Evolution and Prospects of Geographic Information Systems (GIS) Applications in Urban Crime Analysis: A Review of Literature

Authors details

1- Omid Mansourihanis

Department of Geosciences, Texas Tech University, Lubbock, TX, USA

omansour@ttu.edu

https://orcid.org/0009-0007-3009-2902

2- Mohammad Javad Maghsoodi Tilaki*

Department of Geography, Universiti Sains Malaysia (USM), Penang, Malaysia

maghsoodi@usm.my

https://orcid.org/0000-0001-9008-0064

*Corresponding Author

3- Rachel Armitage

Director of Research, Leeds Law School, Leeds Beckett University, UK

R.Armitage@leedsbeckett.ac.uk

https://orcid.org/0000-0002-9106-4119

4- Ayda Zaroujtaghi

Department of Geosciences, Texas Tech University, Lubbock, TX, USA

azaroujt@ttu.edu

https://orcid.org/0009-0007-8637-0836

Abstract

Geographic Information Systems (GIS) applications enable data-driven decision making for sustainable and socially responsible urban development. This paper reviews GIS research on urban crime analysis published during 2000-2023, assessing emerging trends aligned with sustainable development goals. Analysis of 293 articles reveals prevalent focus areas including spatial analysis, crime prevention strategies, socioeconomic factors, and technology integration. Key developments encompass real-time monitoring, predictive policing, machine learning techniques, diverse data integration, and interdisciplinary approaches considering social contexts. Persistent challenges remain regarding data quality, predictive accuracy, and balancing priorities. Yet amidst complex crime shifts during the pandemic, geospatial analytics proves vital for evidence-based policies fostering secure, resilient cities. As GIS leverages big data and AI, enhanced granularity and responsiveness can inform localized interventions tackling inequality, exclusion, and violence per the UN 2030 Agenda. However, community participation is pivotal to ensure ethical technology deployment supporting collective wellbeing. By detailing two decades of research, this systematic review serves as a reference highlighting GIS's transformative role in enabling inclusive urban futures.

Keywords: Urban crime analysis, GIS, predictive modeling, technology integration, sustainable development.

Author contributions

Omid Mansourihanis: Conceptualization, Data curation, Software, Writing- Original draft preparation.
Mohamad Javad Maghsoodi Tilaki: Conceptualization, Methodology, Writing- Original draft preparation.
Rachel Armitage: Conceptualization, Supervision, Review and editing.
Ayda Zaroujtaghi: Data curation, Software, Writing - Original Draft, Validation.

Evolution and Prospects of Geographic Information Systems (GIS) Applications in Urban Crime Analysis: A Review of Literature

Abstract

Geographic Information Systems (GIS) empower data-driven urban crime analysis, fostering sustainable and inclusive cities. This systematic review synthesizes 293 studies from 2000 to 2023, examining GIS applications in spatial analysis, crime prevention, socioeconomic influences, and technology integration, aligned with United Nations Sustainable Development Goals (SDGs). Key trends include AI-driven predictive policing, real-time monitoring via IoT and Remote Sensing, and Crime Prevention Through Environmental Design (CPTED) to deter crime through urban planning. Machine learning enhances hotspot mapping precision, integrating diverse data like social media and demographics, yet challenges persist in data quality, ethical AI use, and hyperlocal analysis. Amid evolving crime dynamics driven by inequality and urbanization, GIS supports evidence-based policies to reduce violence and exclusion. Community engagement ensures ethical technology deployment, prioritizing equity. This review highlights GIS's transformative potential in addressing research gaps and advancing safer urban futures, offering a comprehensive reference for researchers and policymakers.

