UNIVERSITY OF ENERGY AND NATURAL RESOURCES, SUNYANI

DEPARTMENT OF GEOSPATIAL SCIENCES

SCHOOL OF GEOSCIENCES

MODELLING ROAD TRAFFIC CRASHES IN THE SUNYANI MUNICIPAL USING GIS

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UNIVERSITY OF ENERGY AND NATURAL RESOURCES, SUNYANI

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By

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MSC GEOINFORMATION SCIENCE

A DISSERTATION SUBMITTED TO THE DEPARTMENT OF GEOSPATIAL SCIENCES IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF DEGREE OF MASTER OF SCIENCE IN GEOINFORMATION SCIENCE.

FEBRUARY, 2025

DECLARATION

I, Sylvester Kwadjo Asare (UEMS2400523), hereby declare that, except for the references cited, which have been duly acknowledged, this submission is my work towards a Master of Science in Geoinformation Science, and that to the best of my knowledge, it contains no materials previously published by another person. I also declare that this has not been presented either in whole or in part for another degree in this University or elsewhere.

……………………….. …… ……………………….

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ABSTRACT

Road traffic accidents continue to be a major global public health and safety concern, requiring creative mitigation strategies. Using Sunyani Municipal as a case study, this study investigates how effective Geographic Information Systems (GIS) can be applied to model road traffic crashes to influence decision-making and reduce crash occurrence. This study identifies high-risk areas, assesses contributing factors, and suggests data-driven remedies by combining geographic analysis with collision data, road infrastructure characteristics, and traffic flow patterns. Road network layouts, traffic volume figures, and police crash reports from 2018 to 2022 were among the secondary data that were georeferenced and examined using GIS methods such as spatial autocorrelation, hotspot analysis, and Kriging.

The findings showed clear spatial-temporal clusters of crashes, with a significant Moran's I index of 0.080 (z-score = 2.49, p-value = 0.006), confirming non-random clustering. Hotspot analysis (Getis-Ord Gi*) identified the Sunyani Technical
University to Sunyani Senior High School stretch as the most critical hotspot with a
99% confidence level, alongside several other corridors (e.g., Estate Junction to Post Office) at a 95% confidence level. Key contributing factors with high respondent agreement included over-speeding and careless driving (18.67% each) and wrongful U-turns (14.67%). Socioeconomic elements that increased the crash risk included proximity to schools and markets. It is important to note that these findings are subject to uncertainties, primarily due to limitations in data completeness and potential geolocation inaccuracies inherent in the police-reported crash data.

The study illustrates how GIS may be used to visualize risk patterns, which aids policymakers in prioritizing infrastructure improvements, implementing focused traffic laws, and streamlining emergency response routes. Installing traffic-calming measures in designated hotspots, improving street lighting, and incorporating realtime GIS monitoring systems are among the recommendations. This study emphasizes the importance of GIS as a tool for data-driven road safety management, providing urban governments facing comparable difficulties with scalable insights. The findings support the implementation of GIS-driven policies in Sunyani Municipal and similar places to promote safer road ecosystems and lower crash-related injuries and deaths to materialize the country's UN goal by 2030.

DEDICATION

This work is dedicated foremost to my parents and secondly to the memory of those lost to road traffic crashes, whose stories fuel the urgency of this research.

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LIST OF ACRONYMS

BRRI	Building and Road Research Institute
CBD	Central Business District
COCOBOD	The Ghana Cocoa Board Office
CSIR	Council for Scientific and Industrial Research
GIS	Geographic Information Systems
GNP	Gross National Product
HIC	High Income Countries
LMIC	Low- and Middle-Income Countries
IDW	Inverse Distance Weighting
LISA	Local Indicator of Spatial Association
MTTD	Motor Traffic and Transport Department
NRSA	National Road Safety Authority
NRSC	National Road Safety Commission
QGIS	Quantum Geographic Information System
RCC	Regional Coordinating Council
RTC	Road Traffic Crashes
SMA	Sunyani Municipal Assembly
STU	Sunyani Technical University
SUSEC	Sunyani Senior High School
VRA	Volta River Authority
WHO	World Health Organization

CHAPTER ONE

INTRODUCTION

1.1 Background of Study

Road transport systems are vital for the industrial and sectoral growth of nations worldwide. However, the benefits of this mobility are countered by a significant global challenge: road traffic crashes (RTCs). The World Health Organization (WHO, 2023) reports that approximately 1.19 million people die annually from RTCs, with an additional 20-50 million sustaining non-fatal injuries. This crisis represents a major global public health problem, imposing a substantial burden on national economies and healthcare systems, and costing countries approximately 3% of their gross national product.

In Ghana, where road transport is the dominant mode of travel, the situation is particularly acute. The country records one of the highest road traffic fatality rates in sub-Saharan Africa. The National Road Safety Authority (NRSA, 2023) reported that 14,135 road traffic crashes occurred in 2023 alone, resulting in 2,276 fatalities and 15,409 injuries. This has profound economic implications, with annual traffic accident losses estimated at about 1.6% of Ghana's GNP.

A closer examination of national data reveals that crash rates are disproportionately high in urban and regional capitals, largely due to population influx and concentrated economic activity. This trend is clearly observed in the Bono Region, where the regional capital, Sunyani, consistently leads other districts. For instance, the NRSA (2023) reported that Sunyani accounted for 65.6% of the region's crashes and 65.85% of its road traffic deaths, highlighting it as a critical area for intervention.

To effectively address this problem, there is a pressing need for analytical tools that can move beyond simple statistics and uncover the underlying spatial patterns of these crashes.

Geographic Information Systems (GIS) provides a powerful platform for this purpose. As demonstrated by Chen and Washington (2008) and Prasannakumar et al. (2011), GIS enables the identification of RTC patterns through spatial-temporal analyses. It is an influential tool for managing disparate data, visualizing accident locations, and examining crashes spatially to identify high-risk hotspots, thereby facilitating data-driven decision-making for targeted interventions (Shafabakhsh et al., 2017).

It is against this backdrop that this study employs GIS-based spatial analysis to model road traffic crashes and identify accident-prone areas within the Sunyani Municipality. The goal is to generate actionable insights that can guide resource allocation and strategic measures to reduce the occurrence and severity of road traffic crashes.

1.2 Problem Statement

Road traffic crashes (RTCs) in Sunyani Municipality represent a critical and persistent problem that inflicts a severe toll on human lives, property, and local development. Despite the alarming statistics that position Sunyani as the leading hotspot for crashes in the Bono Region, current approaches to road safety remain largely reactive and generalized. The primary problem is the lack of a spatially intelligent, data-driven framework to understand the precise locations and underlying environmental correlates of these crashes. This gap leads to a misallocation of scarce resources and ineffective interventions that fail to address the specific, localized factors causing collisions.

The impact of this problem is multifaceted. On a human level, it results in preventable fatalities, life-altering injuries, and profound emotional trauma for families.

Economically, it places a heavy burden on the municipal healthcare system, drains public funds through emergency response and medical costs, and causes significant property damage. Furthermore, the constant loss of productive citizens stifles local economic growth and development.

This study directly addresses this problem by employing a Geographic Information Systems (GIS) methodology to model road traffic crash prone areas, factoring into consideration underlying environmental factors to achieve a transition from a reactive to a proactive road safety strategy. The core intervention involves using spatial statistics specifically Moran's I for cluster detection and Getis-Ord Gi* for hotspot analysis to precisely identify and map high-risk crash locations (blackspots). This will be complemented by Kriging to create continuous risk surfaces and field observations to correlate hotspots with specific road design flaws, land-use issues, and traffic flow patterns.

The implication of this GIS-driven intervention is a fundamental shift in how road safety is managed in Sunyani. Instead of relying on intuition or scattered incident reports, policymakers and road agencies will be equipped with empirically validated risk maps. This will enable them to:

1. Prioritize infrastructure upgrades (e.g., traffic control measures, improved signage) in the most critical areas.
2. Target enforcement efforts by the police (MTTD) at documented high-risk zones and times.
3. Design public awareness campaigns that are specific to the causes of crashes in identified hotspots.

This approach differs from existing methods by its explicit focus on spatial patterning and data-driven prioritization. While traditional methods may acknowledge blackspots anecdotally, this study provides a quantitative, mappable, and defensible basis for intervention. It moves beyond simply (where) crashes happen to explain (why) they happen there by integrating crash data with environmental and infrastructural data, offering a scalable model for data-driven road safety management not just for Sunyani, but for other similar municipalities in Ghana.

1.3 Significance of Study

The purpose of this study is to identify high-risk routes for road traffic crashes in the Sunyani Municipality using GIS to inform policymakers on measures to curtail road crashes

The study will enhance spatial awareness for targeted interventions on routes in the Sunyani Municipality, representing high occurrences of road crashes. To enable policymakers and transportation agencies to make informed decisions based on empirical evidence rather than intuition, allow the efficient allocation of resources, including law enforcement presence, traffic management, and infrastructure improvements, optimize budget use, and finally enhance public awareness for road
safety.

1.4 Aim and Objectives

The main aim of the study is to use GIS technology to identify blackspots or accidentprone areas in the Sunyani municipality to aid in the allocation of resources for the reduction of road traffic crashes.

The specific objectives are:

1. To identify and map high-risk hotspots or black spots for road traffic crashes in the Sunyani Municipality.

2. To study the causes of road traffic crashes by analyzing the relationship between hotspot or blackspot areas and surrounding features.

3. To propose data-driven recommendations and spatial planning guidelines for road safety interventions, targeted at the identified high-risk zones.

1.5 Research Questions

1. Where are the statistically significant hotspots or blackspots of road traffic crashes located within the Sunyani Municipality?

2. What is the relationship between the identified crash hotspots and specific surrounding environmental features (e.g., road geometry, proximity to schools/markets, traffic volume)?

3. How can the GIS-generated risk maps and spatial analysis findings be translated into specific, data-driven recommendations for road safety policy and infrastructure intervention?

1.6 Research Methodology

The research employed a sequential mixed-methods approach that integrated quantitative spatial analysis with qualitative data collection to ensure a comprehensive understanding of road traffic crash patterns in Sunyani. The process began with a comprehensive literature review and precise definition of research objectives. Data collection involved gathering both primary and secondary data. Primary data included structured interviews with 75 stakeholders and field observations, while secondary data comprised road traffic crash records from 2018-2022 and spatial data including road networks and land use maps. Following data collection, a rigorous data processing phase was undertaken. This involved geocoding crash locations, creating a spatial database, and transcribing interview responses for thematic analysis. The core of the methodology involved spatial and statistical analysis using Geographic

Information Systems (GIS). Three key analytical techniques were employed: Hotspot Analysis using Getis-Ord Gi* to identify statistically significant crash clusters, Spatial

Autocorrelation using Moran's I to assess overall clustering patterns, and Indicator Kriging interpolation to create continuous risk surfaces while quantifying prediction uncertainty.

The final phase involved synthesizing spatial findings with qualitative insights from interviews and field observations. This integration, validated through ground-truthing exercises, enabled the proposal of data-driven recommendations tailored to the specific contextual factors identified in Sunyani Municipality. The entire process ensured that conclusions were derived from robust spatial analysis complemented by real-world contextual understanding.

1.7 Limitations of the Study

This study acknowledges certain limitations. Firstly, it relied on secondary data from institutional archives, which may have contained inaccuracies or omissions, particularly for minor crashes that were not reported to the police. Secondly, the findings may not be fully generalizable beyond Sunyani Municipal due to regional differences in road infrastructure and traffic conditions. However, specific measures were implemented to mitigate the impact of these limitations on the validity and reliability of the research:

1. To address potential inaccuracies in secondary data, a rigorous data cross-validation process was employed. Crash records from the Building and Road Research Institute (BRRI) were cross-referenced with data from the National Road Safety Authority (NRSA) where possible. Furthermore, ground-truthing through field observations were conducted at all identified hotspot locations to verify the environmental and infrastructural conditions, thereby adding a layer of primary data validation.

2. To counteract the effects of incomplete data and imprecise location descriptions, advanced spatial statistics (Moran's I and Getis-Ord Gi*) and Geo statistical analysis (Kriging) were explored. These methods are robust in identifying significant clusters and

hotspots even with sparse or aggregated point data, ensuring that the identified patterns are statistically sound.

3. To manage the issue of generalizability, the study provides a highly detailed description of the study area's context (Chapter 3). This transparency allows other researchers and policymakers to assess the transferability of the methodology and findings to other urban settings with similar characteristics, without overstating the scope of application.

1.8 Organization of Study

This research work is classified into five connected chapters. Chapter One gives the background of the study, the problem statement, the main aim and objectives of the study, the significance of the study, and the limitations of the study. Chapter Two presents a review of the research topic and describes recent trends in the use of GIS in assessing road crashes for safety. The third chapter, Chapter Three, discusses the study area, materials, and methods used for the study. Discussions and analysis of the results are discussed in Chapter Four. Finally, the conclusion and recommendations of the study are presented in Chapter Five.

CHAPTER TWO
LITERATURE REVIEW

2.1 Introduction

This chapter provides a comprehensive review of scholarly works related to road traffic crashes (RTCs), their socio-economic impacts, and the application of Geographic Information Systems (GIS) in their analysis. It begins by defining RTCs and examining their global and local significance. The chapter then compares the causes of RTCs across different contexts, details their socio-economic impacts, and synthesizes the theoretical and empirical foundations of using GIS and spatial statistics for road safety management. The goal is to situate this study within the existing body of knowledge and identify the gaps it aims to fill.

2.2 **Defining Road Traffic Crashes and their Socio-Economic Significance**

A clear definition of the phenomenon under study is crucial. The term "road traffic crash" is preferred over "accident" in scholarly and policy circles because the latter implies a random, unavoidable event, whereas "crash" acknowledges that these incidents are predictable and preventable with the right interventions (Peden et al., 2004).

The World Health Organization (WHO, 2018) defines a road traffic crash as a collision involving one or more vehicles on a public road, resulting in injury or death. The National Road Safety Authority (NRSA, 2023) of Ghana elaborates on this, defining it as any collision or incident involving a vehicle on a public road that leads to fatalities, injuries, or damage to property.

What stands out across these definitions are key elements: the involvement of a vehicle, the location on a public road, and the consequence of harm, be it to persons, property, or both. This study adopts this comprehensive view, recognizing that even minor crashes contribute to the overall pattern of risk and have economic consequences.

The significance of RTCs in Ghana's socio-economic development cannot be overstated. They represent a major drain on the national economy. The World Bank (2018) estimated that road crashes cost Ghana 1.6% of its annual GDP, funds that could otherwise be channelled into healthcare, education, or infrastructure. This loss manifests through direct costs like medical expenses, vehicle repair, and emergency services, and indirect costs such as lost productivity, income loss for bereaved families, and the long-term care of disabled victims (Afukaar et al., 2010). The high rate of fatalities and injuries, particularly among the youthful, productive segment of the population, poses a direct threat to the nation's human capital and economic productivity (Damsere-Derry et al., 2017).

