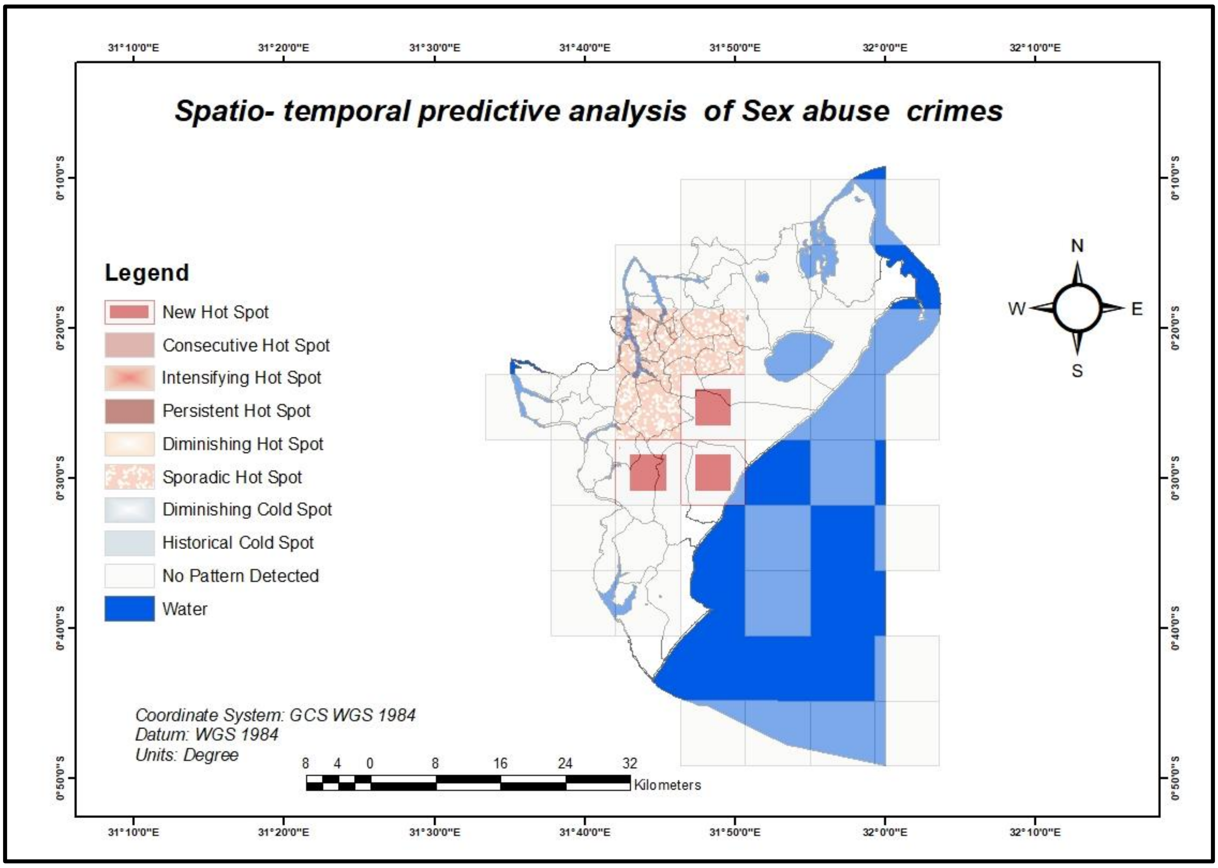

Figure 34: Sex abuse predicted hotspots

As shown in Figure 34 above, three new hotspots for sexual abuse crimes were identified in Buyaga, Kyantale, and Kanywa. In addition, several sporadic hotspots were detected in locations such as Ggulama, Kamwozi, Mazinga, Kirimya, Kyabakuza, Nyendo, Ssenyange, Bulando, and others. Sporadic hotspots are areas that become hotspots during some, but not all, of the time intervals analysed, indicating intermittent spikes in crime activity.

4.6.3 Theft crimes prediction

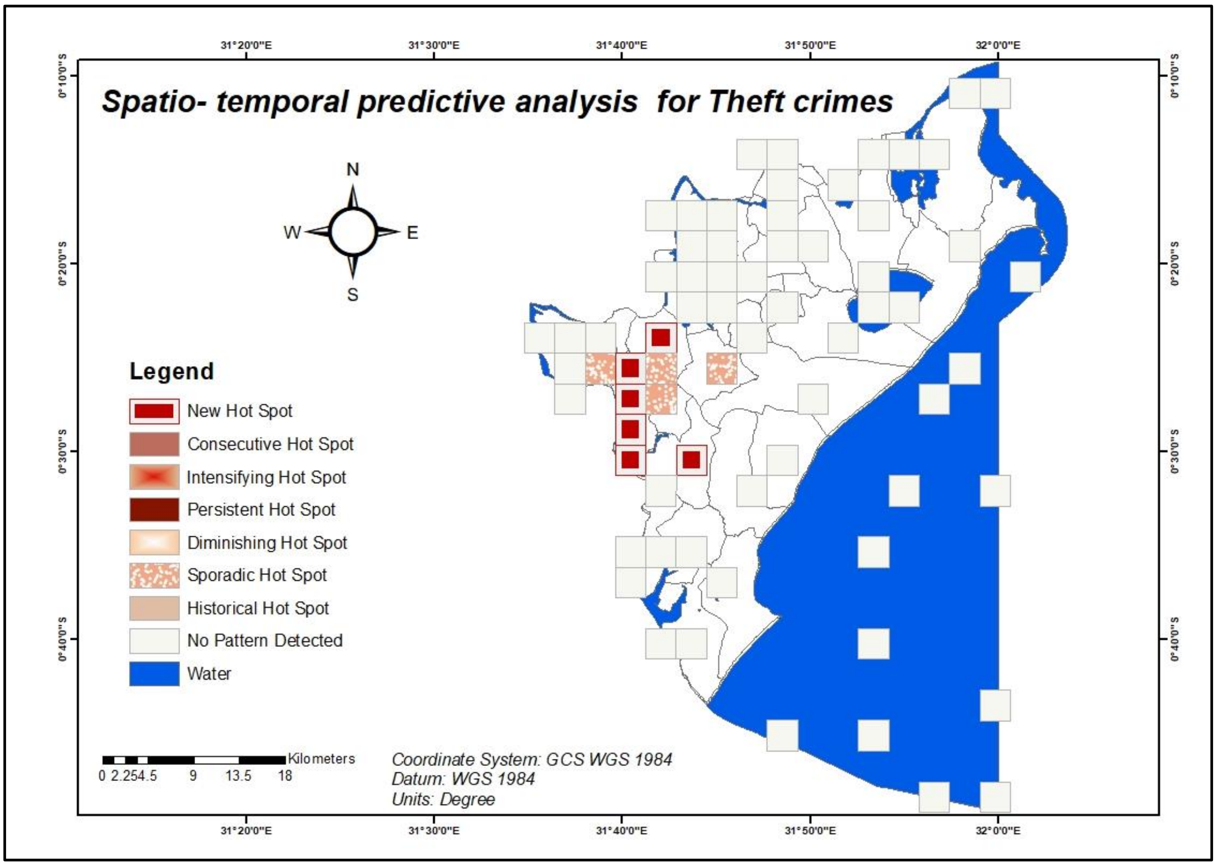

Figure 35: Theft crimes prediction.

The overall trend for theft crimes indicates an increasing direction, with a trend statistic of **2.06849** and a p-value of **0.0736**. Emergency hotspot analysis identified six new hotspots and four sporadic hotspots. Notably, there were no hotspots classified as diminishing, persistent, or oscillating during the study period.

4.6.4 Robbery prediction.

Different parameters were set for robberies due to their number that was very low compared to other crimes. For this crime, the time interval was set to three months with a distance of 4 kilometres. The trend for overall data was: direction was not significant; statistic was 1.2608 and the p-values got was 0.2110.