Keywords: Urban crime analysis, GIS, predictive modeling, technology integration, sustainable development, safer city

1. Introduction

Urban crime has gained attention due to factors like rural-urban migration, climate change, socioeconomic inequality, policing reforms, and technological advancements (Cheng and Chen, 2021). Urban crime analysis has evolved significantly with the advent of Geographic Information Systems (GIS), which enable spatially informed, data-driven approaches to understanding and mitigating crime patterns. The integration of GIS with emerging technologies, such as artificial intelligence (AI) and big data analytics, has transformed crime prevention strategies, offering unprecedented precision in hotspot mapping, predictive policing, and resource allocation (Cheng and Chen, 2021; Ratcliffe, 2019). However, the rapid pace of technological advancements and shifting crime dynamics—exacerbated by global socioeconomic disruptions—necessitate a comprehensive synthesis of GIS applications to guide future research and policy (UN, 2015). This review addresses this gap by systematically analyzing GIS-based urban crime studies from 2000 to 2023, focusing on methodological trends, data integration, and alignment with sustainable urban development goals. The rationale for this review stems from three key needs: (1) to consolidate two decades of GIS advancements in crime analysis, capturing the shift from basic mapping to AI-enhanced predictive models; (2) to identify research gaps, particularly in hyperlocal analysis and real-time monitoring; and (3) to align GIS applications with global priorities, such as the United Nations Sustainable Development Goals (SDGs), for fostering safer cities (UN, 2015).

Urban crime is a multifaceted issue driven by socioeconomic disparities, environmental stressors, and demographic shifts. Income inequality and racial segregation exacerbate crime risks in urban centers, often concentrated in marginalized neighborhoods (Boman and Gallupe, 2020; Moise and Piquero, 2023; Hipp et al., 2020). Rural-urban migration and globalization amplify these challenges, with studies linking cross-border flows to organized crime and illicit markets (Liu et al., 2022; Seyidoglu et al., 2023). Environmental factors, such as urban sprawl and poor infrastructure, further contribute to criminogenic conditions, underscoring the need for spatial analysis (Zhu et al., 2021; Patino et al., 2014). GIS addresses these dynamics by mapping crime hotspots and correlating them with social disorganization, land use patterns, and economic deprivation, providing insights for targeted interventions (Wang et al., 2013; Davies and Bowers, 2020).

Advancements in GIS have revolutionized crime analysis, moving beyond static mapping to dynamic, predictive models. The integration of AI and machine learning enables precise forecasting of crime risks, leveraging diverse datasets like social media, mobility patterns, and historical records (Aneja and Ahuja, 2021; Prathap et al., 2022; ToppiReddy et al., 2018). For example, predictive policing models identify potential burglary hotspots with high accuracy, though ethical concerns about algorithmic bias and over-policing persist (He et al., 2021; Turvey and Freeman, 2023). Real-time monitoring, supported by IoT sensors and Remote Sensing, enhances GIS's ability to track transient crime patterns, facilitating rapid response (Bherwani and Kumar, 2022; Khlem et al., 2022; Tempat et al., 2023). These technologies align with global digitalization trends, where urban governance increasingly relies on data-driven tools for decision-making (UNCTAD, 2022; Houle et al., 2022).

Crime Prevention Through Environmental Design (CPTED) complements GIS by using spatial data to design safer urban environments. Strategies like improved lighting, accessible public spaces, and defensible architecture reduce crime opportunities, aligning with SDG 11's vision of inclusive cities (Wang et al., 2024; Garcia Chueca, 2021). GIS supports CPTED by identifying high-risk areas for targeted urban planning, integrating socioeconomic and environmental data to inform holistic interventions (Newton et al., 2022; Mansourihanis et al., 2023). However, effective implementation requires balancing technological solutions with community engagement to ensure equitable outcomes (Khojastehpour et al., 2022; Lisowska-Kierepka, 2022).

Policing reforms, driven by calls for fairness and accountability, highlight GIS's dual role in enhancing efficiency and addressing systemic issues. Spatial analysis informs resource allocation and patrol strategies, improving public safety while minimizing overreach (Davies and Bowers, 2020; Aziz and Long, 2022; Keatley et al., 2022). Yet, concerns about surveillance and data privacy necessitate ethical frameworks to guide GIS applications, ensuring alignment with public trust and governance goals (Lisowska-Kierepka et al., 2022; Gu et al., 2022). These challenges are amplified in rapidly urbanizing regions, where crime patterns evolve with demographic and economic shifts, requiring adaptive, GIS-driven solutions (Houle et al., 2022; Seyidoglu et al., 2023).