2.3 **Causes of Road Traffic Crashes: Global and Local Comparison**

The causes of RTCs are universally categorized into human, vehicular, and environmental/road factors, though their prevalence varies between high-income countries (HICs) and low- and middle-income countries (LMICs) like Ghana.

Human Factors: Globally, human error is the predominant cause, accounting for over 90% of crashes (WHO, 2021). In HICs, common factors include distracted driving (e.g., mobile phone use) and speeding (OECD, 2021). In Ghana and similar LMICs, speeding and reckless driving are equally pervasive, but are compounded by issues like driver fatigue (especially among long-distance commercial drivers), drunk driving, and a high prevalence of untrained or unlicensed drivers, including motorcycle riders (Okoye et al., 2023; Adonteng, 2012). Pedestrian behaviour, such as crossing at undesignated points, is also a significant contributor in dense urban areas like Sunyani (DamsereDerry et al., 2017).

Vehicular Factors: In HICs, advanced vehicle inspection systems and strict regulations have minimized mechanical failures. In contrast, in Ghana, a large proportion of the vehicle fleet is aged and poorly maintained. The NRSA (2020) reported that 30% of commercial vehicles had defective brakes, tires, or lighting. The proliferation of motorcycles (okada) and tricycles (aboboyaa), often unregulated and poorly maintained, introduces a new dimension of risk (Owusu et al., 2018).

Environmental and Road Factors: HICs invest heavily in road engineering and safety features. In LMICs like Ghana, infrastructural deficiencies are a major problem. Poor road design, inadequate signage, lack of pedestrian facilities (sidewalks, zebra crossings), and poor road maintenance (potholes, eroded shoulders) are common (Ackaah & Salifu, 2011). In Sunyani, specific challenges include congestion near markets, flooding during rainy seasons that obscures road markings, and informal road networks in rapidly urbanizing areas (GSS, 2021; Osei, 2020).

The dataset comprises the recorded road crashes within Sunyani Municipality, including variables such as crash locations and severity. It was observed that crashes were displayed in the northern part of the study area, hence, the study area extent was altered to focus on the northern part or areas displaying the crashes. This is to enhance the appreciation of the hotspot analysis. A total of 199 crashes were analysed, which resulted in 234 casualties. Data records from 2018 to 2022 were used, as shown in Table
2.1. and Figure 2.1.

Table 2.1 Total Road Traffic Crashes from 2018 to 2022.

Years	Sum of Hospitalized	Sum of Injured Not Hospitalized	Sum of Damages Only	Sum of Fatal	Sum of Casualties
2018	10	5	4	5	24
2019	10	26	17	13	66

2020	15	16	9	7	47
2021	13	17	10	13	53
2022	6	22	10	6	44
Grand Total	**54**	**86**	**50**	**44**	**234**

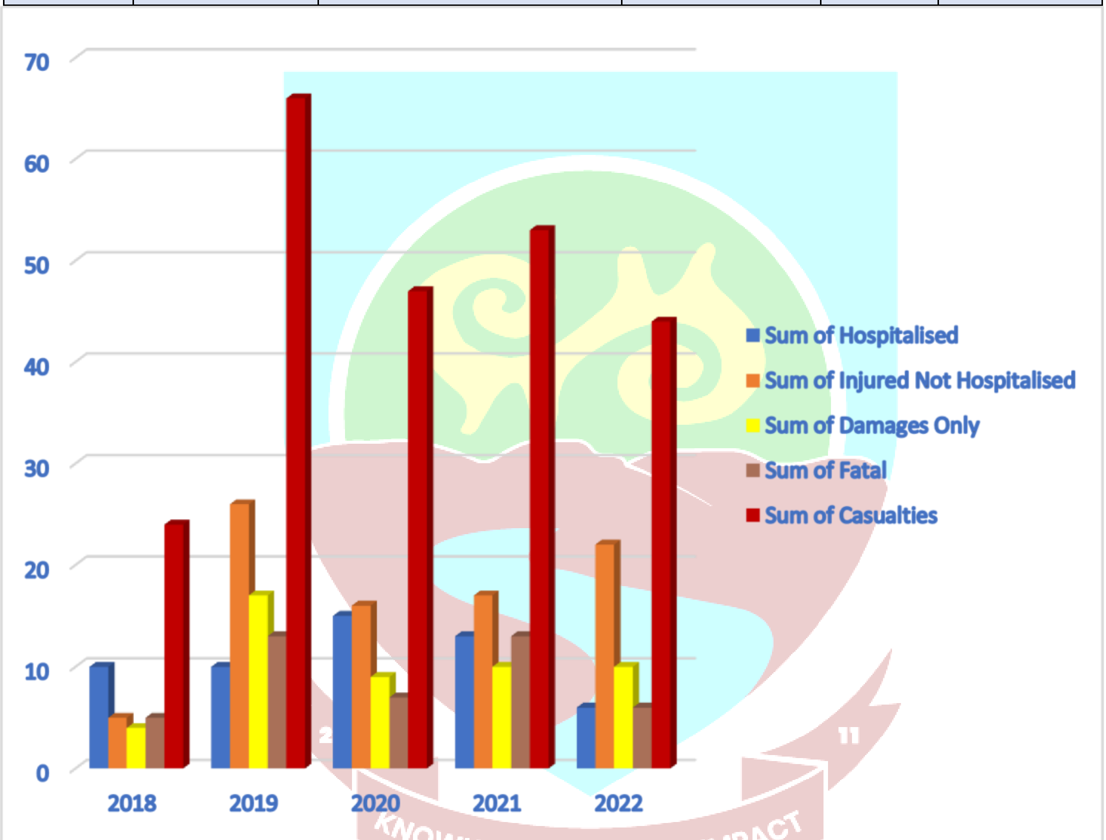


Figure 2.1 Crashes from 2018 to 2022 are visualized in a chart

2.4 **The Socio-Economic Impacts of Road Traffic Crashes**

The impacts of RTCs ripple through societies and economies at both global and local levels.

Global Impacts: The WHO (2023) identifies RTCs as the leading cause of death for children and young adults aged 5-29 years. This results in an immense loss of human potential. Economically, the global cost is estimated at US$1.8 trillion annually, equivalent to a yearly tax of 2-3% on the global GDP (Chen et al., 2022). This burden is disproportionately borne by LMICs, which account for 93% of fatalities but only 60% of the world's vehicles.

Local Impacts in Ghana: The impact is devastating at the household level. The death of a breadwinner can plunge a family into poverty. For those injured, catastrophic healthcare costs can lead to medical impoverishment (Asiamah et al., 2022). At the national level, the strain on the healthcare system is severe, with RTC victims occupying a significant portion of surgical and emergency ward beds (Sunyani Municipal Health Directorate, 2023). The loss of skilled professionals and labourers stifles economic growth and development, undermining national development goals.

2.5 GIS Applications in Traffic Crash Analysis

Geographic Information Systems (GIS) have emerged as a transformative tool for understanding and mitigating RTCs. Their power lies in the ability to capture, manage, analyse, and visualize spatial data, turning raw crash statistics into actionable intelligence (Goodchild, 2009).

Hotspot Identification and Analysis: This is the most common application. Techniques like Kernel Density Estimation (KDE) and spatial statistics (Getis-Ord Gi*, Moran's I) are used to identify locations with statistically significant clusters of crashes. For instance, Anderson (2009) used GIS in London to reveal that 60% of fatalities occurred at just 5% of intersections. In Ghana, studies in Kumasi and Cape Coast have successfully used these methods to prioritize sections of the road network for intervention (Acquah & Fosu, 2017; Owusu et al., 2018).

Spatial-Temporal Analysis: GIS allows researchers to analyse when and where crashes occur. This can reveal patterns related to time of day, day of the week, or season, helping to tailor enforcement and public awareness campaigns (Li et al., 2007).

Risk Factor Analysis: By overlaying crash data with other spatial layers (e.g., road type, land use, traffic volume, location of schools/markets), GIS enables a deeper understanding of contributing factors. A study in Tehran demonstrated a strong correlation between poor lighting and night-time crashes (Moeinaddini et al., 2013). This integrative capability is critical for moving beyond mere description to explanatory analysis.

Evaluation of Interventions: GIS provides a platform for monitoring the effectiveness of road safety measures. By comparing pre- and post-intervention crash data spatially, authorities can objectively assess the impact of measures like new roundabouts, traffic signals, or speed bumps (Gómez et al., 2017).

2.6 Theoretical Frameworks for Spatial Analysis of Crashes

The GIS applications discussed above are underpinned by robust theoretical frameworks from spatial statistics.

Spatial Autocorrelation (Moran's I): Developed by Patrick Moran (1950), this theory posits that geographically proximate features are often more similar than would be expected by chance. Moran's I is a global measure that tests whether a spatial dataset such as crash points is clustered, dispersed, or random. A significant positive value indicates clustering, confirming that crashes are not random events but are influenced by local underlying factors (Anselin, 1995). This theory justifies the search for localized causes.

Hotspot Theory (Getis-Ord Gi*): While Moran's I confirm global clustering, Getis and Ord's (1992) Gi* statistic is a Local Indicator of Spatial Association (LISA) that identifies the specific locations of high-value (hotspots) and low-value (cold spots) clusters. This theory allows for the precise pinpointing of road segments or intersections that require immediate intervention, moving from the general question "Is there clustering"? to the specific "Where are the clusters"? (Ord & Getis, 1995).

Indicator Kriging Interpolation: While Kernel Density Estimation (KDE) is a common non-parametric technique for creating continuous surfaces of crash density (Xie & Yan, 2008), this study employs Indicator Kriging for a more statistically robust, probabilistic risk assessment. Grounded in geostatistical theory, Indicator Kriging moves beyond simple density visualization to estimate the probability that a location exceeds a specific crash risk threshold (Goovaerts, 1997). This method is particularly advantageous as it directly models spatial uncertainty, providing not only a prediction surface of hotspot probability but also a quantifiable measure of the associated error (Isaaks & Srivastava, 1989). This allows for a more nuanced interpretation of spatial risk, distinguishing areas of high-confidence hotspots from those where predictions are less reliable due to data sparsity.

Together, these theoretical frameworks form the analytical backbone of modern, datadriven road safety research, guiding the methodology of this study.

2.7 **Conceptual Framework**

The conceptual framework for this study, illustrated Figure 2.2, synthesizes the literature and theories reviewed. It outlines the pathway from data input through spatial analysis to the ultimate output of data-driven recommendations.

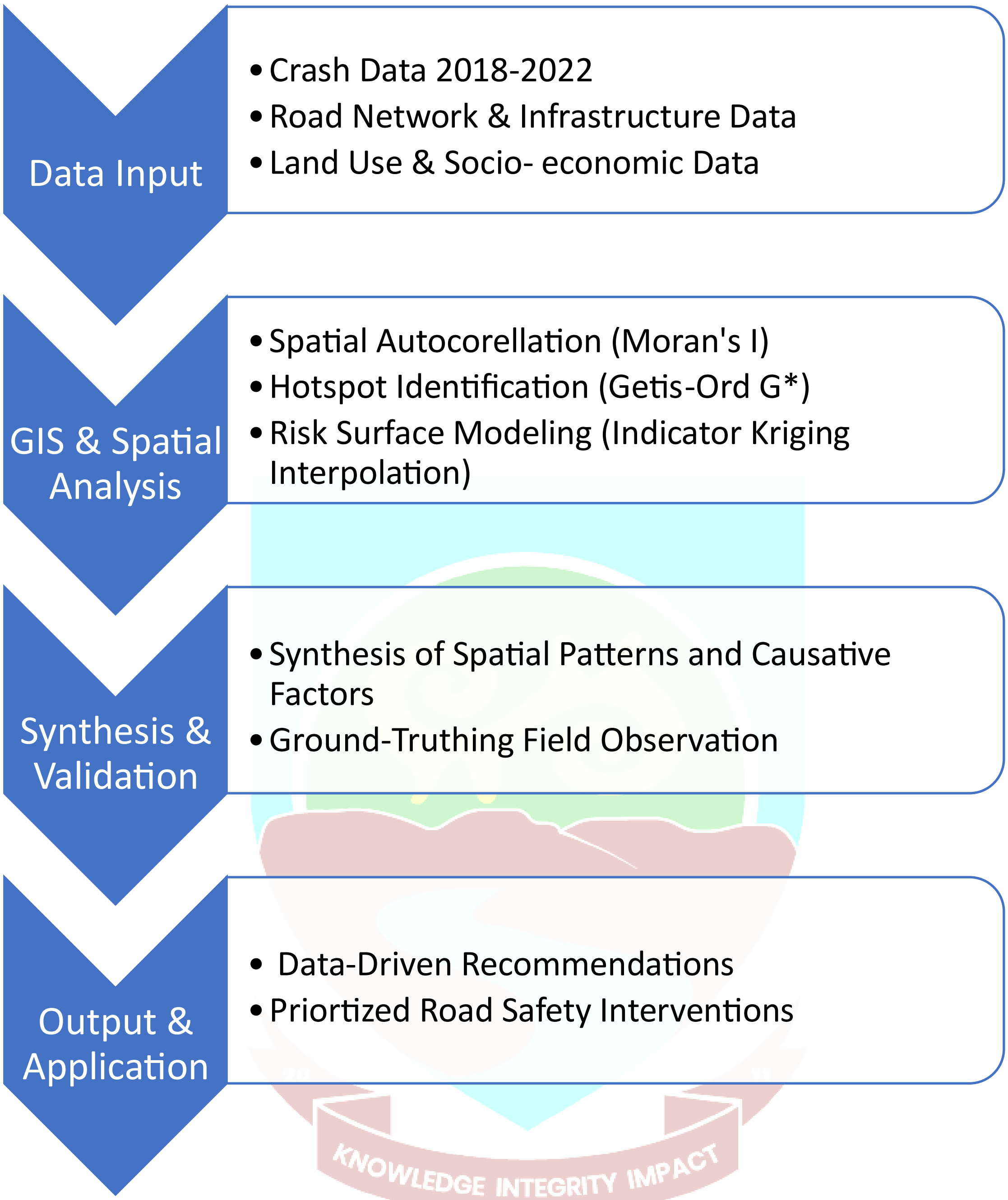


Figure 2.2 Conceptual Framework for this study

2.8 Summary

The literature confirms that RTCs are a predictable and preventable scourge with profound socio-economic consequences, particularly in LMICs like Ghana. While the causes are multi-faceted, GIS provides a powerful suite of tools, grounded in spatial theory, to move from a reactive to a proactive safety management approach. However, many studies in Ghana have focused on major metropolises like Accra and Kumasi. This leaves a gap in the context of rapidly urbanizing secondary cities like Sunyani, which face unique infrastructural and data challenges. This study will apply these established GIS methodologies and theoretical frameworks to fill this contextual gap, generating localized, actionable insights for Sunyani Municipality.