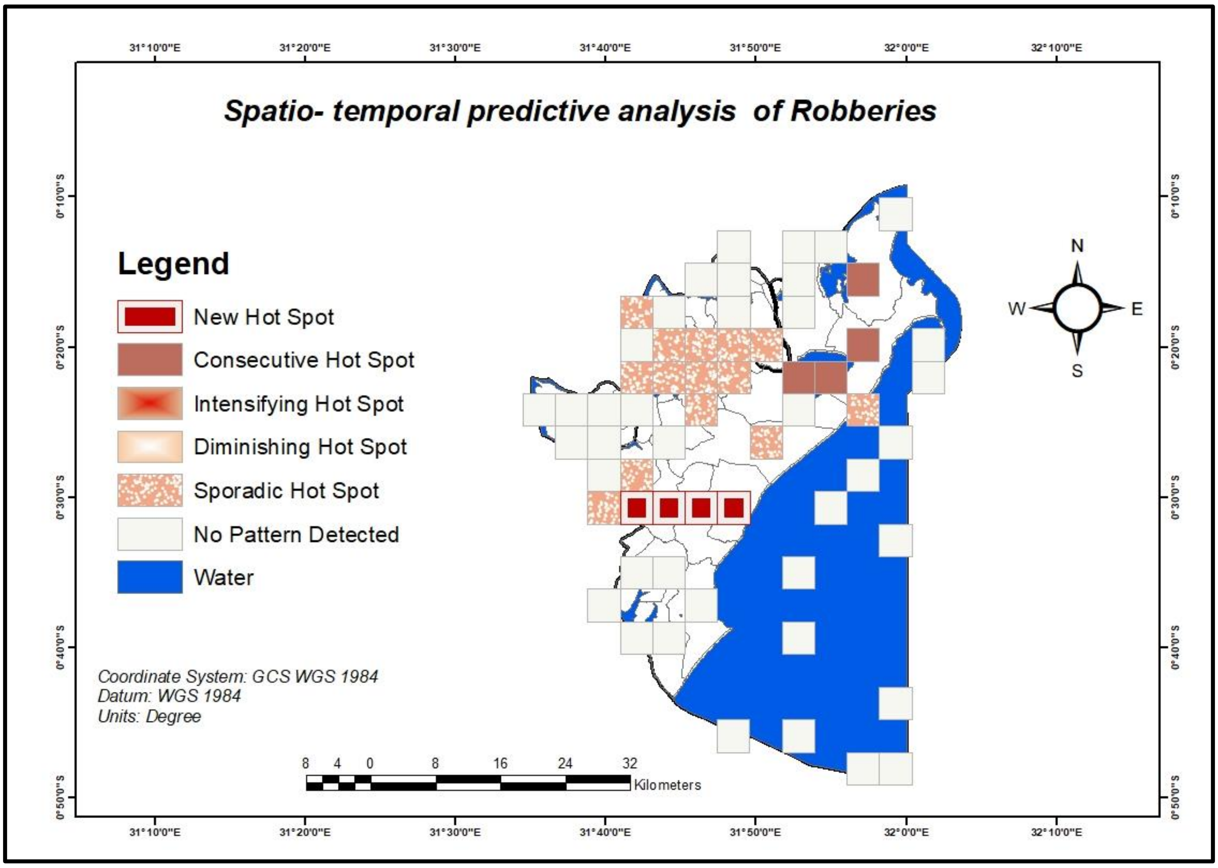

Figure 37: Robbery crimes prediction

As shown in Figure 37 above, the analysis revealed four new hotspots, four consecutive hotspots, and fourteen sporadic hotspots. Consecutive hotspots are defined as locations exhibiting a continuous sequence of hot time step intervals, comprising less than 90% of all intervals, indicating sustained but not constant activity.

The new hotspots were identified in Kyantale, Zzimwe, and Buyaga. Consecutive hotspots were found in Kasaka, Sunga, Bukibonga, and Makonzi. Meanwhile, sporadic hotspots characterized by intermittent spikes in crime appeared in areas including Mazinga, Buwunga, Kirimya, Kitengesa, Katwe, Ssenyange, Katwadde, and several others.

This distribution highlights both emerging areas of concern as well as locations experiencing persistent or fluctuating crime patterns, offering valuable insights for targeted crime prevention effort

4.6.5 Assault crimes prediction.

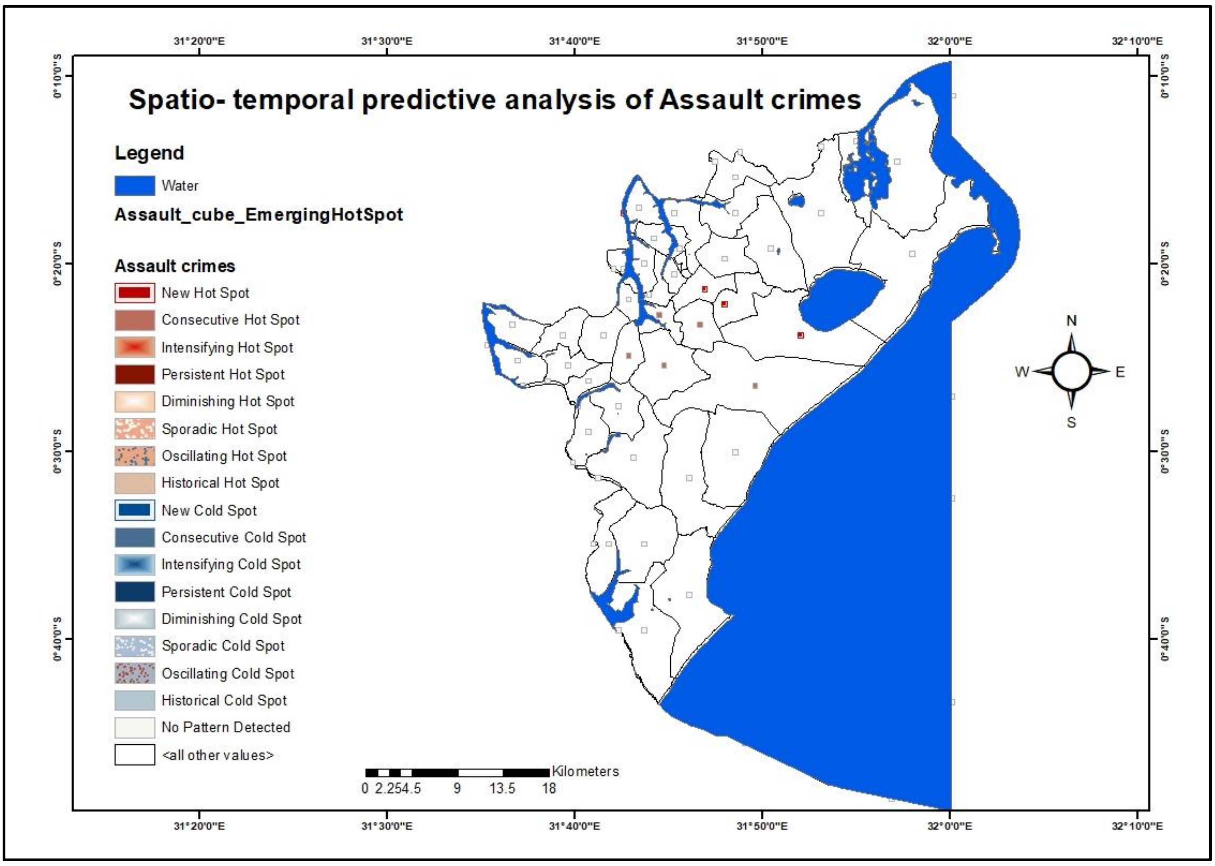

Figure 37: Assault crimes prediction results

As presented in Figure 37, the distance interval for assault crimes was set at 500 meters, with a time step interval of one year. The results identified three new hotspots, three consecutive hotspots, and three intensifying hotspots. New hotspots are defined as areas where the most recent time interval is hot for the first time; these were observed at Mazinga, Bulando, and Kasaka. Intensifying hotspots refer to locations where at least 90% of the time intervals are hot, and the intensity of the hotspot increases over time.

4.6.6 Breakings prediction

For breakings or break-in crimes, the overall trend for crime counts was as follows:

Trend direction	Increasing
Trend statistic	2.6186
Trend p- value	0.0088.