Previous reviews, such as Uittenbogaard and Ceccato (2012) and Li and Zhu (2023), explored GIS in crime mapping but offered limited insights into AI integration, hyperlocal analysis, and long-term trends across 2000–2023. While studies like Newton et al. (2022) and Mansourihanis et al. (2023) highlight GIS's potential for micro-scale interventions, gaps remain in real-time monitoring, ethical AI deployment, and alignment with SDGs (Khojastehpour et al., 2022; Lisowska-Kierepka, 2022). This review synthesizes 293 studies to address these gaps, examining: (1) evolving GIS methodologies, data sources, and models, and their implications for urban crime research; (2) the role of AI-GIS integration in advancing crime prevention and fostering safer, sustainable urban environments (Gu et al., 2022; Lisowska-Kierepka et al., 2022; Wang et al., 2013).

2. Methodology

When conducting a systematic review, a methodical approach is followed to analyze abstracts and synthesize relevant studies. This section provides a detailed summary of the systematic review methodology used to analyze the abstracts in this review article, focusing on the relationship between GIS and urban crime analysis. This systematic review builds upon the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) protocol, a widely recognized framework for conducting rigorous and transparent systematic reviews (Moher et al., 2009). The PRISMA guidelines were chosen for their comprehensive approach, which ensures methodological transparency, minimizes bias, and enhances reproducibility. Following PRISMA, our review process encompassed several key steps: formulation of research questions, development of a comprehensive search strategy, screening of abstracts, application of selection criteria, evaluation of full-text articles, data extraction, and data synthesis and analysis. (No meta-analysis or statistical tests were conducted, as the review focuses on qualitative synthesis of trends, with absolute frequencies reported for objectivity) This structured approach allows for a thorough and unbiased assessment of the current state of knowledge regarding GIS applications in urban crime analysis. The methodology encompasses several steps, including the formulation of research questions, development of a search strategy, screening of abstracts, application of selection criteria, evaluation of full-text articles, data extraction, and data combination and analysis. The systematic search was conducted across Web of Science databases, and others. To capture variations of relevant terms, the search queries employed wildcards, such as 'crime*' to include 'crime' and 'crimes. This systematic approach ensures the inclusion of relevant studies and allows for a comprehensive analysis of the evolution and prospects of GIS applications in urban crime analysis. The search queried Web of Science, Scopus, and PubMed, selected for their coverage of geospatial and criminological literature. Queries used Boolean operators (e.g., “GIS” AND “crime*”). Exclusion criteria included non-English articles and non-empirical studies. A supplementary table (Table S1) details screening outcomes, available upon request.

The time period of 2000-2023 was chosen for this literature review to provide an overview of developments and trends in GIS applications for urban crime analysis over the past two decades. The year 2000 was selected as the starting point as it marked the emergence of more advanced GIS technologies and spatial analysis techniques that began to be applied to crime pattern analysis (Wang et al., 2013). The 2000 starting point aligns with the proliferation of empirical GIS applications in crime analysis, as earlier studies (pre-1990s) focused on theoretical frameworks or basic mapping with limited advanced spatial analytics (Levine, 2006). Reviewing studies from 2000 onwards enables the identification of shifts in research objectives, data sources, methodologies, and technologies used over time. The end date of 2023 was chosen to incorporate the most recent advancements and provide an up-to-date perspective on the state of the field. Furthermore, a 20+ year period allows for the analysis of changes in the geographical distribution of case studies and collaborations over time. This range offers a balanced view of progress made and gaps still persisting in knowledge, providing insights to guide future research directions. The 2000 starting point aligns with the proliferation of empirical GIS applications in crime analysis, as earlier studies (pre-1990s) focused on theoretical frameworks or basic mapping with limited advanced spatial analytics (Levine, 2006).

Analysis of the relationship between GIS and crime analysis was conducted using a systematic review methodology. A reliable database search was performed to identify relevant articles, supplemented by searches in other sources. Duplicate articles were removed, and the remaining articles were screened based on title and abstract. A full-text assessment was conducted to select relevant and high-quality articles, with reasons for exclusion documented. Articles meeting the inclusion criteria were included in the systematic review. These articles were categorized and analyzed based on various aspects, revealing trends and potential research gaps.