CHAPTER THREE

STUDY AREA, MATERIALS AND METHODS

3.1 Introduction

This chapter outlines the study area, materials, and methods used to assess the role of GIS in reducing road traffic crashes (RTCs) in the Sunyani Municipality. The study employs spatial statistics, including Moran's I, Getis-Ord Gi, and Kriging Interpolation to identify crash patterns, hotspots/blackspots, and contributing factors.

3.2 Study Area

3.2.1 Administrative Scope: Sunyani Municipal

Sunyani Municipal is among the 12 Administrative Districts in the Bono Region of Ghana, which lies between latitudes 7□05'N and 7□20'N, and longitudes 2□10'W and 2□30'W and covers a land size of 506.7 Square Kilometres. It has a population of 193,595 (Ghana Statistical Service, 2021). The population is predominantly young, with about 60% under the age of 30, reflecting a high level of urbanization and economic activity. Sunyani is one of the fastest-growing cities in Ghana, with a significant influx of migrants from rural areas seeking employment and educational opportunities. The population density is highest in the central business district and decreases towards the outskirts of the municipality. The municipality borders Sunyani

West District to the North, Asutifi District to the South, Dormaa East District to the West, and Tano North District to the East. The three largest suburbs within the Municipality are Sunyani, Abesim, and New Dormaa, accommodating 74.3 per cent of the total Municipal population. Sunyani, the regional capital, solely accommodates approximately sixty per cent (60%) of the total population and is growing rapidly in terms of size and business activities. The strategic location of Sunyani attracts neighbouring localities into the municipality, leading to an increase in traffic congestion and pedestrian activities, which are key factors in road traffic crashes (SMA, 2023).

3.2.2 Analytical Scope: The Northern Built-Up Area (Focus of Analysis)

While the administrative boundary of Sunyani Municipal is extensive, the spatial analysis for this study is deliberately confined to the northern built-up area of the municipality. This focus is defined by the spatial distribution of the available crash data, as all recorded road traffic incidents from 2018 to 2022 occurred within this zone. This area encompasses the core urban centre of Sunyani and its immediate suburban expansions, including key suburbs such as Sunyani Town, Abesim, New Dormaa, and surrounding developed corridors. It contains the municipality's most critical
infrastructure:

- The Central Business District (CBD)
- Major governmental institutions (Regional Coordinating Council, Sunyani Municipal Assembly)
- Key educational institutions (Sunyani Technical University, Sunyani Senior High School)
- Major markets (Nana Bosoma Market)
- The primary road networks, including the Sunyani-Kumasi and SunyaniTechiman highways.

Justification for the Analytical Scope: Confining the analysis to this data-rich area ensures methodological rigor. It prevents the misrepresentation of results that would occur by including the southern, more rural parts of the municipality where no crash data was reported for the study period. Therefore, all maps, hotspot analyses, and subsequent findings in this thesis are explicitly representative of this northern built-up area, as depicted in Figure 3.1.

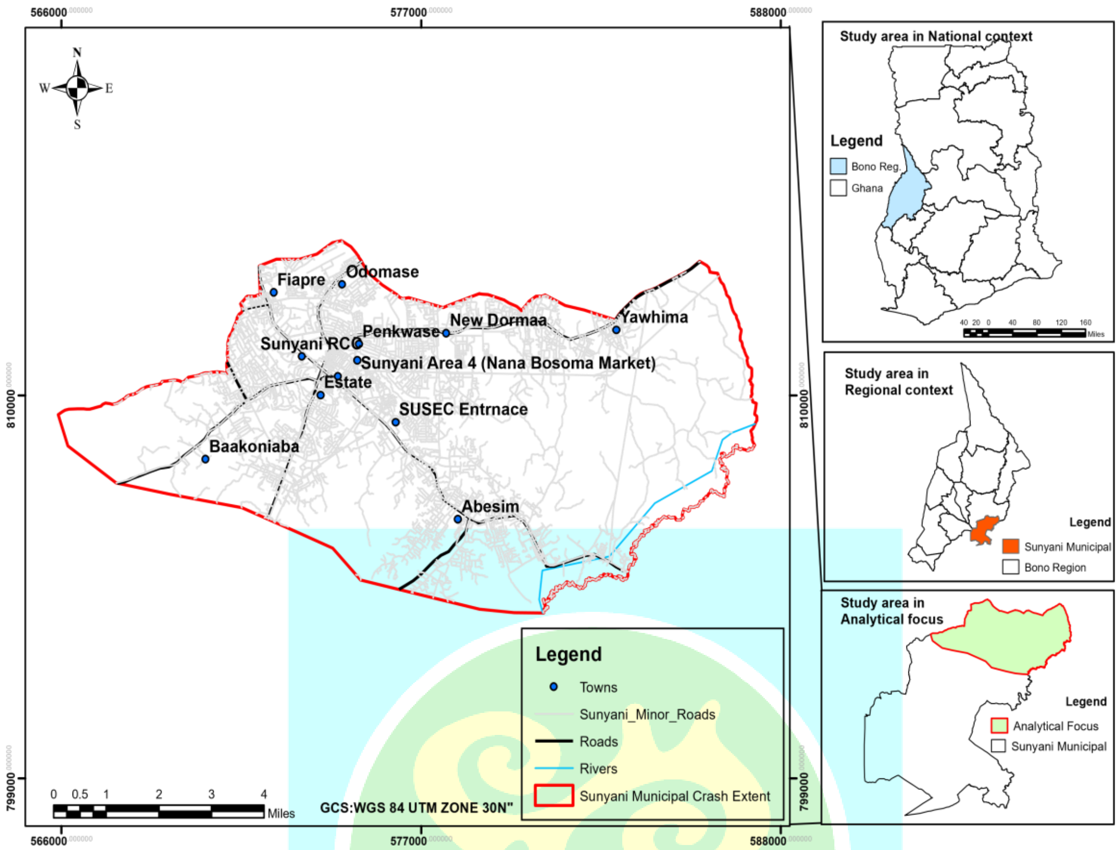


Figure 3.1 Study Area Map of Sunyani Municipal, highlighting the northern focus area for crash analysis

3.2.3 Demographics and Socio-Economic Profile

The population within the analytical scope is predominantly young and urban, with high levels of commercial and pedestrian activity. The concentration of businesses, schools, and administrative functions in this zone leads to significant daily traffic influx and complex traffic dynamics, creating the conditions that this study seeks to analyze.

3.2.4 Road Network and Traffic

The northern built-up area contains a dense and complex road network, characterized by a mix of high-speed highways, urban arterial roads, and local access streets. This mix, combined with high volumes of vehicles, motorcycles, and pedestrians, defines the unique road safety challenges that are the focus of this research.

3.2.5 Occupation

The economy of Sunyani Municipal is diverse, with most of the population engaged in the following sectors: Agriculture, Commerce and Trade, Public Sector and Education. Agriculture is the primary occupation, with crops such as cocoa, maize, cassava, and plantain being the mainstay. The municipality is also known for its cashew production (Ghana Statistical Service, 2021). Sunyani serves as a commercial hub for the Bono Region, with a vibrant market (Sunyani Central Market) that attracts traders from neighbouring towns and countries. As the regional capital, Sunyani hosts numerous government offices and institutions, employing a significant portion of the population. The municipality is home to several educational institutions, including the Sunyani Technical University and nursing training colleges, which attract students from across the country. The occupational activities influence traffic patterns, with peak traffic occurring during market days and rush hours when workers and students commute to and from the city centre.

3.2.6 Topography

Sunyani Municipal is situated on a gentle, undulating plateau, with an average elevation of 300 meters above sea level. The topography is characterized by: The northern and eastern parts of the municipality feature rolling hills, which influence road design and gradient. The central and southern areas are relatively flat, making them suitable for urban development and agriculture. The topography affects road safety by influencing road alignment, drainage, and the likelihood of crashes, particularly in hilly areas where sharp bends and steep gradients are common.

3.2.7 Climate and Weather

Sunyani Municipal experiences a tropical wet and dry climate, characterized by two distinct seasons: the rainy season and the dry season. The rainy season typically occurs from April to October, with peak rainfall in June and September. The average annual rainfall ranges between 1,200 mm and 1,500 mm (Ghana Meteorological Agency, 2023). The dry season spans from November to March, with relatively low humidity and temperatures ranging between 25°C and 35°C. Harmattan winds, characterized by dry and dusty conditions, are common during this period. The climate significantly influences road safety, as heavy rainfall can lead to poor visibility, slippery roads, and flooding, while the dry season often results in dusty conditions that reduce visibility and increase the risk of crashes.

3.2.8 Vehicular Statistics of the Municipality

This study's population centers on automobile accidents in Sunyani Municipal, to employ Geographic Information Systems (GIS) to analyze spatial patterns, identify RTC hotspots, and investigate trends. The chosen population includes all documented RTCs in the region, encompassing both small and serious incidents throughout a certain timeframe. The study population comprises all vehicles that got involved in a road traffic accident within the Sunyani Municipality. The vehicles comprise both commercial and private. Vehicle categories include buses, minibuses, trucks, saloon cars, taxis, SUVs/4x4, tricycles (Abobo Yaa, Pragea), motorcycles, hand carts, and bicycles.

The population comprises all vehicular incidents that occurred in Sunyani Municipal from 2018 to 2022. This timeframe was selected to yield sufficient data for the analysis of long-term trends, thereby preventing transient abnormalities from distorting the outcomes. As demonstrated in previous research, such as that conducted by Wang et al. (2020), multi-year accident data facilitate strong conclusions and aid in the identification of persistent accident hotspots.

The study encompasses all types of vehicle incidents, including those involving pedestrians and cyclists, thereby ensuring thorough examination of road safety concerns in the Sunyani Municipality.

3.3 Materials

This section presents material used for the study. Both primary and secondary materials/data were used in this study.

3.3.1 Sources of Materials / Data

This study employed a mixed-methods approach, utilizing both secondary and primary data sources to ensure comprehensive analysis and validation.

3.3.1.1 Secondary Data Sources

Secondary data constituted the foundational dataset for spatial modelling and contextual understanding. These datasets were collected by various institutions for administrative and research purposes prior to this study.

Crash Incident Data: Five years (2018–2022) of historical Road Traffic Crash (RTC) records were obtained from the Building and Road Research Institute (BRRI). This dataset, aggregated from police reports compiled by the Motor Traffic and Transport Department (MTTD), included variables such as location descriptions, severity categories (Fatal, Hospitalized, Injured Not Hospitalized, Damage Only).

Spatial and Infrastructure Data: Geographic base data including road network layers, land-use maps, and administrative boundaries of the Sunyani Municipality were sourced from the Sunyani Municipal Assembly and relevant Road Agencies (Ghana Highways Authority and Department of Urban Roads).

Demographic and Supplementary Data: Population statistics and other relevant demographic information were obtained from the Ghana Statistical Service (GSS, 2021) to provide socio-economic context to the analysis.

3.3.1.2 Primary Data Sources

To validate, contextualize, and add explanatory power to the secondary data, original primary data was collected firsthand by the researcher through the following methods: Structured Interviews: A total of 75 stakeholders were purposively selected from key groups involved in road safety within the municipality. The breakdown was: 35

Commercial and Private Drivers, 20 MTTD Officers, 10 NRSA Officials, and 10 Planners/Engineers from the Sunyani Municipal Assembly. Face-to-face interviews, lasting approximately 15-20 minutes each, were conducted using a structured questionnaire (Appendix A) to gather insights on perceived crash hotspots, common causes, and the potential role of GIS in road safety management.

Field Observation and Geotagging: Ground-truthing field surveys were conducted at all statistically significant hotspots identified in the preliminary spatial analysis. Using handheld smartphones with mapping applications, researchers collected:

1. Geotagged photographs documenting road geometry, signage, and environmental conditions
2. Precise GPS point locations at the centre of identified hazardous locations
3. Field notes describing observable risk factors and contextual features This combination of secondary and primary data sources ensured both the statistical robustness of the spatial analysis and the real-world validity and contextual relevance of the findings.

3.4 Methods

This section outlines the systematic approach employed to analyze road traffic crashes in Sunyani Municipality. The methodology consisted of four main phases, as illustrated in the research process flowchart below:

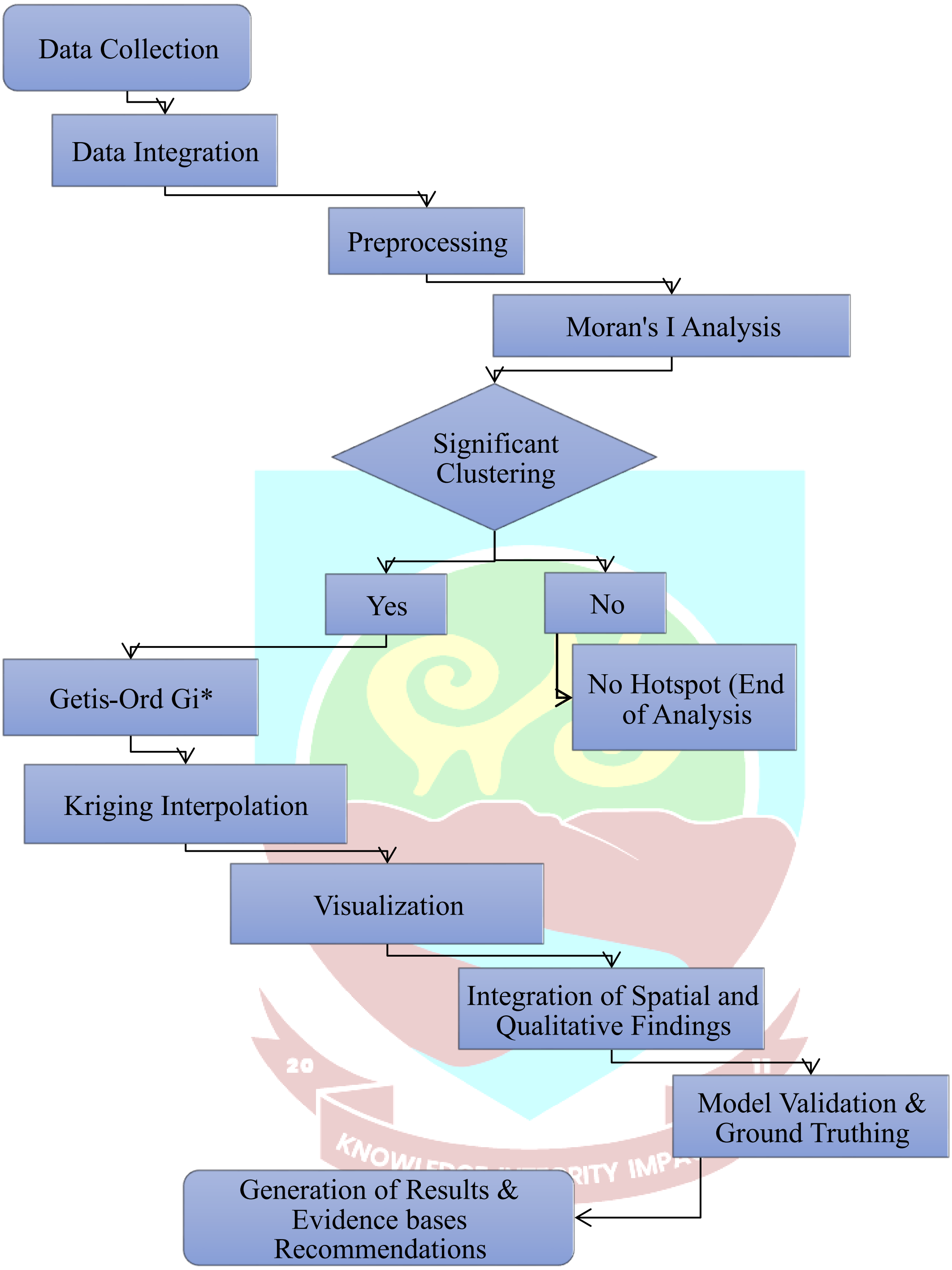


Figure 3.2: Research Methodology Flowchart

The research process began with a comprehensive literature review and precise definition of research objectives. Data collection involved gathering both primary and secondary data, including structured interviews with 75 stakeholders, field observations, road traffic crash records from 2018-2022, and spatial data including road networks and land use maps.