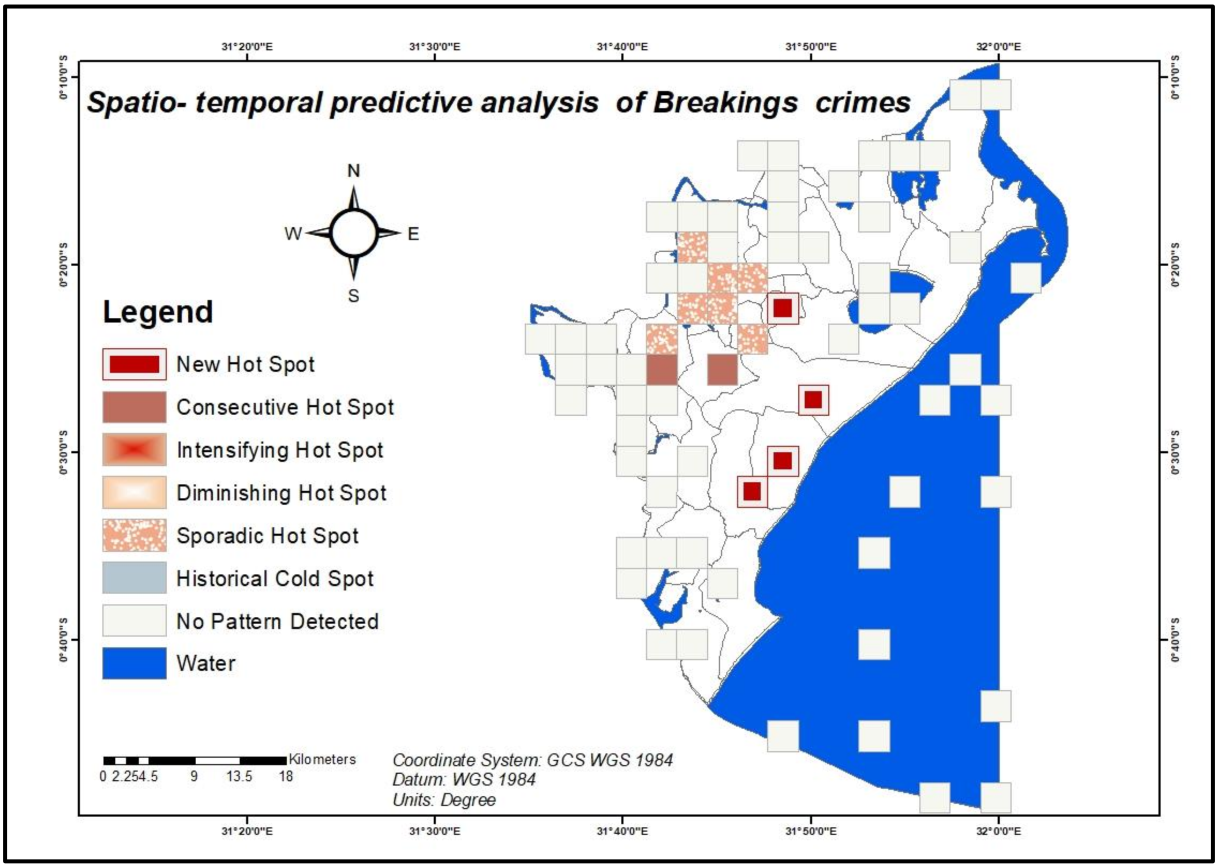

Figure 38: Breakings crime prediction.

According to the figure above, there were four new hotspots, two consecutive hotspots, and seven sporadic hotspots identified. The new hotspots were located at Zzimwe, Buyaga, Kanywa, and Mazinga. The consecutive hotspots appeared at Kamwozi and Kiziba. Sporadic hotspots were observed in areas such as Ssenyange, Bulando, Katwe, Buwunga, Butego, and others.

4.7 Possible interventions that can be leveraged to mitigate crime occurrences.

For crimes that occur in built-up areas, one effective solution is to improve the physical environment. This includes completing unfinished houses and ensuring that unoccupied homes are inhabited. Such actions reduce the opportunities for offenders to operate unnoticed and limit the chances of offenders encountering potential victims. Additionally, installing street lights in poorly lit areas can deter criminals who rely on darkness to carry out their activities, thereby making the environment safer.

In areas where overgrown vegetation contributes to crime, improving visibility through natural surveillance is key. Cutting down tall grass, trimming trees, and removing other visual obstacles can make it easier for people to see and be seen, which discourages criminal behaviour due to the increased risk of being observed.

Vacant spaces should also be repurposed to serve more useful and community-focused functions. For example, building a marketplace on an unused plot of land can transform it from a potential hiding spot for criminals into a vibrant public space that promotes safety through activity and presence.

Finally, the installation of CCTV cameras in strategic locations such as streets, public buildings, and around residential areas can enhance security. These cameras help deter criminal activity and assist law enforcement in monitoring and investigating incidents

4.8 Conclusion

The analysis of the results revealed varying concentrations of crime across different areas. Some locations recorded low crime rates, while others experienced high concentrations.

Nyendo-Mukungwe, Masaka City, and Kimanya-Kabonera were identified as the primary hotspots for sex abuse crimes. Theft crimes were most prevalent in Nyendo-Mukungwe, which emerged as the largest hotspot for this type of crime. A smaller theft hotspot was also observed in Kimanya-Kabonera.

Robbery incidents were also most concentrated in Nyendo-Mukungwe, where a significant portion of the area was categorized as a high-crime zone. Assault crimes showed multiple hotspots, notably in Kimanya-Kabonera, Nyendo-Mukungwe, and the Masaka Rural area near Buwunga Police Station.

Finally, break-ins were concentrated in Masaka City, with the hotspot extending into Masaka Rural and Nyendo-Mukungwe. Notably, Nyendo-Mukungwe had the largest portion affected by high levels of break-in crimes.

CHAPTER FIVE

5.0 DISCUSSION OF RESULTS

5.1 Introduction

This chapter presents a blend of the research findings on the spatial pattern and temporal trends of crimes in Masaka district, correlation between land use and land cover (LULC) features, areas with hotspots and the intervention measures to curb crime occurrence using GIS and remote sensing of data got from Masaka district,2022 to 2024. This is done by discussing the findings got, their implications, significance and limitations of the study.

5.2 Spatial patterns and temporal trends of crimes in Masaka district.

Crime data got from the different police divisions was analysed with a column chart as showed in figure 3. This indicated an upward trend in crime incidence happening in Masaka district from 2022 to 2023 the percentage change (increase) was 28%, from 2023 to 2024, it was 11% and from 2022 to 2024 it was 42%. Crimes increased as a result of urbanisation.

Urbanisation comes with a high population density which creates more potential targets for certain types of crimes as opined by (Jawadi et al.,2020). With a high population there is greater mobility, reduced guardianship and increased targets. High crimes cost government dearly as Van (2023) reported that crimes cost South Africa at least 10% of their Gross domestic product (GDP) annually. More crimes happen as years pass and so a call for better detection, prevention and mitigation measures by both police and community.

An analysis of crime distribution across the four police divisions in Masaka, focusing on the five selected crime categories, reveals that theft was the most prevalent. The highest number of theft cases was recorded in the Nyendo-Mukungwe division, with a total of 701 incidents, while the lowest was in Kimanya–Kabonera, with 451 cases. Other commonly reported crimes included assaults and sex-related offenses, while robberies were the least frequent among the five categories.

From 2022 to 2023, Sex abuse crimes had an increase of 9% and between 2023 to 2024, the percentage increase was 16%. The sex abuse trend was also an upward trend, meaning more sex abuse crimes were committed as years went on.

For theft crimes, between 2022 and 2023, there was 42% increase, between 2023 and 2024, it was approximately 7% increase,

For robberies, between 2022 and 2023, there was 27% increase and between 2023 and 2024, it was approximately 31% increase as per table 5. According to Figure 9, Nyendo-Mukungwe had the highest number of robbery cases followed by Masaka city, then Masaka rural and Kimanya-Kabonera respectively. Urban police divisions had higher crimes than rural divisions which can be as a result of unemployment and poverty as claimed by (Lee,2025; Reshaping the World of On-Demand Security, 2025) or areas with reduced family and neighbourhood cohesiveness can experience poor integration among communities of different races, religions, and ethnicities, leading to social disorganization and increased incidents of robbery and BE (Law and Abdullah, 2024). Additionally, specific economic indicators such as inflation and people's negative sentiment toward the economy can significantly affect robbery rates as reported by Lee (2025). Most of the robberies occur at midnight or between midnight to 4 a.m. The darkness of these hours remains at its peak, people are asleep, and the surroundings become calm—hence robbers find it as a perfect opportunity to strike. Another source gives robbery time as between 10am to 3pm with June and August as the robbery peak months (Legalknowledgebase.com, 2025)**.**

For breakings, it was 28% and 11% increase respectively.

From a general perspective, the most dangerous divisions in Masaka district were Nyendo-Mukungwe and Masaka City Division. This conclusion is based on both the average number of reported crimes and the population density in these areas.

Higher population density often correlates with increased criminal activity due to greater anonymity, strained public services, and more opportunities for crime as claimed by (Fry, 2014).

As presented in Figure 11, assault crimes were highest in the Kimanya-Kabonera division, followed by Nyendo-Mukungwe, Masaka City, and Masaka Rural, respectively. In 2022, Masaka City recorded the highest number of assault cases. However, in 2023, both Nyendo-Mukungwe and Kimanya-Kabonera reported nearly equal and the highest number of assault cases, followed by Masaka City and Masaka Rural with the least. In 2024, Kimanya-Kabonera again had the highest number of assault cases, exceeding 100 incidents, followed by Nyendo-Mukungwe, Masaka City, and Masaka Rural. Over the three years, assault cases showed a general increasing trend. This trend highlights the varying levels of assault crimes across the divisions and the growing challenge of managing violence within these areas.

Assault crimes have far-reaching consequences. Victims often suffer physical injuries, emotional trauma, and long-term psychological effects. Beyond the individual, these crimes also impact families and communities disrupting social trust, increasing fear, and placing additional strain on local healthcare and law enforcement systems.

Assault offenders often commit crimes near their homebase or places they are familiar with, which impacts the layout and spacing of crime locations. Assault crimes are normally committed at certain times of day like evenings and nights, often due to factors like gatherings, alcohol consumption and darkness (Movers,2022; Bellis et al.,2012).

In line with the above, research from the NSW Bureau of Crime Statistics and Research reported that assault rates spike on public holidays such as New Year's Eve and New Year's Day, with incidents concentrated during late-night hours (Chan and Cook, 2024). Similarly, emergency department data from England confirm higher assault rates on Friday and Saturday nights, as well as on the eves of public holidays. These findings indicate that social activities and alcohol consumption are key drivers of temporal spikes in assaults.

In Kimanya-Kabonera, the high number of assault crimes could be linked to the abundance of alcohol outlets, such as those in Kimanya-Katafari. Numerous bars there broadcast various games, including the Premier League, which often lead to fights as rival football supporters bet on outcomes. This social environment, combined with alcohol consumption, likely contributes to the elevated assault rates in the area. The findings for assault spatio patterns align with research done by (Chan and Cook,2024; Jarvis,2022).

The above trend can also be as a result of socioeconomic disparities among the people as cited by Legal Clarity (2025) and family instability and dysfunction where an individual may fail to integrate positively into society and resort to criminal acts (CS& CPC,1996). This can be overcome by carrying out community engagement and changing economic conditions that create offenders.

5.3 Crimes and land use landcover features.

From the imagery (see Figure 20), the key land-use/land-cover (*LULC*) types identified in Masaka include: built-up areas; swamps (locally referred to as "rivers"); water bodies; forests or forest reserves, agricultural land, and bare land which are areas used for brickmaking, rock extraction, and sand mining. Built-up areas encompass all constructed structures and paved surfaces such as roads.

Masaka District exhibits a mix of urban and semi-urban landscapes, which shapes how environmental features influence crime dynamics. For example, swamps particularly the Nabajjuzi wetlands are being degraded through activities like brick making, agriculture, and construction, driven by rapid urban expansion, waste disposal, and unclear land tenure arrangement. Such environmental degradation can disrupt natural buffers, increasing risks of flooding, habitat loss, and vector-borne disease all conditions that may indirectly elevate crime rates by exacerbating social stress and weakening infrastructure.

Moreover, Masaka's landscape is characterized by a high population density over 700 people per square kilometre and about half of the district is wetland (Muchelo et al.,2024; Wikipedia contributors,2024). This pressure has contributed to fragmented agricultural land, deforestation, and soil fertility decline (Muchelo er al.,2024; Nataliya and Nyairo, 2025), creating economic vulnerabilities and land-use conflicts that can foster criminal behaviour.

5.3.1 Sex crimes

Figure 21 above demonstrates that sex abuse crimes were more prevalent in built-up areas such as commercial zones, residential neighbourhoods, and entertainment venues. Several factors contribute to this trend. As Caroline et al. (2024) noted in their study, many of these offenses occur within homes and are often perpetrated by individuals known to the victims, such as family members or acquaintances.

Further research by Noreña and Rodríguez (2022) highlights contributing factors such as previous exposure to violence, histories of child abuse, mental health disorders, substance abuse, family dysfunction, and inadequate supervision of children. These conditions create environments where perpetrators especially those within the household can easily access and exploit vulnerable victims.

The most common forms of sex abuse identified in these settings include defilement, incest, and rape. The impact of such crimes on the community is profound: victims often suffer long-term psychological trauma, social stigma, disrupted education or work life, and increased vulnerability to further exploitation. Communities as a whole may experience a breakdown of trust, increased fear, and reduced social cohesion when such offenses go unchecked.

Outdoor rapes in urban areas often occur in public places with poor visibility and easy escape routes, such as parks, isolated streets, or areas near transport nodes and industrial edges. These locations enable offenders to act opportunistically while minimizing detection. Studies in Stockholm highlighted that such spatial features matter more for outdoor assaults, which represent roughly 20–30% of all rape cases there (Ceccato, 2014). These crimes were shown to occur in places with roads intersecting which supports Ceccato's argument that they happen in areas near roads.

Masaka City and Nyendo-Mukungwe host several small-scale industries, which attract a large number of people seeking employment. As a result, these areas experience high population densities. Many of the workers live in low-cost housing, particularly in slum areas, due to limited financial means.

This situation is further supported by a recent study by Caroline et al. (2024), which found that municipalities with a lower Human Development Index (MHDI) reported higher rates of sexual violence. In such areas, the availability of cheap lodgings makes it easier for workers and even school-going children to afford accommodation, either by renting rooms or staying in lodges. This easy access to low-cost housing, often lacking proper regulation or security, may contribute to increased vulnerability and a higher risk of crime.

Sexual abuse also follows temporal patterns, with fluctuations in incidence over time. According to Mathews and Guddattu (2024), sexual crimes such as rape exhibit clear seasonal trends, with a noticeable increase in cases reported during the summer months. These patterns suggest that certain times of the year may create conditions that increase vulnerability to sexual violence.

Additionally, night-time plays a significant role in facilitating such crimes. As noted by Ezechi et al. (2016), sexual abuse is more likely to occur at night when surveillance is minimal. Locations such as bars, nightclubs, and lodges are particularly associated with a higher occurrence of sex-related crimes, often due to poor lighting, lack of security, and overcrowding.

To address these issues, Cadera-Urzua, Gardiola, and Montes (2025) advocated for safe urban planning. Their recommendations include the development of well-lit recreational spaces, enhanced community policing, and thoughtful urban design that prioritizes safety, particularly in areas prone to sexual violence.