Following data collection, a rigorous data processing phase was undertaken, involving manual geocoding crash locations, creating a spatial database, and transcribing interview responses for thematic analysis. The core analysis employed three spatial statistical techniques: Hotspot Analysis (Getis-Ord Gi*) to identify statistically significant crash clusters, Spatial Autocorrelation (Moran's I) to assess overall clustering patterns, and Kriging interpolation to create continuous risk surfaces while quantifying prediction uncertainty.

The final phase involved synthesizing spatial findings with qualitative insights from interviews and field observations, validated through ground-truthing exercises, to develop data-driven recommendations tailored to Sunyani Municipality's specific contextual factors.

3.4.1 Data Analysis Methods

3.4.1.1 Spatial Autocorrelation (Moran's I)

Moran's I was used to assess clustering/dispersion of RTCs (Anselin, 1995). The choice of Moran's I is to be able to determine whether similar values (i.e., Crash occurrences) cluster spatially. Using the Equation incorporated in the ArcGIS software shown below,

Equation 3.1 Spatial Autocorrelation (Moran's I)

The Moran's I statistic for spatial autocorrelation is given as:

$$A = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} z_i z_j}{\sum_{i=1}^{n} z_i^2} \tag{3.1}$$

where z_i is the deviation of an attribute for feature i from its mean ($x_i - \bar{x}$), $w_{i,j}$ is the spatial weight between feature i and j, n is equal to the total number of features, and S_0 is the aggregate of all the spatial weights:

$$S_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} \tag{3.2}$$

The z_I-score for the statistic is computed as:

$$z_I = \frac{I-E[I]}{\sqrt{V[I]}} \tag{3.3}$$

where

$$E[I] = -1/(n-1) \tag{3.4}$$

$$V[I] = E[I^2]-E[I]^2 \tag{3.5}$$

A significant positive I ($p < 0.05$) indicate clustering. All analyses were performed in ArcGIS 10.8.

3.4.1.2 Hotspot Analysis (Getis-Ord Gi)

The Getis-Ord Gi statistic identified hotspots/cold spots (Getis & Ord, 1992). GetisOrd Gi will help to identify hotspots of road crashes, highlighting areas with significantly high concentrations of incidents. The equation incorporated in ArcGIS was used to identify and prioritize crash hotspots, as seen in **Equation 3.6.**

Equation 3.6 Getis-Ord Gi*

The Getis-Ord local statistic is given as:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - X \sum_{j=1}^{n} w_{i,j}}{S\sqrt{\left[\frac{n \sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2}{n-1}\right]}} \tag{3.6}$$

where $\boldsymbol{x_j}$ is the attribute value for feature $\boldsymbol{j}$, $\boldsymbol{w_{i,j}}$ is the spatial weight between feature $\boldsymbol{i}$ and $\boldsymbol{j}$, $\boldsymbol{n}$ is equal to the total number of features, and

$$X = \frac{\sum_{j=1}^{n} x_j}{n} \tag{3.7}$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - (\bar{X})^2} \quad (3.8)$$

The G^*_i statistic is a z-score, so no further calculations are required. High ***Gi*** z-scores ($p < 0.05$) marked significant hotspots.

3.4.1.3 Risk Surface Modelling with Kriging Interpolation

To create a continuous surface mapping the probability of a location being a crash hotspot, Indicator Kriging (IK) was employed. Unlike methods that predict continuous values, IK is designed to estimate the probability that a value at an unmeasured location exceeds a specific threshold—in this case, the threshold for being a high-risk crash hotspot. This method is superior for binary outcomes (hotspot vs. non-hotspot) as it directly models spatial uncertainty for probabilistic assessment. The implementation of Indicator Kriging followed these steps:

- Data Transformation and Threshold Definition: The crash point data was first transformed into a binary format. A critical threshold was defined to classify locations as crash hotspots. Each data point was converted to an indicator value of 1 (if it met or exceeded the hotspot threshold) or 0 (if it did not).
- Exploratory Spatial Data Analysis (ESDA): The spatial structure of the transformed indicator data was analyzed using the Semivariogram/Covariance Cloud tool in ArcGIS. This step examined how the spatial dependency of crash hotspots changes with distance.
- Semivariogram Modelling: A mathematical model was fitted to the empirical semivariogram derived from the indicator data. This model quantifies the spatial autocorrelation of hotspots. Common models (Spherical, Exponential, Gaussian)

were tested, and the model that best fit the data was selected. The key parameters defined were:

- Nugget: Represents micro-scale variation and/or measurement error.
- Sill: The value at which the semivariogram levels off, representing the maximum variance.
- Range: The distance at which the semivariogram reaches the sill, beyond which observations are spatially independent.

- Kriging Interpolation: Using the fitted semivariogram model, Indicator Kriging was performed to interpolate a continuous surface of hotspot probability across the study area. This was executed using the Geostatistical Wizard in ArcGIS's Geostatistical Analyst extension.
- Validation and Uncertainty Quantification: The IK process produces two primary outputs:
  - Prediction Surface: The best unbiased estimate of the probability (from 0 to 1) that a location is a crash hotspot.
  - Prediction Standard Error Surface: A map quantifying the uncertainty associated with the probability predictions. Higher standard errors indicate areas where the model is less confident, typically at the edges of the study area or in locations with sparse data.

This method provides a statistically robust and defensible analysis of spatial risk, directly modelling the probability of an event and its associated uncertainty.

Equation 3.9 Kriging

The continuous crash data is first transformed into binary indicator values based on a specific threshold value z_c:

$$I(s_i; z_c) = \{01 \text{if } Z \text{if } (Zs_i()s^i<) \geq_{z_c} z_{(^c}\text{non}^{(\text{hotspot}}\text{-hotspot})^{)}$$
(3.9)

Where:

- $I(s_i; z_c)$ = Indicator value at location s_i
- $Z(s_i)$ = Observed crash value at location s_i
- z_c = Critical threshold value defining a hotspot

The probability that location s_0 exceeds the threshold z_c is estimated as:

$$\hat{P}\{Z(s_0) \geq z_c\} = \sum_{i=1}^{n} \lambda_i I(s_i; z_c) \tag{3.10}$$

Where:

- $\hat{P}\{Z(s_0) \geq z_c\}$ = Estimated probability of being a hotspot at unknown location s_0
- λ_i = Optimal weights determined by the kriging system
- $I(s_i; z_c)$ = Indicator value (0 or 1) at known location s_i
- n = Number of neighboring points used for estimation

The weights λ_i are obtained by solving the following system:

$$\sum_{j=1}^{n} \lambda_j \gamma_I(s_i, s_j) + \mu = \gamma_I(s_i, s_0) \text{for } i = 1, \ldots, n \tag{3.11}$$

$$\sum_{i=1}^{n} \lambda_i = 1 \tag{3.12}$$

Where:

- $\gamma_I(s_i, s_j)$ = Semivariance of indicator data between known locations □ $\gamma_I(s_i, s_0)$ = Semivariance between known location and prediction point
- μ = Lagrange multiplier ensuring unbiasedness

The uncertainty of the probability estimate is given by:

$$\sigma_{IK}{}^2 = \sum{}^{n}{}_{i=1} \lambda_i \gamma_I(s_i, s_0) + \mu \tag{3.13}$$

Where:

- σ_{IK}^2= Prediction variance at location s_0
- This represents the uncertainty associated with the hotspot probability prediction

The application of Indicator Kriging provided a robust probabilistic framework for modelling crash risk across the study area. This method moved beyond simple point mapping to generate two critical outputs: a continuous hotspot probability map predicting the likelihood of a crash occurrence at any given location, and a companion standard error map quantifying the uncertainty associated with each prediction. These surfaces allowed for a nuanced interpretation of spatial risk, distinguishing areas of high-confidence hotspots from those where predictions were less reliable due to data sparsity.

3.4.2 Primary Data Collection: Stakeholder Interviews and Field Observations

To ground-truth the spatial analysis and gain a contextual understanding of the causative factors behind road traffic crashes, primary data was collected through structured stakeholder interviews and systematic field observations. This mixedmethods approach ensured that the quantitative spatial patterns were explained by qualitative, on-the-ground insights.

3.4.2.1 Stakeholder Interviews

A purposive sampling technique was employed to identify and recruit 75 key stakeholders directly involved in or affected by road safety within the municipality.

This non-probability sampling method was chosen to ensure that respondents possessed specific knowledge and experience relevant to the research problem (Etikan, 2016). The sample was stratified into four key groups to capture a holistic perspective: 35

Commercial and Private Drivers, 20 officers from the Motor Traffic and Transport Department (MTTD), 10 officials from the National Road Safety Authority (NRSA), and 10 Planners and Engineers from the Sunyani Municipal Assembly. Data collection was conducted through face-to-face, structured interviews using a pre-designed questionnaire (see Appendix A). The questionnaire was designed to elicit information on perceived high-risk locations, common causes of crashes, and evaluations of existing road infrastructure. Each interview lasted approximately 15-20 minutes. The responses were manually recorded and subsequently transcribed for thematic analysis. This process allowed for the quantification of perceived causes (e.g., Table 4.3) and provided critical narrative data that explained the why behind the statistical where of the crash hotspots.

3.4.2.2 Field Observations and Geotagging

Field observation served as a direct validation mechanism for the statistically identified hotspots. Following the preliminary GIS analysis, ground-truthing surveys were conducted at all significant hotspot locations. A systematic protocol was developed for data collection in the field. Researcher used handheld smartphones with integrated GPS capabilities and mapping applications (e.g., Google Maps with location services enabled). At each visited site, the following data was collected: (1) Precise GPS coordinates of the centre of the identified hazardous location; (2) Geotagged photographs capturing the road geometry, traffic control devices, signage, and overall environmental conditions; and (3) Structured field notes documenting observable risk factors such as pedestrian activity, vehicle speeds, and infrastructural deficiencies like faded markings or poor drainage. This protocol ensured consistent and geospatially referenced primary data. The collected geotagged points and photographs were later integrated into the GIS project (as shown in Figure 4.6) to visually and spatially corroborate the model outputs, thereby strengthening the validity of the findings and providing tangible evidence for the proposed recommendations. A sample of the field data collection form and geotagged photographs is provided in Appendix C.

CHAPTER FOUR

RESULTS AND DISCUSSIONS

4.1 Introduction

This chapter presents the findings from analysing road crash data in the Sunyani Municipality from 2018 to 2022, utilizing Moran's I and Getis-Ord Gi* statistics to assess spatial autocorrelation and identify hotspots to create a visualized map using Kriging. The analysis aims to provide insights into the spatial distribution of road crashes and inform local policymakers about targeted interventions.

4.2 Spatial Autocorrelation Analysis

Moran's I was used to assess clustering/dispersion of RTCs (Anselin, 1995). Weights were added to the points using integrate in data management tools. Weights were then collected using spatial Statistics tools to enable the spatial autocorrelation analysis to be carried out.

4.2.1 Integrate Event Points

The possibility of inaccurate geographical points provides the need for point integration. Integrating the event points, allows the road crash locations within the specific xy tolerance (80m) to be considered equal or identical. This allows the integrity of the shared feature boundary to be maintained.

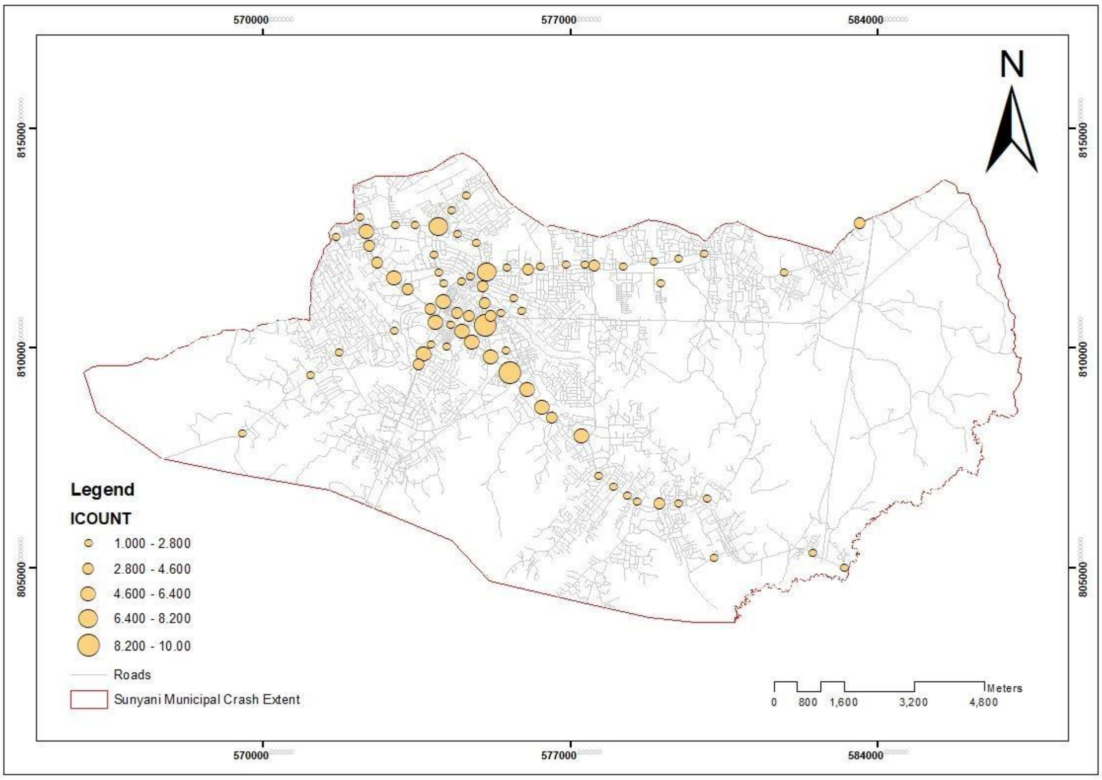


Figure 4.1 Weighted Point Data (field: ICOUNT).

4.2.2 Collect Events

The Collect Events tool converts the crash points to weighted point data. This is done by combining identical points in a weighted point feature class (ICOUNT) and holding the sum of all the event data at each unique location as shown in **Figure 4.1**

4.2.3 Spatial Autocorrelation (Moran's I)

Moran's I was applied to assess the spatial autocorrelation of road crashes, indicating whether similar values (i.e., Crash occurrences) cluster spatially. Using the Equation incorporated in the ArcGIS software, the resulting Moran's I value was found to be 0.080472, with a p-value of 0.006344 (see **Table 4.1**), indicating a significant positive autocorrelation. This suggests that road crashes are not randomly distributed across the municipality but exhibit a clustering behaviour, and it will be necessary to proceed with

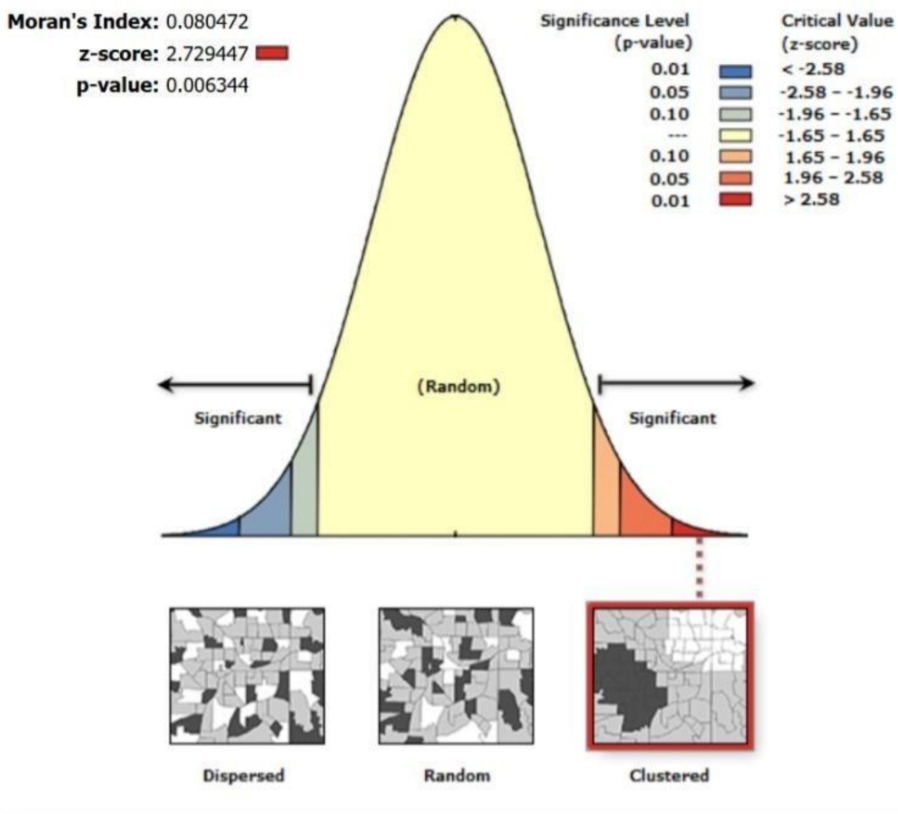
Getis-Ord Gi*(Hotspot Analysis). As shown in **Figure 4.2**.

Table 4.1 Summary of the Moran's I Spatial Autocorrelation Assessment.

Global Moran's I Summary

Moran's Index:	0.080472
Expected Index:	-0.013889
Variance:	0.001195
z-score:	2.729447
p-value:	0.006344

Spatial Autocorrelation Report



Given the z-score of 2.7294472503, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

Figure 4.2 Spatial Autocorrelation output report.

4.2.4 Interpretation

The positive autocorrelation indicates that other areas with high counts surround areas with high crash counts, while low-crash areas cluster together. High traffic volume, proximity to major intersections, road conditions and other factors influence this spatial pattern.

4.3 Hotspot Analysis

To better appreciate the spatial clustering and satisfy the first objective of identifying and mapping high-risk or black spots of road traffic crashes, another spatial statistical analysis was conducted to derive hot and cold spots. Getis-Ord Gi* analysis made it possible to visualize the hot and cold spots.

4.3.1 Getis-Ord Gi* Statistic

The Getis-Ord Gi* statistic was employed to identify hotspots of road crashes, highlighting areas with significantly high concentrations of incidents. The analysis revealed several hotspot areas, notably the road from Sunyani Technical University (STU) to Sunyani Senior High School (SUSEC), where the Gi* values were significantly greater than zero, with p-values below the 0.05 threshold. Observation of this spot identified speeding to be the major cause, coupled with the high presence of human engagement on this stretch, particularly students.

4.4 Mapping and Visualization

Maps generated from the analysis illustrated the identified hotspots, facilitating a visual understanding of crash distribution. The hotspots corresponded to key road segments and intersections, notably STU to SUSEC, showing a confidence level of 99%, and Mama Lawson (Penkwase) stretch to VIP Bus Terminal (Area 4), VRA station to the CBD, STU roundabout, Police Experimental School, Dr. Berko, Sunyani Ridge (RCC), Sunyani Area 3 (Court), also with confidence level 95% which are characterized by e.g., heavy traffic and commercial zones. **Figure 4.3** shows points of hotspots in the municipality. Points of hotspots were interpolated with IDW to generate raster map as shown in **Figure 4.4**.

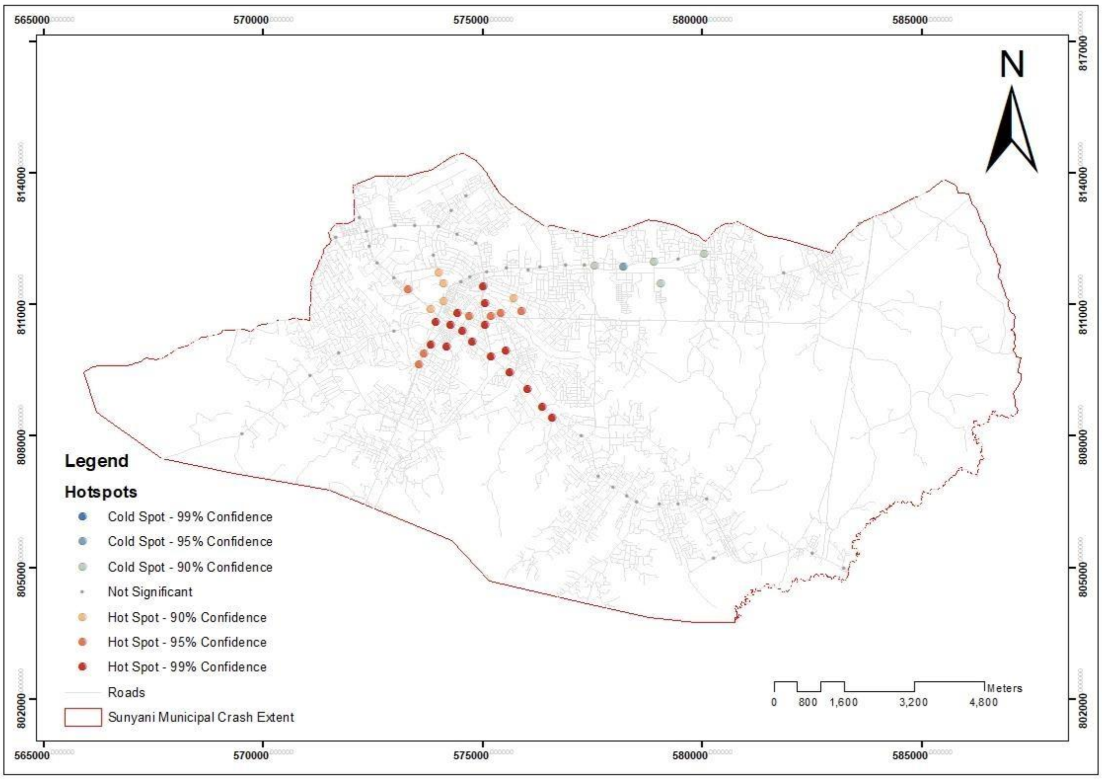


Figure 4.3 Points map of hotspot areas.

4.4.1 Hotspot Probability Map

The primary output of the analysis is a hotspot probability map (Figure 4.4). This map identifies areas with a high likelihood of crashes, with probabilities ranging from 0 (Low) to 1 (High). The map reveals distinct high-probability zones (hotspots) within the municipality. Critical areas include Sunyani RCC, the SUSEC Entrance, STU Entrance, VRA, Nana Bosoma Market, Sunyani Area 3 (Court), and parts of Penkwase. These locations are central, high-traffic zones, suggesting a strong link between traffic density, urban activity, and crash occurrence.

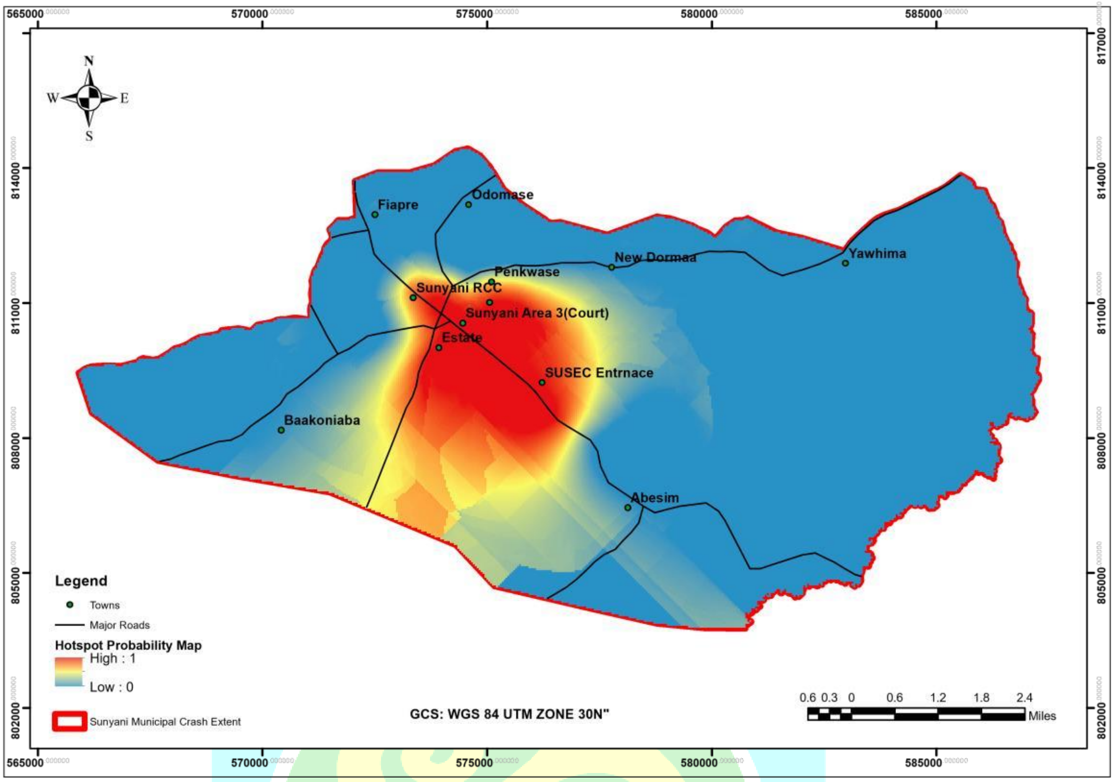


Figure 4.4 Hotspots probability map

4.4.2 Reliability of the Hotspot Map (Standard Error)

To understand how much confidence to place in the hotspot predictions, a Standard Error map was created (Figure 4.5). This map shows the reliability of the predictions, where a lower error means higher confidence. The standard error across the study area ranges from approximately 0.16 (Low) to 0.75 (High). The highest errors are often found at the edges of the mapped area or in locations with few data points. In the central, high-risk zones identified, the error is generally moderate to low, increasing our confidence in those specific hotspot predictions.

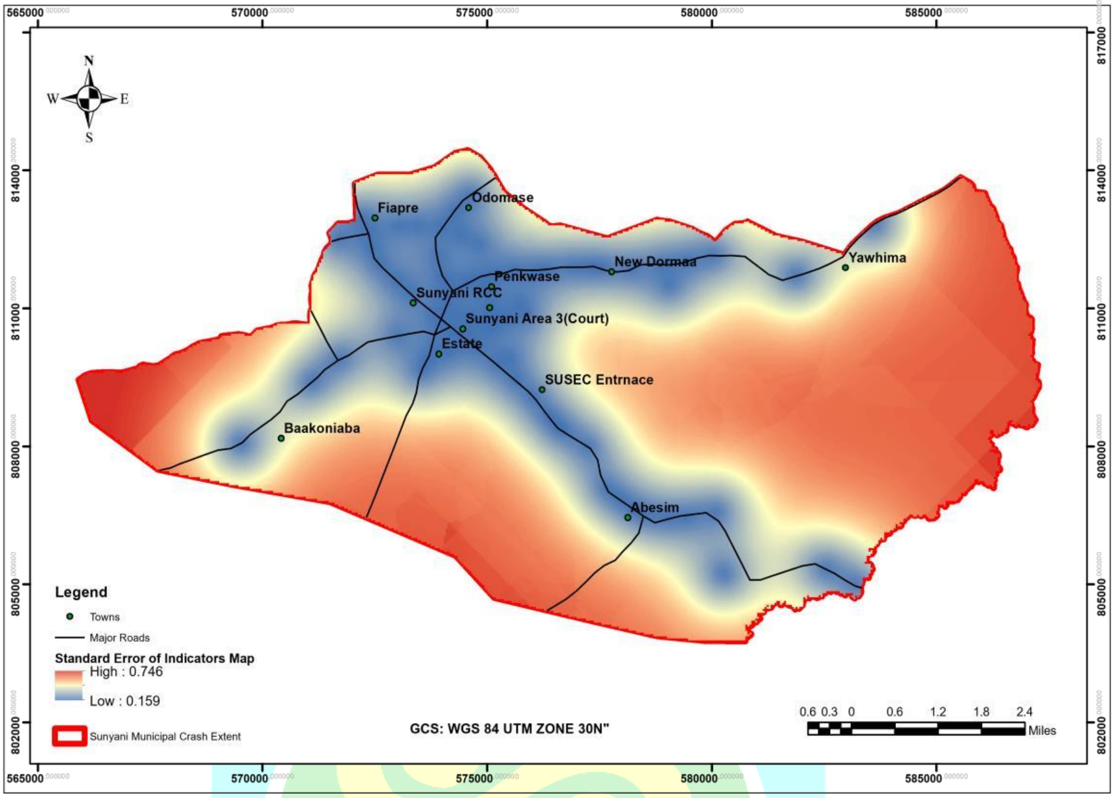


Figure 4.5 Standard Error map

4.4.3 Model Performance and Validation

The statistical measures from the kriging process confirm that the model performed well (Table 4.2). A Root-Mean-Square Standardized value close to 1 (0.955) indicates that the model accurately estimated the uncertainty in its predictions. The Mean Standardized error near zero (0.028) shows that the model did not consistently overpredict or under-predict crash probability.