5.3.2 Theft crimes and the land use land covers of Masaka district.

In this study, property theft was the focal category and was notably more prevalent in built-up urban zones especially commercial streets and unfinished structures as illustrated in figure 22. This was in agreement with studies viewed in literature which include: (Mao et al.,2025; Bacer et al., 2025; Ludin et al., (n.d)). Such environments inherently support criminal activity by offering numerous hiding places: incomplete buildings, narrow alleys, and construction debris provide easy concealment, enabling offenders to snatch valuables and vanish quickly which is in agreement with (NTV Uganda, 2024) on Tues, 17^{th} dec, 2024; Dube,2024; New Ziana,2024). This pattern also aligns with Crime Prevention Through Environmental Design (CPTED) theory, which emphasizes how poorly maintained or low-surveillance spaces elevate crime risk, while enhancing visibility reduces it.

Research from Africa further confirms that unsafe built environments characterized by dense, poorly legible neighbourhoods and deteriorating infrastructure—are statistically linked with higher rates of burglary and property crimes (Silva and Li,2020). This was evidenced form the data collected which showed some places with unsafe built-ups like Nyendo with high crimes of theft.

Similarly, snatch theft commonly occurs in linear or fragmented street networks, where perpetrators exploit limited oversight and escape routes as opined by (Sakip and Salleh,2018).

This calls for joint efforts from police and communities to ensure criminal places are reduced and properties are guarded well.

5.3.3 Robbery crimes and the land use land covers of Masaka district.

Some studies show that robberies tend to cluster in places with high human activity (Inlow, 2021), such as commercial, industrial and lower levels are in less populated areas such as forests as it was shown in figure 23. The findings for this study, align with previous research findings. Robbery cases in Masaka district were more in divisions with commercial buildings and less in places with forests as shown in figure 22 and figure 23.

For robbery cases, offenders are less likely to encounter suitable targets since potential victims or valuable property are scarce. Additionally, the presence of natural barriers, limited accessibility, and the potential for natural guardianship such as wildlife or environmental surveillance reduce the chances of a crime occurring. As a result, robberies and similar offenses are less likely to take place in such settings compared to more densely populated or urban areas where these three elements frequently coincide

5.3.4. Assault crimes with land use landcover features

According to Figure 24, Kimanya-Kabonera recorded the highest number of assault crimes, followed by Nyendo-Mukungwe with a high incidence, Masaka City with moderate cases, and Masaka Rural with the lowest. The high concentration of assaults in Kimanya-Kabonera, despite its relatively lower built-up area compared to Masaka City and Nyendo-Mukungwe, raises important questions. Kimanya-Kabonera is predominantly composed of commercial and residential land uses and is surrounded by swamps or wetlands. Among the commercial establishments are entertainment venues such as clubs, pubs, and bars. Research by Kim et al.

(2024) indicates that areas with numerous alcohol outlets and late-night entertainment venues provide more opportunities for motivated offenders to encounter suitable targets.

Additionally, Wiebke Bomas (2024) highlights that areas adjacent to swamps or wetlands are often inaccessible, which reduces natural surveillance and creates isolated environments conducive to criminal acts like assaults. Supporting this, studies by Nubani et al. (2023) and Kim et al. (2024) link assault crimes to alcohol consumption and social gatherings, which are more common in built-up areas.

Assault crimes have far-reaching consequences. Victims suffer not only physical injuries but also emotional trauma and long-term psychological effects. Beyond the individual level, these crimes disrupt social trust within families and communities, increase fear, and place strain on local healthcare and law enforcement systems.

To address these challenges, it is essential to employ real-time data collection techniques to monitor activities in wetlands and swamp areas effectively. Such monitoring enables rapid responses to illegal activities and aids crime prevention, as suggested by UNDP (2025) and Hou et al. (2025).

This comprehensive understanding underscores the complex interplay between land use, social behaviour, and crime, emphasizing the need for targeted interventions in high-risk areas like Kimanya-Kabonera.

5.3.5. Breakings with land use landcover features

As presented in figure 25, Masaka city had the highest number of breakings over the study period followed by Nyendo- Mukungwe with high crimes, Moderate crimes in Masaka rural and Kimanya- Kabonera with the lowest. Breakings concentrated in areas with built-up most. This shows a positive correlation between built-up and breakings. The study findings agree with what Bowera, Anthony and Summer (2022) found from their study of examining violent crimes in commercial and public properties. The found out that breakings were much attracted in built-up areas.

The International Crimes against Business Survey (ICBS) found that retail and business premises suffer much higher breakings compared to households (Prenzlen,n.d). This also aligns with the study findings because Masaka city has a lot of retail business.

Breakings erode social trust, increase fear, and may lead to community disintegration as claimed by Williams (n.d). The ripple effects create stress on families, health care providers and law enforcement.

Studies show that investment in property security and community safety measures can reduce breakings in built-up areas (Walter, Acolin and Tillyer,2024).

5.4. Crime hotspots and cold spots

In this study, different types of crimes showed varying levels of concentration across locations. Areas with a high concentration of crimes were identified as "hotspots," while those with little or no crime concentration were termed "coldspots." Understanding the characteristics and patterns of crime hotspots can provide valuable information to authorities, helping them to effectively manage and control crime by focusing resources on these high-activity areas (Eftelioglu et al., 2020).

5.4.1 Sex abuse hotspots and coldspots

As illustrated in Figure 26, hotspots of sexual abuse were predominantly identified in urban centres, including Masaka City, Kimanya-Kabonera, and Nyendo-Mukungwe. The victims of these crimes are mostly girls, women and a few young boys. This is attributed to the urban settings of the place which come with a high population.

High population comes with high crime rates as opined by Muller and Romano (2024) who they said that urban regions are typically acknowledged as criminal breeding grounds and are more likely to experience a higher incidence of crimes than rural areas due to their higher population density and near proximity of dwellings.

This study's sex abuse hotspot findings are in line with what Jiang et al.,2023 put forward after their study that sex crimes happed a lot in places like hotels, beauty salons, teahouses, footbath and other commercial places. These are always in urban places and so high concentration of sex crimes.

Some semi-urban areas are prone to sex abuse crimes due to various contributing factors, including a high proportion of slum populations, a large number of slums, easy access to sexual content on the internet, and a significant increase in liquor consumption, among others, as noted by Mondal, Singh, and Kumar (2022). Slum areas often face overcrowding, poverty, lack of proper policing, which can create an environment where vulnerable population especially women and children are at a greater risk of abuse due to weaker community surveillance and high levels of alcohol consumption can impair judgement and inhibit self-control, often leading to crimes.

The findings for this study also align with information got from observation and unstructured interview findings: Entertainment and bar places such as Plan A, Kiyovu (The Golden Elephant bar), Villa lounge, breed sex abuse crimes.

Understanding sex abuse crime hotspots help police officers gain insight into the most common sex abuse hotspots. This helps in faster combating of the crime (Olayemi Falope and Thakur, 2022).

5.4.2 Theft cold and hotspots.

The hotspots for theft crimes were three, one in Kimanya- Kabonera, Nyendo-Mukungwe and Masaka rural as presented in figure 27. The bigger part is covered by high crimes and coldspots.

Theft crimes are as a result of many factors including the land use and landcover of a place. In Masaka's Nyendo-Mukungwe division, the specific hotspot of **"Kyakyafu"** has seen rising property theft incidents. According to local reports, daily crime at the police station includes two or more cases mainly along transit corridors and unlit zones driven in part by opportunistic gangs exploiting the built environment. The results got for theft hotspot align with what other researchers found out.

During an unstructured interview with a police officer, it was noted that theft crimes are more prevalent in areas with high population density, particularly during nighttime. The locations identified as having high incidences of theft include Nyendo Market, Bukakata Stage (Park), Nyendo- Kitaka, and Kakyafu. These areas are characterized either by large concentrations of people or by insufficient lighting at night, which may contribute to the higher rates of theft.

5.4.3 Robbery coldspot and Hotspot

Only one hotspot was identified in the Nyendo-Mukungwe division, while the rest of the area experienced generally high crime rates as shown in figure 28. Nyendo, in particular, has a high concentration of businesses such as bars, clubs, and merchandise shops, which are often associated with robbery crimes. The presence of a robbery hotspot in Nyendo-Mukungwe aligns with the findings of Sypion-Dutkowska and Leither (2017), who noted similar patterns in such commercial areas**.**

Bukakata is identified as a coldspot, and other areas around Lake Victoria also show coldspot patterns, as illustrated in Figure 28. This observation contradicts Lewyn's (1993) findings, which suggested that criminals are more likely to commit crimes in less densely settled, quieter neighbourhoods. Akiner et al. (2023) similarly cited that criminals tend to target such areas. However, the evidence from Bukakata and its surroundings challenges this claim, indicating that crime patterns may differ in these locations.