Table 4.2 Kriging Model Cross-Validation Statistics results

Regression function (Prediction Errors)	
Samples	74 of 74
Mean	0.013918810018818145
Root-Mean-Square	0.21090192473684624
Mean Standardized	0.028176933362245617

Root-Mean-Square Standardized	0.9553202065138309
Average Standard Error	0.2693204954577989

4.5 Road Traffic Crashes relationship with Surrounding Features

The analysis of the 75 stakeholder interviews provided critical context to the spatial patterns. Table 4.3 summarizes the perceived causes of crashes, with 'Over-speeding' and 'Careless Driving' being the most frequently cited factors.

Table 4.3: Perceived Causes of Road Crashes from Stakeholder Interviews

Cause of Crash	**Number of Respondents**	**Percentage (%)**
Over-Speeding	14	18.67
Careless Driving	14	18.67
Wrongful U-Turning	11	14.67
Poor Road Conditions	7	9.33
Faulty Traffic Controls	6	8.00
Wrongful Overtaking	5	6.67
Brake Failure	4	5.33
Road Blockage (Construction)	3	4.00
Wrongful Turning	3	4.00
Wrongful Parking	3	4.00
Swerving Rumps	3	4.00
Pothole	2	2.67
TOTAL	**75**	**100.00**

A cross-tabulation of interview responses with the hotspot map revealed clear relationships:

- STU to SUSEC Hotspot: Respondents attributed crashes here primarily to over-speeding on the highway, compounded by high pedestrian activity from students crossing at undesignated points and inadequate crossing facilities.
- Estate Junction & VRA to CBD Hotspots: These areas were linked to wrongful U-turns, careless driving, and faulty traffic controls (ineffective traffic lights), exacerbated by congestion from commercial activities near the market.
- Mama Lawson to VIP Terminal Hotspot: This was associated with a mix of over-speeding on the wide avenue, high pedestrian activity and wrongful parking, which obstructs traffic flow and sightlines.
- Post Office to RCC Hotspots: This was associated with over-speeding coupled with wrongful U-turns.

Field observations confirmed these relationships, noting a lack of speed calming measures, faded road markings, and an absence of pedestrian footbridges in the highrisk zones.

4.6 Field Validation of Hotspots through Geotagging

The field observations successfully validated the statistically significant hotspots. The geotagged points collected in the field showed a strong spatial correlation with the high-risk zones identified by the Getis-Ord Gi* analysis. For example, the geotagged photographs from the STU to SUSEC corridor visually confirmed the factors inferred from the model: a high-speed multi-lane highway with no pedestrian crossing facilities, corroborating the interview data on speeding and risky pedestrian crossings. A map (Figure 4.6) overlaying the geotagged field points onto the statistical hotspot model was created to demonstrate this congruence visually.

Figure 4.6: Validation of Statistical Hotspots with Geotagged Field Observations.

4.7 Data-Driven Recommendations

The synthesis of the hotspot maps, and causative factors directly informs targeted recommendations. The output is a prioritized action plan for high-risk zones, as summarized in Table 4.4. This table translates spatial data into actionable policy and engineering interventions.

Table 4.4: Data-Driven Recommendations Derived from GIS and Interview Analysis

Identified Hotspot	Key Contributing Factors	Proposed Data-Driven Intervention
STU to SUSEC (99% Conf.)	Over-speeding, Student Pedestrian Crossings	Install speed cameras, Construct a pedestrian footbridge, Implement rumble strips.
Estate Junction to Post Office (95% Conf.)	Wrongful U-turns, Congestion, Faulty Signals	Redesign junction with a roundabout, Upgrade and maintain traffic signal system.

VRA to CBD (95% Conf.)	Careless Driving, Mixed Traffic, Market Activity	Enforce traffic laws, Create dedicated loading bays, Improve Street lighting and signage.
Mama Lawson to VIP Terminal (95% Conf.)	Over-speeding, High Pedestrian activity, Wrongful Parking	Implement timed parking restrictions, Deploy periodic police patrols.
Post Office to RCC (95% Conf.)	Over-speeding, Wrongful U-turns	Install speed cameras, Implement rumble strips

4.8 Discussion

4.7.1 Discussion on the Spatial Clustering of Crashes

The significant spatial autocorrelation (Moran's I = 0.080, p = 0.006) confirms that road crashes in Sunyani are concentrated in specific clusters. This finding aligns with global literature which asserts that RTCs are not random events but are strongly influenced by local environmental and infrastructural factors (Anderson, 2009). The identified hotspots, particularly the STU-SUSEC corridor, function as "blackspots" similar to those documented in studies in Accra and Kumasi (Ackaah & Salifu, 2011; Acquah & Fosu, 2017). The implication is clear: municipal resources for road safety should not be dispersed evenly but must be strategically concentrated on these high-yield locations to achieve maximum impact on crash reduction.

4.7.2 Discussion on the Causative Factors and Local Context

The relationship between hotspot locations and factors like over-speeding, pedestrian activity, and faulty traffic controls underscores a systemic failure in integrating road safety into urban planning. The STU-SUSEC hotspot, for instance, is a classic case of a high-speed corridor intersecting with a high-pedestrian generator a dangerous combination well-documented in other African cities (Damsere-Derry et al., 2017). The prevalence of "careless driving" and "wrongful U-turns" in the CBD hotspots reflects a broader issue of inadequate traffic management and enforcement in rapidly urbanizing commercial zones, a challenge also noted in studies from Nigeria (Aderamo, 2012) and India (Kumar & Toshniwal, 2016). This implies that engineering solutions alone are insufficient; they must be coupled with sustained enforcement and public education targeting specific high-risk behaviours in these specific locations.

4.7.3 Discussion on Data Driven Recommendations

The value of this study lies in its ability to move from generic recommendations to spatially explicit, data-driven interventions. Recommending a footbridge at the STUSUSEC stretch, for example, is a direct data-driven response to the confirmed cluster of pedestrian-vehicle conflicts. This approach is supported by the World Health Organization's Safe Systems approach, which advocates for targeted interventions that account for the specific vulnerabilities of each road user group (WHO, 2021). By providing a clear, map-based rationale for interventions, this study empowers the MTTD, NRSA, and Municipal Assembly to prioritize budgets, justify infrastructure projects, and design targeted enforcement campaigns, thereby enhancing accountability and the efficient use of limited public resources.

CHAPTER FIVE

CONCLUSIONS, LIMITATIONS, AND RECOMMENDATIONS

5.1 Introduction

The research indicates that STU to SUSEC (Sunyani - Kumasi Highway) appeared to be the hotspot in the municipality with a confidence level of 99%, followed by the distance between the Estate junction and the Post Office, Mama Lawson to the V.I.P terminal on the J.H. Owusu Acheampong Avenue, and VRA Station to the Main Taxi Station on the Bosoma High Street, were all identified as hotspot areas with a confidence level of 95%. Accessing the severity trends also identified Ohene Djan, Rafchick Hospital, and Glammosay Hotel areas as fatal spots. For hospitalized crash cases, STU. Traffic Light to SUSEC was identified as a hotspot area with a confidence level of 99%, with other areas like Estate, Municipal Assembly to COCOBOD roundabout, Night market (Little Wood Avenue), and STU roundabout to Nana Bosoma market on the J.H. Owusu Acheampong Avenue representing hotspot areas with a 95% confidence level. Crashes resulting in only damages revealed New Dormaa to Barracks as the hotspot area with a confidence level of 90. For injured but not hospitalized cases, it was observed that there was a non-significant pattern, hence no hotspots.

5.2 Conclusions

This study successfully achieved its aim by applying GIS and spatial statistics to model road traffic crashes in the Sunyani Municipality. The conclusions are drawn directly from the findings related to each specific objective:

1. Regarding the identification of high-risk blackspots, the study conclusively identified non-random spatial clustering of crashes, confirmed by a statistically significant Moran's I value of 0.080 (p-value = 0.006, z-score = 2.49). The

   Getis-Ord Gi* analysis pinpointed the Sunyani-Kumasi Highway (STU to SUSEC stretch) as the most critical hotspot with a 99% confidence level (high z-score). Other significant corridors, including the Estate Junction and VRA to CBD routes, were also identified as priority intervention zones with 95% confidence. The spatial distribution maps provide an unambiguous visual guide for targeting resources.
2. Regarding the causes of crashes, the integration of hotspot maps with interview data revealed a clear and interesting relationship. The primary causative factors in the identified hotspots were over-speeding and careless driving (18.67% each), followed by wrongful U-turns (14.67%). What was particularly notable was how these human factors were exacerbated by specific environmental features: high-speed highways adjacent to educational institutions, commercial market congestion leading to erratic maneuvers, and a lack of traffic calming measures. This synergy between driver behavior and road environment underscores the need for a combined engineering and enforcement approach.
3. Regarding the data-driven recommendations, the study produced validated spatial distribution maps that directly translate into actionable interventions. The reliability of these maps is qualified by the calculated uncertainties, with the overall Kriging model showing a Root Mean Square Error (RMSE) of 0.211. This indicates a reasonable level of accuracy for planning purposes, though it also acknowledges the inherent uncertainty in modelling sparse point data. The findings provide a robust, data-driven foundation for the recommended infrastructure upgrades and targeted

enforcement strategies, moving municipal road safety planning from intuition to evidence.

In summary, this research has provided a scientifically grounded and spatially explicit profile of road traffic crash risk in Sunyani. By conclusively identifying (where) crashes cluster, explaining (why) they occur there through localized factors, and quantifying the certainty of its findings, the study offers a powerful blueprint for strategic and effective road safety management in the municipality.

5.3 Limitations

While the study provides valuable insights, the study acknowledges limitations, including incomplete crash reporting, underrepresentation of actual crash occurrences, particularly minor incidents that do not result in police reports, and exclusion of temporal factors like seasonal variations. Additionally, the BRRI data were aggregated annually from the police archives, which are highly susceptible to omissions. Finally, crash data locations were recorded with the description of the crash location or nearby landmarks instead of the precise coordinates. That made it impossible for the exact locations of road crashes to be mapped precisely. To address data gaps, ground-truthing surveys were conducted at identified hotspots, validating spatial patterns through field observations

5.4 Recommendations

1. Infrastructure upgrade and Environmental Adjustments: The municipal assembly with the help of the Ghana Highways Authority, should construct an overpass at STU, install speed limiters on highways and improve road design near high traffic zones.

2. The MTTD of the police service should develop a system for continuous data collection, factoring geographical information and environmental factors into the collection exercise.
3. The MTTD and sister institutions should intensify enforcements on the highways to promote compliance and attitudinal changes.
4. The road agencies in the municipality, particularly GHA and DUR should conduct periodic monitoring and evaluation for good road conditions.
5. The NRSA should intensify campaigns and educational projects with a particular focus on hotspot areas through advertising mediums such as billboards and the media.
6. Future studies could integrate machine learning models to predict dynamic crash risks or incorporate real-time traffic data for adaptive management to further enhance understanding and intervention strategies.
7. The constant evaluation and modification of safety measures would be critical in creating a safer road environment for all Sunyani citizens.

REFERENCES

Ackaah, W., & Salifu, M. (2011). Crash prediction model for rural roads in Ghana. Journal of Safety Research, 42(2), 105–110.

Acquah, P. C., & Fosu, O. T. (2017). GIS-based hotspot analysis of road traffic accidents in Ghana. Journal of Transport Geography, 63, 86–94.

https://doi.org/10.1016/j.jtrangeo.2017.07.007

Aderamo, A. J. (2012). Analysis of road traffic accidents in Nigeria: A case study of Kwara State. Journal of Geography and Regional Planning, 5(8), 212–219. https://doi.org/10.5897/JGRP11.135

Adonteng, K. O., et al. (2020). Urban road traffic crashes in Sunyani: Patterns and preventive strategies. Ghana Journal of Geography, 12(2), 45–67.

Adonteng, P. (2012). An assessment of driver behavior and road traffic accidents in Ghana. Lambert Academic Publishing.

Afukaar, F. K., Antwi, P., & Ofosu-Amaah, S. (2003). Pattern of road traffic injuries in Ghana: Implications for control. Injury Control and Safety Promotion, 10(1), 69–

76.

Afukaar, F. K., Antwi, P., & Ofosu-Amaah, S. (2010). Road safety interventions in Ghana: A spatial analysis. Traffic Injury Prevention, 11(3), 289–295. https://doi.org/10.1080/15389581003623218

Ahmed, M. (2011). Spatiotemporal analysis of road accidents using GIS. In Proceedings of the International Conference on Geoinformatics (pp. 1–8). IEEE.

Alkhadour, W., Zraqou, J., Al-Helali, A., & Al-Ghananeem, S. (2021). Traffic accidents detection using geographic information systems (GIS). *International Journal of Advanced Computer Science and Applications*, *12*(4).

Anderson, T. K. (2009). Kernel density estimation and K-means clustering to profile road accident hotspots. *Accident Analysis & Prevention*, 41(3), 359-364. https://doi.org/10.1016/j.aap.2008.12.014

Anselin, L. (1995). Local Indicators of Spatial Association—LISA. Geographical Analysis.

Anselin, L. (1995). *Spatial statistical analysis and geographic information systems*. Taylor & Francis.