To reduce the high number of robbery cases, increased police patrols are needed. This is supported by Chainey et al. (2021), who found that police presence at robbery hotspots was associated with a significant 23% reduction in crime.

5.4.4 Assault coldspot and hotspot

According to figure 29, assault hotspots were three with biggest in Kimanya-Kabonera and Masaka rural, another hotspot was in Nyendo-Mukungwe and the smallest of all appeared in Masaka rural. The schools shown were in a hotspot and the coldspots were few. From figure 29, it is shown that assault concentrate in area with urban settings. Assault being a human crime cannot concentrate in places with few settlements or built-up.

5.4.5 Hotspot and cold spot for breakings.

Breakings happen in places with human settlement (residential or commercial). There were two breakings hotspot got according to figure 30. According to the narrative of ex-offender in south Africa, breakings areas are as a result of socio-economic factors such as poverty, inequality, substance abuse and unemployment, and intra- and interpersonal factors such as low self-control, peer pressure and greed (Fumba and Magadze,2022).

Masaka City is characterized by densely built-up areas with limited vegetation, long walkways, and a mix of residential and commercial compounds. These urban features, especially the high concentration of properties and limited natural surveillance, make the city more susceptible to break-ins compared to less developed or more sparsely populated areas such as Masaka Rural. Property crimes like breakings tend to concentrate in both commercial and residential areas. Commercial blocks experience a higher number of incidents at night, primarily due to the lack of natural surveillance from ground-floor windows after shops close. This vulnerability can be attributed to reduced guardianship, as burglars target locations that are less monitored or easier to access (Miranda and van Nes, 2020).

This emphasizes the need for improved security measures in denser urban settings to counteract the higher risk of property crimes.

5.5 Prediction of crime results- map

Though this study did not predict individual crime victims, probable crime locations were forecasted. Crime prediction offers police officers an advantage by enabling them to secure areas that are sensitive to criminal activities, as noted by Khatun et al. (2021). By identifying high-risk locations in advance, law enforcement can proactively increase patrols and resources in these areas, helping to deter crimes before they occur and improve overall community safety.

5.5.1 Sex abuse prediction

The identification of three new hotspots for sexual abuse crimes in Buyaga, Kyantale, and Kanywa, along with several sporadic hotspots in other areas, reflects complex underlying causes, significant effects, and points to targeted solutions (figure 34).
The emergence of new and sporadic hotspots for sexual abuse crimes can often be linked to various social and economic factors. These may include poverty, limited educational and employment opportunities, social disintegration, and cultural norms that tolerate or conceal abuse (Wager, Myers and Parkinson, 2021). Additionally, weak law enforcement presence and underreporting due to stigma can contribute to the persistence and emergence of such hotspots.

Changes in population dynamics or community structures may also lead to fluctuating crime patterns in sporadic hotspots.
Sexual abuse hotspots create severe negative impacts on individuals and communities. Victims often suffer long-term psychological trauma, and the fear of crime in these areas can lead to reduced social cohesion, decreased property values, and hindered community development. Sporadic hotspots complicate law enforcement and social service responses because of their

intermittent nature, leading to challenges in resource allocation and prevention efforts. Addressing sexual abuse hotspots requires a multifaceted approach. Strengthening law enforcement capacity through hotspot policing can help increase deterrence and rapid response in identified areas. Community engagement and awareness programs are vital to reduce stigma, encourage reporting, and educate the public about prevention.

Social support services, including counselling and victim assistance, should be expanded in hotspot areas. Moreover, addressing root socioeconomic factors through education, employment programs, and social development initiatives can reduce vulnerability to sexual abuse over time.

5.5.2. Theft crimes prediction

Theft crime prediction is shown in figure 35.The increasing trend in theft crimes, as reflected by the trend statistic of 2.06849 and a p-value of 0.0736, along with the emergence of six new hotspots and four sporadic hotspots, can be attributed to multiple social and environmental factors.

These may include economic challenges such as unemployment and poverty, which can drive individuals towards theft as a means of survival. Additionally, changes in population density, urban development, and inadequate or unevenly distributed law enforcement resources can create opportunities and incentives for theft crimes to proliferate in certain areas.

The effect of these emerging and sporadic hotspots is considerable. They contribute to heightened insecurity and fear within communities, impacting residents' quality of life and economic development. The fluctuating nature of sporadic hotspots also complicates resource allocation and crime prevention efforts, as these areas require adaptive and flexible policing strategies.

To address these challenges, a combination of evidence-based hotspot policing strategies should be employed. Research shows that focused police interventions in high-crime areas effectively reduce crime rates, including property crimes like theft. Key approaches include increasing police presence through directed patrols, problem-oriented policing that seeks to address underlying causes of criminal behaviour, and community engagement to enhance trust and cooperation between residents and law enforcement (Gill et al., 2024 ;Collazos et al., 2019; Braga, 2006).

Hotspot policing has been demonstrated to produce statistically significant reductions in crime without simply displacing it to other locations. Instead, it can generate diffusion effects that improve safety in surrounding areas as well (Braga, 2019; Gill et al., 2024). Specifically, increasing patrol times and adopting problem-solving approaches tailored to hotspot contexts can yield more substantial and sustainable crime reductions.

5.5.3. For robberies crimes

The emergence of new, consecutive, and sporadic crime hotspots as observed in figure 36, the analysis can be attributed to several underlying causes. These include social, economic, and environmental factors such as poverty, unemployment, population density, and lack of social cohesion, which can create conditions conducive to crime.

Additionally, inadequate law enforcement presence or inconsistent policing efforts in these areas may allow criminal activities to persist or emerge suddenly. Changes in community dynamics, like migration or urban development, could also shift crime patterns, resulting in new hotspot formation or fluctuating activity in sporadic hotspots.

Consecutive hotspots, which show a sustained period of high criminal activity, often indicate deep-rooted issues specific to those locations—such as longstanding socioeconomic disadvantages or the presence of organized crime networks. Sporadic hotspots, on the other hand, reflect temporary or situational crime spikes, possibly related to specific events, seasonal factors, or changes in offender behaviour.

To effectively address these hotspots, a comprehensive hotspot policing strategy should be implemented. This involves the continual use of spatial and temporal data analytics to dynamically identify and monitor hotspots, ensuring timely detection of new or emerging crime patterns and also increase visible police presence in hotspot areas through targeted patrols to deter criminal activity. High-visibility policing can create a perception of greater risk for offenders, thereby reducing crime.

By combining these approaches, law enforcement agencies can achieve both immediate crime reduction through deterrence and longer-term improvements by addressing structural issues. This multi-faceted strategy is key to managing new, consecutive, and sporadic hotspots effectively and enhancing overall community safety.

This approach is supported by extensive research demonstrating that hotspot policing, when executed with both high-visibility patrols and problem-oriented interventions, reduces crime significantly without simply displacing it to other area (Lopa,2024; Braga, n.d.). Protecting planned patrols and ensuring community collaboration are critical to its success.

Implementing these measures will enable timely responses to crime trends and foster safer environments in affected parishes.

5.5.4. For Assault predictions

As presented in figure 37, assault crimes had hotspots with new, consecutive, and intensifying areas at a 500-meter distance and annual time intervals suggest several root causes, significant community effects, and potential solutions.

Assault crimes often arise from a combination of social, economic, and environmental factors. Poverty, unemployment, substance abuse, domestic conflicts, and weak social cohesion contribute to increased violence in neighbourhoods such as Mazinga, Bulando, and Kasaka where new hotspots appeared. The intensification of certain hotspots, where crime remains consistently high and worsens over time, may indicate entrenched problems like persistent gang activity, lack of effective policing, or ongoing social disintegration (State of the Nation, 2024). Additionally, inadequate community services and limited conflict-resolution frameworks exacerbate vulnerability to assault-type crimes.

The existence and intensification of assault hotspots profoundly affect local communities. They create environments of fear, reduce the quality of life, discourage investment, and strain local healthcare and law enforcement resources. Persistent hotspots may also hinder community development and perpetuate cycles of violence and victimization, particularly affecting marginalized groups and youth. The growth of intensifying hotspots signals escalating risks which, if unaddressed, can lead to broader social instability.

Focused police efforts in high-risk areas increase deterrence and enable rapid response, as supported by evidence indicating hotspot policing reduces violent crime when sustained and combined with community trust-building (Braga et al., 2021) can help curb assaults plus empowering local communities through social programs, improved access to education, conflict-resolution training, and substance abuse treatment addresses underlying social drivers of assault (State of the Nation, 2024), and collaboration among law enforcement, social services, and health agencies provides a comprehensive response to violence, including victim support and preventive interventions (SEARCHLIGHT, 2025).

5.5.4 For Breakings

According to figure 38, the analysis identified a total of four new hotspots, two consecutive hotspots, and seven sporadic hotspots. The four new hotspots were located in Zzimwe, Buyaga, Kanywa, and Mazinga, indicating emerging areas of increased criminal activity that were not previously identified as hotspots. These new hotspots suggest a shift or expansion in crime patterns that warrant further attention and targeted interventions.

The two consecutive hotspots, found in Kamwozi and Kiziba, represent areas where high crime intensity has persisted consistently over multiple time intervals. This persistence highlights underlying factors in these locations that may contribute to sustained criminal activity, such as socioeconomic conditions or insufficient law enforcement presence.

Additionally, seven sporadic hotspots were detected in locations including Ssenyange, Bulando, Katwe, Buwunga, Butego, and several others. Sporadic hotspots are characterized by intermittent spikes in crime during certain time periods, reflecting temporary fluctuations rather than continuous trends. These fluctuations may result from seasonal factors, specific incidents, or short-term changes in criminal behaviour.

Understanding the distribution and temporal dynamics of these hotspots is crucial for developing effective crime prevention and response strategies. The identification of new, consecutive, and sporadic hotspots allows law enforcement agencies and policymakers to allocate resources more efficiently and implement tailored interventions to address the unique challenges presented by each type of hotspot.

5.6. Possible Intervention that can be leveraged to mitigate crimes

Violent crime is spatially concentrated in hot spots of all major cities, suggesting that there are endemic features of places that may be changed as claimed by MacDonald et al., (2024), to prevent such crimes as discussed below:

In May 2023, the White House released the first-ever United States National Plan to *End Gender-Based Violence: Strategies for Action*, which emphasized the prevention and addressing of sexual violence, intimate partner violence, stalking, and other forms of gender-based violence. (Lu et al., 2024). This study also gives intervention measures to end crimes such as sex abuse. A place- based approach is suitable to end sex abuse crimes.

Most of the offenders and victims are concealed by the place or at a place, so using a place - based approach would be good to end sex abuse crimes. Crime prevention at places makes specific locations unattractive for offenders to commit crimes. These interventions do not necessarily result in the arrest and incarceration of offenders, nor do they usually assist in the rehabilitation of offenders. They may not even keep offenders away (Eck and Guerette,2012). The impact of place- based approach is to reduce all the chances of committing crime or to make committing of crime riskier on the side of offenders.

There are specific sex abuse hotspots which need to be focused on by the police other than wasting resources patrolling neighbourhoods. Sex abuse temporal trend is also known which should help in curbing such offence or menace.

Place-based approach also involves changing the built-up of a place. The abandoned houses, unfinished houses and slums can be changed to a better settlement and unfinished houses completed and given to people to stay in. By doing so, offenders places are eliminated and this leads to a reduction in crime rates.

The intervention for theft crimes could be to increase the surveillance which is also place-based approach. Both natural through community watch and artificial (through use of CCTV cameras on streets, construction of houses with views from different sides to watch activities taking place outside.

For properties that are easy to steal, a GPS tracking device is the best. An offender will be discouraged to steal a car that has locator in it.

A study by Cuevas et al. (2016) demonstrated that CCTV cameras are effective in monitoring suspicious behaviour and enhancing security, which helps deter criminal activities such as robbery and theft. Therefore, to prevent robberies, it is essential to install CCTV cameras in various locations, including homes and businesses, as they serve as a strong deterrent by recording incidents and aiding in the identification and apprehension of offenders. This approach contributes significantly to crime prevention and improves overall safety.

There is also a need to increase street lighting in areas where it is currently inadequate or non-existent, as this can help prevent robbery cases. Chalfin et al. (2022) highlighted that street light outages may displace robberies and theft to adjacent street segments, suggesting the importance of consistent lighting coverage. Similarly, Welsh et al. (2022) found that interventions to improve street lighting are associated with a significant reduction in total crimes, particularly property crimes. These findings support efforts to enhance street lighting as an effective crime prevention measure.

5.7 Limitations of the study

This study offers valuable insights into the relationship between land use landcover features and crime patterns, yet it is constrained by numerous limitations as presented below.

The study was to use primary crime data from different police stations but the permission was not got from the IGP's office. So, the data used was secondary, from different Uganda annual crime reports of 2022,2023 and 2024. The intended study was from 2020 to 2024 but the annual crime reports only had division crimes data from 2022, leaving other years out. This may bring a change into the analysis and the results got.

The method used to generate incident points (Poisson distribution) gives a random distribution which cannot create any hotspots. The incidents had to be copied and pasted in other places; this could change the analysis results.

Due to the inability to obtain primary data, the study was limited in performing detailed temporal analysis. Consequently, the analysis was conducted annually rather than on a monthly or weekly basis.

Due the fact that crime incidents were simulated, all of attributes were missing which hinders data manipulation and analysis. Some tools could not be used with relevant missing attributes in the crime table.

Free satellite imagery with unclear features and a lot of cloud cover may distort the spatial resolution resulting into failure to capture fine-scale urban features relevant to crime occurrence. Other satellite's imageries were commercial and others did not cover land use landcover features.

CHAPTER SIX:

6.0 CONCLUSION AND RECOMMENDATIOS.

6.1 Introduction

This chapter presents the key conclusions drawn from the study and provides actionable recommendations based on the findings discussed in previous chapters. It offers guidance to relevant stakeholders on how to address the identified issues effectively and also highlights gaps in the research that should be explored in future studies.

6.2 Conclusions

The findings from this analysis align with existing literature in several key ways. Although this study lacked detailed time and date data for individual crimes, the general observations regarding the timing of criminal activity remain relevant. It is well established that many crimes occur at night, exploiting reduced visibility and fewer witnesses. Additionally, some offenses involve perpetrators known to the victims, influenced by social relationships and opportunities that vary by time, month, or season.

Seasonal factors also affect crime patterns. For example, crime rates often rise during certain holidays or harvest seasons, when people are more likely to carry valuables or alcohol consumption increases. Understanding these temporal dynamics is crucial for effective crime prevention and resource allocation, such as scheduling police patrols during peak risk periods.

Although this study was limited to annual data, the findings support broader trends identified in prior research. Future studies with more detailed, time-specific data could provide deeper insights into short-term fluctuations in crime, enabling more targeted interventions.

The study focused on analysing spatial patterns and temporal trends of selected crimes in Masaka district, along with predicting future crime locations using GIS and remote sensing techniques. It examined the relationship between crimes and land use/land cover (LULC), identified crime hotspots, and analysed spatial and temporal distributions.

Spatial analysis revealed higher crime rates in urban police divisions like Masaka city, Nyendo-Mukungwe, and Kimanya-Kabonera compared to rural areas such as Masaka rural. Temporal analysis showed an upward trend in crime between 2022 and 2024, highlighting escalating challenges and the urgent need for proactive intervention and ongoing monitoring.

A significant finding was the strong correlation between crime occurrences and LULC features. Areas with high built-up and green spaces, particularly in Nyendo-Mukungwe and Masaka city, exhibited concentrated crime hotspots across the studied offenses.