Ayati, E., & Abbasi, E. (2011). Application of GIS in the analysis of road traffic accidents (a case study in Iran). *Journal of Traffic and Transportation Engineering (English Edition)*, 1(1), 49-54. https://doi.org/10.1016/S2095-7564(15)30115-6

Chen, S., Kuhn, M., Prettner, K., Bloom, D. E., & Yamey, G. (2022). The global economic burden of road injuries: A cost-benefit analysis of interventions. The Lancet Planetary Health, 6(2), e144-e152. https://doi.org/10.1016/S2542-5196(21)00328-7

Chen, W., & Washington, S. (2008). New criteria for evaluating methods of identifying hotspots. *Transportation Research Record: Journal of the Transportation Research Board*, 2083(1), 76–85. https://doi.org/10.3141/2083-10

Damsere-Derry, J., et al. (2017). Prevalence of alcohol and other drug use among motorcycle riders in northern Ghana. Accident Analysis & Prevention, 101, 124–130.

Damsere-Derry, J., Palk, G., & King, M. (2017). Pedestrian road safety in Ghana: A public health concern. Journal of Traffic and Transportation Engineering, 4(2), 143–151.

Effati, S., Karami, G. H., Kaveh, F., & Rashidi, R. (2012). Determining road black spots using spatial information systems and multicriteria decision-making processes. *Transportation Engineering*, (4), 349–363.

Erdogan, S., et al. (2008). GIS-based analysis of pedestrian-vehicle crashes in Turkey. Journal of Transportation Safety & Security, 1(2), 89–105.

Etikan, I., Musa, S. A., & Alkassim, R. S. (2016). Comparison of convenience sampling and purposive sampling. American Journal of Theoretical and Applied Statistics, 5(1), 1-4. https://doi.org/10.11648/j.ajtas.20160501.11

Getis, A., & Ord, J. K. (1992). The Analysis of Spatial Association by Use of Distance Statistics. Geographical Analysis.

Ghana Statistical Service. (2019). Sunyani Municipal analytical report. Accra: GSS.

Ghana Statistical Service. (2021). *2021 population and housing census: General report*. Accra: Ghana Statistical Service.

Gómez, J., Oviedo-Trespalacios, O., & Candia, L. (2017). Hotspot analysis of traffic accidents in Bogotá: A GIS approach. Journal of Transport & Health, 5, 88–97. https://doi.org/10.1016/j.jth.2017.02.003

Goovaerts, P. (1997). Geostatistics for Natural Resources Evaluation. Oxford University Press.

Huang, H., Song, B., Xu, P., & Zeng, Q. (2020). A hybrid GIS-based approach for hotspot identification: A case study of traffic crashes in Shanghai. *Accident*

Analysis & Prevention, 137, 105455. https://doi.org/10.1016/j.aap.2020.105455

Isaaks, E. H., & Srivastava, R. M. (1989). An Introduction to Applied Geostatistics. Oxford University Press.

Kumar, S., & Toshniwal, D. (2016). A data mining approach to analyze road accident hotspots. Accident Analysis & Prevention, 92, 244–252.

https://doi.org/10.1016/j.aap.2016.04.017

LaScala, E. A., Gerber, D., & Gruenewald, P. J. (2000). Demographic and environmental correlates of pedestrian injury collisions: A spatial analysis. *Accident Analysis & Prevention, 32*(5), 651–658. https://doi.org/10.1016/S0001-4575(99)00100-2

Lassarre, S., Papadimitriou, E., Yannis, G., & Golias, J. (2007). Measuring accident risk exposure for pedestrians in different urban environments. *Accident Analysis & Prevention*, 39(6), 1102-1111. https://doi.org/10.1016/j.aap.2007.02.001

Li, Y., Wang, S., Hu, Z., & Ding, X. (2007). Analyzing the spatial-temporal distribution of traffic accidents with GIS. *International Journal of Geographical Information Science*, 21(2), 293-307. https://doi.org/10.1080/13658810600852336

Mesic, E., Hrelja, D., & Avdic, M. (2024). Evaluating urban traffic safety through GIS-based hotspot analysis: A case study of Sarajevo. Transportation Research

Procedia, 75, 123–134. https://doi.org/10.1016/j.trpro.2024.02.015

Moeinaddini, M., Asadi-Shekari, Z., & Shah, M. Z. (2013). Analyzing the spatial and temporal patterns of pedestrian crashes in Tehran. Journal of Transportation

Safety & Security, 5(3), 224-237. https://doi.org/10.1080/19439962.2013.813216

Mohan, D., Tiwari, G., Khayesi, M., & Nafukho, F. M. (2006). *Road traffic injury* *prevention: Training manual*. World Health Organization. https://apps.who.int/iris/handle/10665/43271

National Road Safety Authority (NRSA). (2022). Annual Road Traffic Crash Report. Accra: NRSA.

National Road Safety Authority. (2007). *Annual report*. National Road Safety Authority, Ghana.

National Road Safety Authority. (2020). *Annual report*. National Road Safety Authority, Ghana.

National Road Safety Authority. (2021). *Annual report*. National Road Safety Authority, Ghana.

National Road Safety Authority. (2023). *Annual report*. National Road Safety Authority, Ghana.

Obiri-Yeboah, A., et al. (2016). Corruption and road safety in Ghana: A case study of law enforcement. Journal of Transportation Safety & Security, 8(3), 234–248.

Ord, J. K., & Getis, A. (1995). Local spatial autocorrelation statistics: Distributional issues and an application. *Geographical Analysis, 27*(4), 286–306. https://doi.org/10.1111/j.1538-4632.1995.tb00912.x

Osei, K. K. (2020). Road traffic crashes in Sunyani Municipality: Causes and preventive strategies (Master's thesis). Kwame Nkrumah University of Science and Technology.

Owusu, P. A., Afukaar, F. K., & Donkor, P. (2018). Spatial analysis of motorcycle accident hotspots in Ghana. Accident Analysis & Prevention, 112, 78–85. https://doi.org/10.1016/j.aap.2018.01.004

Peden, M., Scurfield, R., Sleet, D., Mohan, D., Hyder, A. A., Jarawan, E., & Mathers, C. (2004). *World report on road traffic injury prevention*. World Health Organization. https://apps.who.int/iris/handle/10665/42871

Plug, C., et al. (2011). Spatial interpolation of traffic accidents. Accident Analysis & Prevention, 43(3), 993–1001

Prasannakumar, V., Vijith, H., Charutha, R., & Geetha, N. (2011). Spatio-temporal clustering of road accidents: GIS-based analysis and assessment. *Accident Analysis & Prevention*, 43(1), 317-325. https://doi.org/10.1016/j.aap.2010.09.011

Satria, R. (2016). GIS-based spatial analysis of traffic accidents in Yogyakarta, Indonesia. International Journal of Transportation Science and Technology, 5(1), 17–24.

Schermers, G., & Wegman, F. (2004). Meeting global road safety targets: The need for national road safety strategies. *Journal of Safety Research*, 35(3), 383-393. https://doi.org/10.1016/j.jsr.2004.03.007

Shafabakhsh, G. A., Famili, A., & Bahadori, M. S. (2017). GIS-based spatial analysis of urban traffic accidents: A case study in Mashhad, Iran. *Journal of Traffic and Transportation Engineering (English Edition)*, 4(3), 290-299. https://doi.org/10.1016/j.jtte.2017.05.005

Silverman, B. W. (1986). Density estimation for statistics and data analysis. Chapman and Hall.

Steenberghen, T., Dufays, T., Thomas, I., & Flahaut, B. (2004). Intra-urban location and clustering of road accidents using GIS: A Belgian example. *International Journal of Geographical Information Science*, 18(2), 169-181. https://doi.org/10.1080/13658810310001620967

Sunyani Municipal Assembly. (2023). *Annual Budget.* Sunyani: SMA

Sunyani Municipal Health Directorate. (2023). Annual Health Sector Report. Sunyani: SMHD.

Wazana, A., Rynard, V. L., Raina, P., & Krueger, P. (2006). Child pedestrian injuries: Review of risk factors and prevention strategies. Canadian Journal of Public Health, 97(2), 115–121.

WHO (World Health Organization). (2021). Global Status Report on Road Safety.

World Health Organization (WHO). (2018). Global status report on Road safety. Geneva: WHO.

World Health Organization. (2023). *Global status report on road safety 2023: Summary. Geneva: World Health Organization. https://www.who.int/publications/i/item/9789240066578

Xie, Z., & Yan, J. (2008). Kernel density estimation of traffic accidents in a network space. Computers, Environment and Urban Systems, 32(5), 396–406. https://doi.org/10.1016/j.compenvurbsys.2008.05.001

APPENDIX A: QUESTIONNAIRE

Data Collection on Locations of Road Crashes in Sunyani Municipality

Spatial Data Collection

sylvesterasare1@gmail.com Switch account

* Indicates required question

Email *

☐ Record sylvesterasare1@gmail.com as the email to be included with my response

○ Option 1

Name of respondent *

If Driver ,Specify route of association (e.g Abesim,Fiapre ,etc)

Your answer

Ever witnessed or been involved in a road crash within the Municipality?

○ Yes

○ No

If Yes , Date of incident?

Date

mm/dd/yyyy

Time

○ Morning

Possible Cause(s) of crash?

Your answer

Vehicles involved in crash (1 car, tricycle, 2 motorcycles...etc)

Your answer

Type of Crash

○ Car to Car (head on collision)

○ Car to Car (rear collision)

○ Car to Motorcycle

○ Pedestrian knockdown by car

○ Pedestrian knockdown by motorcycle

○ Other:

Name of respondent *

Your answer

Sex *

○ Male

○ Female

Occupation *

Your answer

If Driver ,Specify route of association (e.g Abesim,Fiapre ,etc)

Your answer

Time

○ Morning

○ Afternoon

○ Evening

Location of crash?

Your answer

Closest landmark to location?

Your answer

Possible Cause(s) of crash?

○ Car to Motorcycle

○ Pedestrian knockdown by car

○ Pedestrian knockdown by motorcycle

○ Other:

Impact of Crash (Injuries / Fatalities)

Your answer

Injuries impact

○ Minor

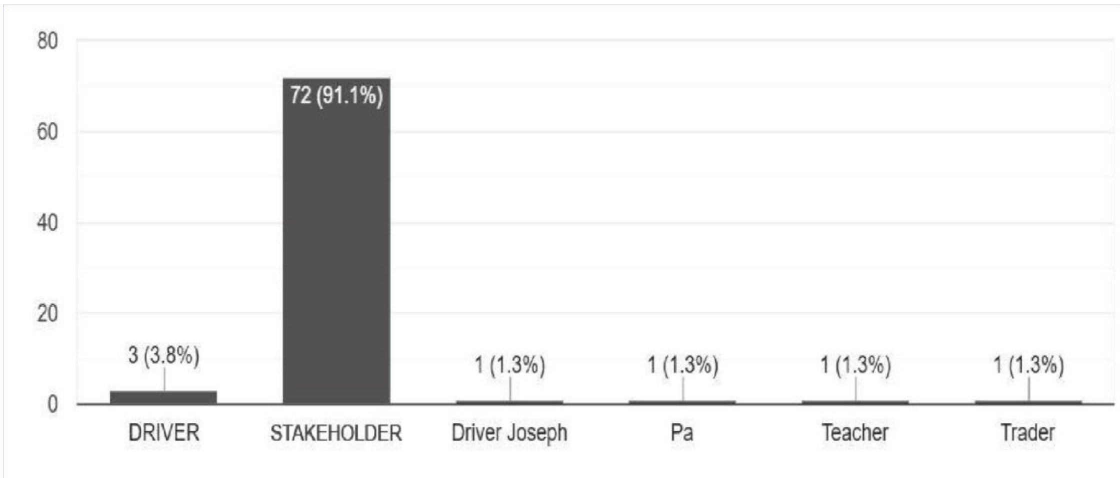
○ Major

Submit

Clear form

APPENDIX B: RESPONSES

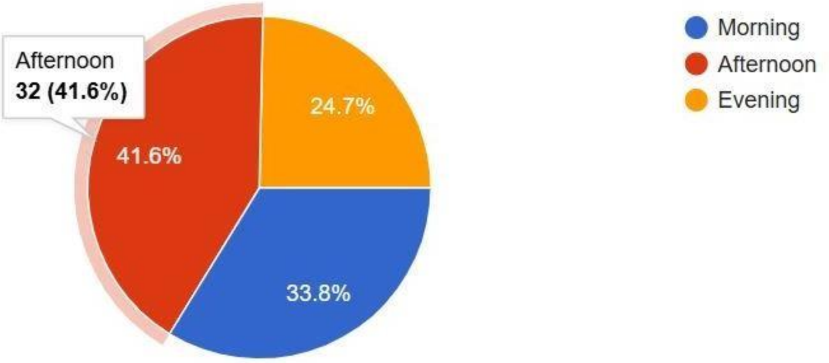
a) Occupation of interview respondents



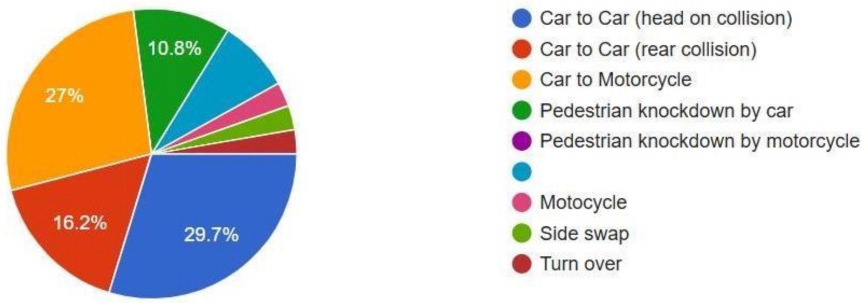
b) Locations of crashes witnessed

CRASH LOCATIONS	NUMBER OF RESPONDENTS	PERCENTAGE (%)
SDA Hospital	12	16
Eusbett Hotel	8	10.67
Ssnit Traffic Light	6	8.00
Military Barracks	4	5.33
Dr.Berko	6	8.00
STU	10	13.33
Magazine Gate	4	5.33
Residency	3	4.00
Lands Commission Office	5	6.67
Prison Service Office	3	4.00
Bank of Ghana	2	2.67
Baakoniaba Washing Bay	4	5.33
Kotokrom	3	4.00
RCC	5	6.67
TOTAL	**75**	**100.00**