Predictive modelling offered valuable insights into the spatial dynamics of crime, distinguishing persistent hotspots -areas with consistently high crime rates from cold spots, which experience low crime levels over time. Recognizing these patterns enables law enforcement and policymakers to allocate resources more efficiently, implement targeted interventions, and develop tailored strategies to prevent crime in high-risk areas while maintaining safety in low-crime zones.

This research supports Sustainable Development Goal 16 by facilitating improved planning, decision-making, and resource utilization within police departments and divisions, ultimately contributing to enhanced community safety and justice.

6.3. Recommendations

Crimes in Masaka district are attracted and detracted by land use landcover features of a place. There is need to plan for ways of curbing crimes by using the land use landcover features. Crime attractors need to be changed to crime detractors.

The following will help in attainment of crime reduction in Masaka:

To better analyse the spatial patterns of crimes, it is essential to record the precise locations of crime occurrences along with the corresponding land use and land cover characteristics associated with each incident.

For effective temporal analysis, the exact date and time of each crime incident should be recorded. This information is crucial for gaining a better understanding of crime trends over different periods.

Crime mapping and analysis should be conducted at the divisional level to identify hotspots early, enabling timely interventions to reduce crime in those areas.

Police should leverage high-resolution satellite data to enhance the accuracy of crime mapping and spatial analysis. Using detailed satellite imagery (most especially the commercial ones) allows for better identification of specific locations, land use patterns, and environmental features associated with crime occurrences, ultimately improving the effectiveness of crime prevention and resource allocation.

For more effective crime analysis, police officers should receive training in the use of GIS and remote sensing technologies. This training will enhance their ability to detect, prevent, and forecast crimes by leveraging spatial data and advanced mapping techniques.

In areas identified as crime hotspots, police officers should increase the frequency and visibility of patrols to deter potential offenders and intervene early. Proactive policing in these high-risk locations can help prevent crimes from escalating, thereby maintaining public safety and reducing overall crime rates.

There is a need for increased crime awareness programs to encourage community participation in crime detection and prevention strategies established by the police. Such sensitization efforts can empower residents to actively engage in safety measures, improve collaboration with law enforcement, and contribute to creating safer neighbourhoods.

Research conducted by Nubani et al. (2023) shows that community engagement and education significantly enhance the effectiveness of crime prevention strategies by building trust, increasing vigilance, and fostering collective responsibility among residents.

Police should not only concentrate on finding evidence to convict criminals but also capture other factors leading to the commitment of crimes such as land use, landcover, education levels of the criminals and others. Data analysis is more than putting data in charts, visualisation of crime area should be done.

6.4. Future work

For this study, a model was created from space time cube to forecast or predict future crime locations and analyse crime trends. In details are the future research tasks to improve crime detection, prevention and prediction.

Future research could try to include number of crimes at a new crime location in the predictive model created.

The model used for prediction is better for many years up to ten (10) years slices and bins (locations/records) up to 2 billion, next research could try prediction using a bigger range of years 10 years.

Try out different tools with the real primary data from different police stations. Since it is not easy to access crime data by civilians, this study can be done by those within police departments.

This study employed GIS and remote sensing techniques to analyse spatial and temporal crime patterns in Masaka district. While these methods proved effective in mapping crime hotspots, analysing land use correlations, and predicting future crime locations, there is significant potential to enhance crime analysis through the integration of advanced computational approaches.

Future research could combine GIS and remote sensing with AI-driven analytics to facilitate improved crime hotspot prediction and also find deeper insights into the underlying social factors influencing criminal behaviour.

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Appendix A – Introduction letter.

Uganda
Martyrs
University

making a difference

OFFICE OF THE DEAN, FACULTY OF SCIENCE

Email:deanscience@umu.ac.ug

Date: 27th Feb 2025

To………………………………………………………………
………………………………………………………………..
………………………………………………………………..
………………………………………………………………..

Dear Sir/Madam,

Re: Assistance for Research – Ms.NAMAGEMBE ALLEN (2023-M132-21513)

Greetings from the Faculty of Science, Uganda Martyrs University.

This is to introduce to you **Ms. Namagembe Allen**, registration Number **2023-M132-21513**, a final-year student pursuing a Master of Science in Information Systems at Uganda Martyrs University. She is researching the topic "**Leveraging Geospatial Technologies in Crime Detection and Mitigation Measures"** as part of the curriculum requirements for the award of a master of Science in Information Systems of this Uganda Martyrs University.

I kindly request you to render her such assistance as may be necessary for the research.

I hope that her application will receive your favourable consideration.

Any assistance rendered to her will be highly appreciated.

Please do not hesitate to contact our office for any further information.

Yours faithfully,

For Rev. Fr. Henry Nsubuga Kiwanuka (PhD)
Dean.

Uganda Martyrs University P.O. Box 5498 – Kampala - Uganda
Tel: (+256)382 – 410 611 Fax: (+256)382 – 410 100 Email: umu@umu.ac.ug

Appendix B. Request Letter

Uganda Martyrs University,

P.o box 5498,

Kampala- Uganda.

12th March 2025

The Inspector General of Police,

Uganda Police Headquaters

P.o Box 7055,

Katalima Road,Naguru,

Kampala.

Dear Sir,

Re: **Permission to access Crime data for Masaka District**.

I am writing to request your permission and support in my academic research project titled "**Leveraging Geospatial Technologies in crime Detection and Mitigation Measures."** My study area is Masaka District. My research involves studying crimes of previous years, do their mapping and where a given crime type concentrate a lot, find factors that may have favoured.

I believe that your organization's expertise and data would be invaluable for my research. I kindly request access to Crime dataset from 2020 -2024, crime type and a place where it happened, Police crime annual reports, or statistics that could contribute to the success and validity of my study. Rest assured that any information provided will be used solely for research purposes and will be treated with the utmost confidentiality.

I understand the significance of your time and resources, and I assure you that the data collected will be utilized responsibly and ethically. In return, I am more than willing to share the findings of my research with your organization and provide you with a copy of my research paper upon its completion.

If you have any questions or require additional information, please feel free to contact me at 0784910596 or contact Uganda Marty's University. I am grateful for your consideration and support in this endeavour and look forward to hearing from you soon.

Thank you for your time and cooperation.

Yours faithfully,

……………………………………….

Namagembe Allen

Appendix C – Data collection form

Year	Divisions	Sex abuse	Theft	Robberies	Assaults	Breakings

Appendix D. Plagiarism Report

DrillBit

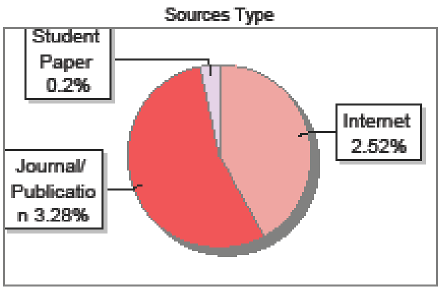
The Report is Generated by DrillBit Plagiarism Detection Software

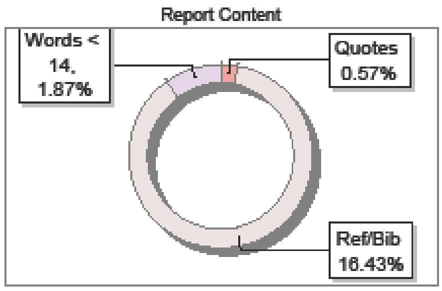
Submission Information

Author Name	Namagembe Allen
Title	Modelling of Crimme
Paper/Submission ID	4284760
Submitted by	jpmasereka@umu.ac.ug
Submission Date	2025-08-27 18:47:46
Total Pages, Total Words	157, 32686
Document type	Thesis

Result Information

Similarity **6 %**





Exclude Information

Quotes	Not Excluded
References/Bibliography	Excluded
Source: Excluded < 14 Words	Not Excluded
Excluded Source	0 %
Excluded Phrases	Not Excluded

Database Selection

Language	English
Student Papers	Yes
Journals & publishers	Yes
Internet or Web	Yes
Institution Repository	Yes

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