c) **The time of day the crash was recorded.**



d) **Type or kind of crash.**

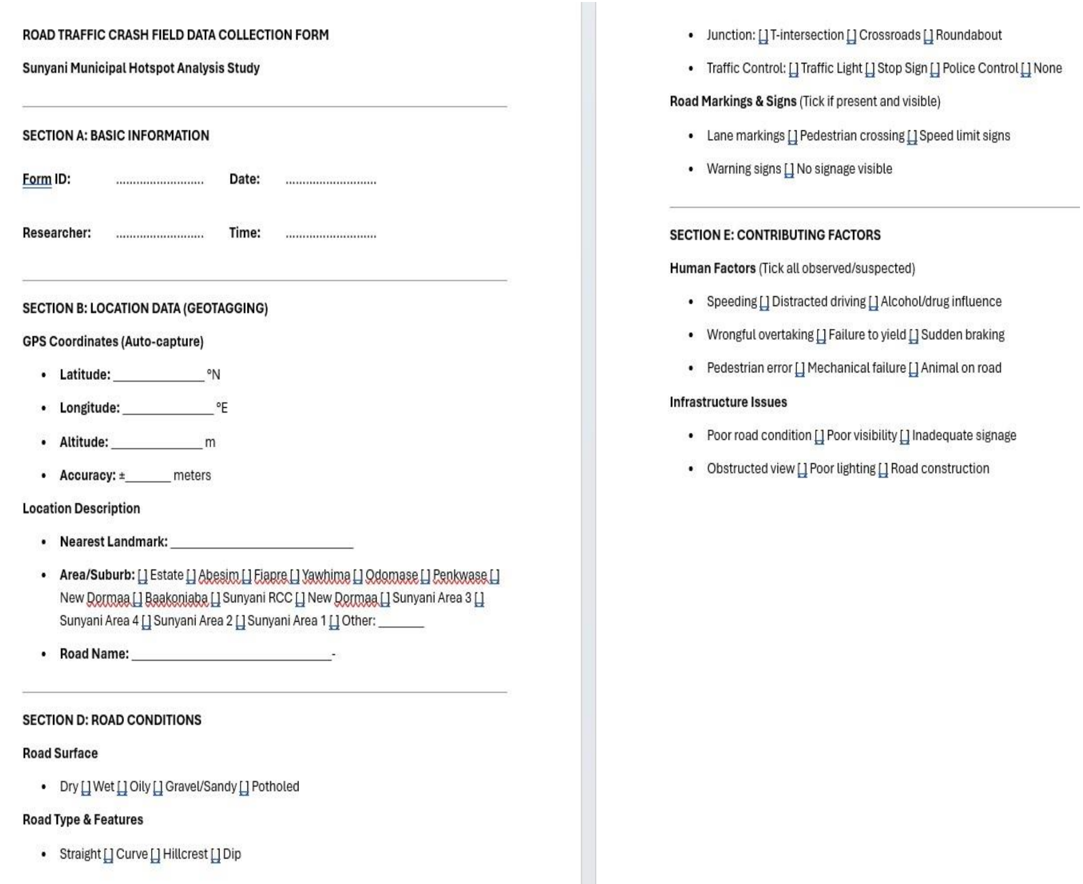


e) **Possible causes of crashes.**

CAUSES OF CRASHES	NUMBER OF RESPONDENTS	PERCENTAGE (%)
Over Speeding	14	18.67
Brake Failure	4	5.33
Road Blockage due to construction	3	4
Wrongful turning	3	4
Wrongful Overtaking	5	6.67
Wrongful Parking	3	4
Wrongful U-Turning	11	14.67
Swerving Rumps	3	4
Careless Driving	14	18.67
Faulty Traffic	6	8
Poor Road	7	9.33
Pothole	2	2.66
TOTAL	**75**	**100.00**

APPENDIX C: FIELD GEOTAGGING PROTOCOL AND SAMPLE DATA

a) **Screenshot of the field data collection form.**



ROAD TRAFFIC CRASH FIELD DATA COLLECTION FORM

Sunyani Municipal Hotspot Analysis Study

SECTION A: BASIC INFORMATION

Form ID: .... Date: ....

Researcher: .... Time: ....

SECTION B: LOCATION DATA (GEOTAGGING)

GPS Coordinates (Auto-capture)

- Latitude: ____________ °N
- Longitude: ____________ °E
- Altitude: ____________ m
- Accuracy: ±______ meters

Location Description

- Nearest Landmark: ________________________
- Area/Suburb: [ ] Estate [ ] Abesim [ ] Fiapre [ ] Yawhima [ ] Odomase [ ] Penkwase [ ] New Dormaa [ ] Baakoniaba [ ] Sunyani RCC [ ] New Dormaa [ ] Sunyani Area 3 [ ] Sunyani Area 4 [ ] Sunyani Area 2 [ ] Sunyani Area 1 [ ] Other: ______
- Road Name: __________________________-

SECTION D: ROAD CONDITIONS

Road Surface

- Dry [ ] Wet [ ] Oily [ ] Gravel/Sandy [ ] Potholed

Road Type & Features

- Straight [ ] Curve [ ] Hillcrest [ ] Dip
- Junction: [ ] T-intersection [ ] Crossroads [ ] Roundabout
- Traffic Control: [ ] Traffic Light [ ] Stop Sign [ ] Police Control [ ] None

Road Markings & Signs (Tick if present and visible)

- Lane markings [ ] Pedestrian crossing [ ] Speed limit signs
- Warning signs [ ] No signage visible

SECTION E: CONTRIBUTING FACTORS

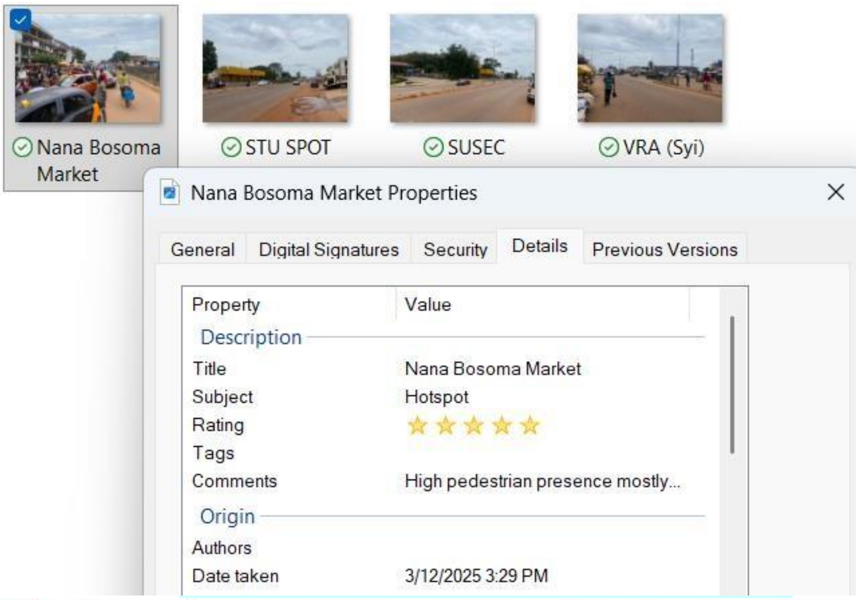
Human Factors (Tick all observed/suspected)

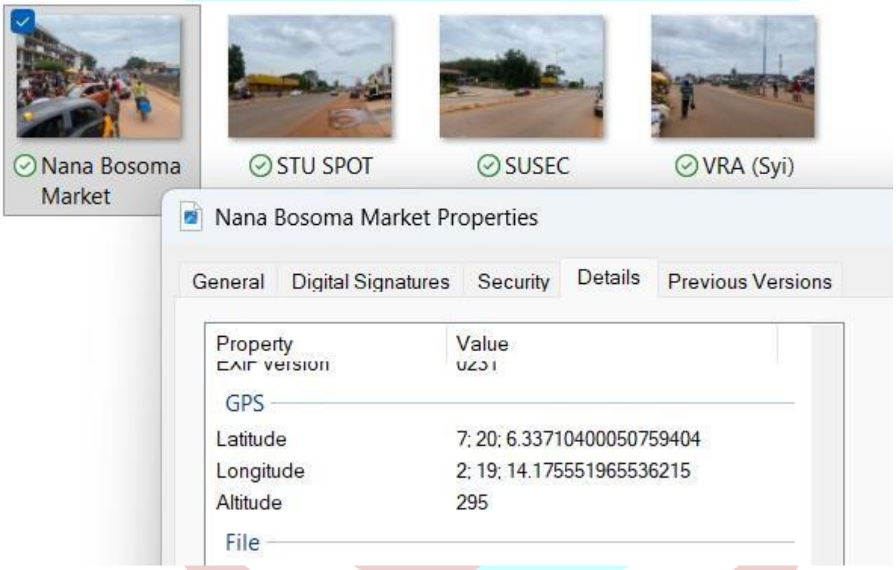
- Speeding [ ] Distracted driving [ ] Alcohol/drug influence
- Wrongful overtaking [ ] Failure to yield [ ] Sudden braking
- Pedestrian error [ ] Mechanical failure [ ] Animal on road

Infrastructure Issues

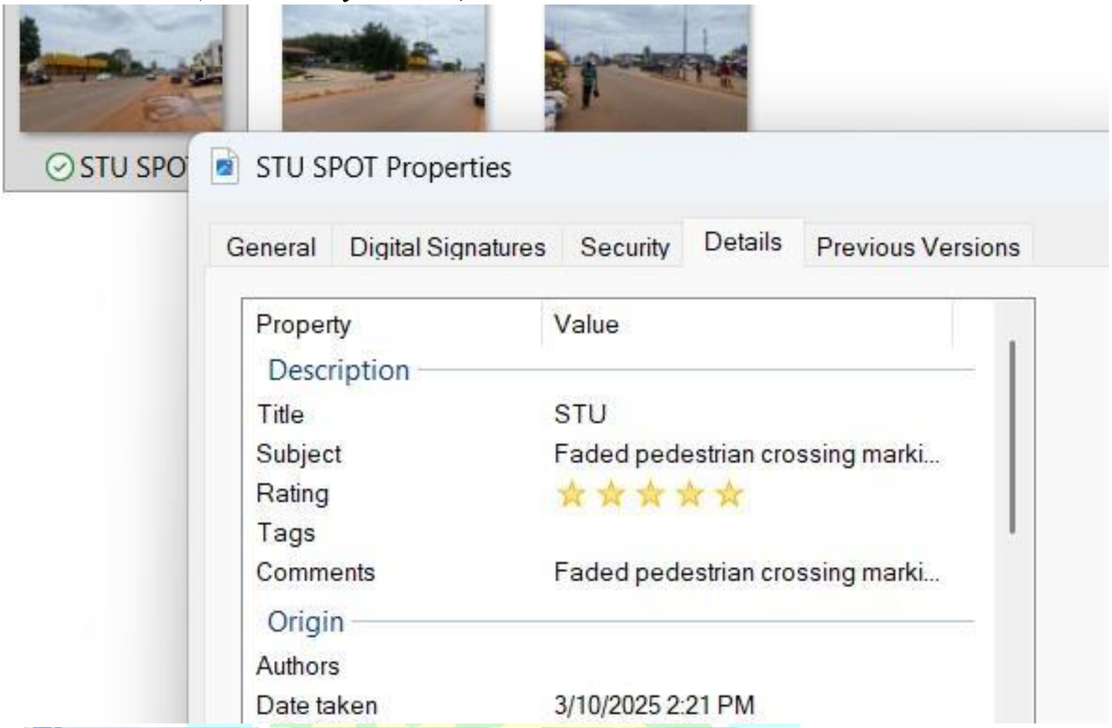
- Poor road condition [ ] Poor visibility [ ] Inadequate signage
- Obstructed view [ ] Poor lighting [ ] Road construction

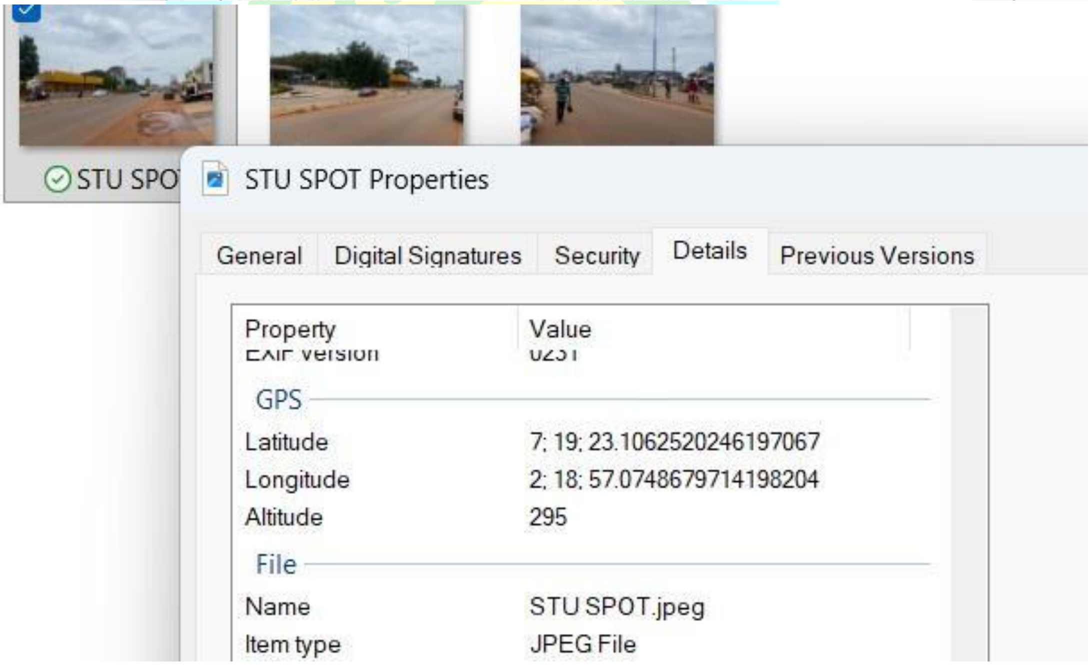
b) **Sample of the geotagged photographs with their coordinates and captions.**


Nana Bosoma Market
STU SPOT
SUSEC
VRA (Syi)
Nana Bosoma Market Properties
General
Digital Signatures
Security
Details
Previous Versions
Property
Value
Description
Title
Nana Bosoma Market
Subject
Hotspot
Rating
Tags
Comments
High pedestrian presence mostly...
Origin
Authors
Date taken
3/12/2025 3:29 PM


Nana Bosoma Market
STU SPOT
SUSEC
VRA (Syi)
Nana Bosoma Market Properties
General
Digital Signatures
Security
Details
Previous Versions
Property
Value
GPS
Latitude
7; 20; 6.33710400050759404
Longitude
2; 19; 14.175551965536215
Altitude
295
File

Nana Bosoma Market(Wednesday Market)





STU ENTRANCE

c) Table listing all field-visited coordinates and their brief observations.

VISITED LOCATIONS	GPS COORDINTES (X, Y)	OBSERVATION

Nana Bosoma Market	7.33509363, -2.32060432	High pedestrian activity, wrongful parking and lack of pedestrian crossing facilities
STU Entrance	7.32308507, -2.31585413	Over-speeding, Lack of pedestrian crossing facility, high pedestrian activity before lectures begin and after lectures
VRA Entrance	7.33307717, -2.32014835	Over-speeding, high pedestrian activity, wrongful parking, lack of pedestrian crossing
SUSEC Entrance	7.31856248, -2.31079817	Over-speeding, Lack of pedestrian crossing facility, high pedestrian activity during mornings and school closing times