This systematic review methodology allowed for a rigorous analysis, providing valuable insights into the use of GIS in urban crime analysis.

The key search terms were identified based on an initial review of relevant literature and consultation with experts in the fields of crime analysis and GIS. The main keywords like "GIS", "crime analysis", "mapping", and "crime prevention" cover the key concepts of interest.

Additional keywords related to more specific elements of crime analysis were included, such as "hotspot analysis", "spatial analysis", "crime trends", "crime mapping techniques", "predictive modeling", and "geospatial data".

Keywords pertaining to technology developments like "remote sensing", "machine learning", and "artificial intelligence" were added to retrieve literature on emerging techniques.

Terms associated with social factors like "socioeconomic status", "demographic factors", "neighborhood characteristics", and "urban planning" were incorporated given their importance in contextualizing crime research.

Finally, keywords related to criminology and types of crime like "property crime", "violent crime", "drug crime" were included to allow for a detailed analysis of literature focused on specific crime categories.

A set of keywords was strategically compiled to capture all relevant studies across the interdisciplinary domains of crime analysis, GIS, advanced analytics, social factors, criminology, and urban policy. The search terms were iteratively refined to optimize the retrieval of pertinent articles. This keyword selection strategy aimed to conduct an exhaustive literature search and minimize the omission of significant publications in the field. (Table 1)

Table 1: outline structure of the Search Formula

Item	**Sub-item**	**Details**
Keywords	Main keywords	GIS; Crime analysis; Spatial analysis; Mapping; Crime prevention; Social factors; Technological advances; Urban development;

		Crime trends; Criminal justice system; Cybercrime; Juvenile delinquency;
		Victimization; White-collar crime; Crime prevention through environmental design (CPTED); International perspectives
	Supplemented Keywords	Hot Spot Analysis; Crime Mapping Techniques; Crime Pattern Analysis; Crime Prediction and Forecasting; Crime Prevention Strategies; Community-based crime prevention programs; Hotspot policing strategies; Target hardening techniques; Rehabilitation and reintegration programs; Crime prevention through social development; Socioeconomic status and crime; Demographic factors and crime rates; Neighborhood characteristics and crime; Social disorganization and crime; Cultural influences on crime; Geographic Information Systems (GIS) in crime analysis; Predictive policing models; Data mining and pattern recognition techniques; Video surveillance and facial recognition systems; Crime mapping and visualization tools; Gentrification and crime; Urban planning and crime prevention; Neighborhood revitalization strategies; Urban design and crime prevention; Impact of transportation systems on crime rates; Seasonal variations in crime rates; Temporal patterns of crime; Spatial clustering of crimes; Repeat victimization and crime patterns; Patterns of specific types of crimes; Arrest and conviction rates in urban areas
Operators	"OR" , "AND"	
Period	2000-2023	
Language	English	
Document type (included)	Indexing Journal paper (WoS)	
Document type (excluded)	Excluded document types include conference papers, non-peer-reviewed papers, books, book chapters, governmental or consultancy reports, research reports, working papers, theses, and dissertations	
Inclusion	A rigorous qualitative coding process was employed to identify and synthesize the trends and subdomains presented in the results. Each study was carefully analyzed, and relevant information was extracted and categorized based on a predefined coding scheme. This coding scheme was iteratively refined throughout the analysis process to capture emerging themes and patterns accurately. The identified trends and subdomains were further validated through consultations with subject matter experts and cross-referencing with existing literature. Papers aligning with the research scope were taken into account.	
	Studies with a clear explanation of the data linkage process and its components were chosen.	
Exclusion	Studies were excluded if they lacked sufficient detail on the process of integrating diverse datasets with geospatial data in a GIS environment. In urban crime analysis, this 'data linkage process' involves combining crime reports, socioeconomic data, and environmental variables with spatial data. 'Detailed features' refer to specifics on data sources (e.g., police records, census data), preprocessing techniques (e.g., geocoding), and spatial join methods. Clear documentation of these steps is crucial for assessing data validity and ensuring reproducibility.	
	Studies that were not conducted in English were excluded from the study.	
Search date	Tuesday, May 16, 2023	

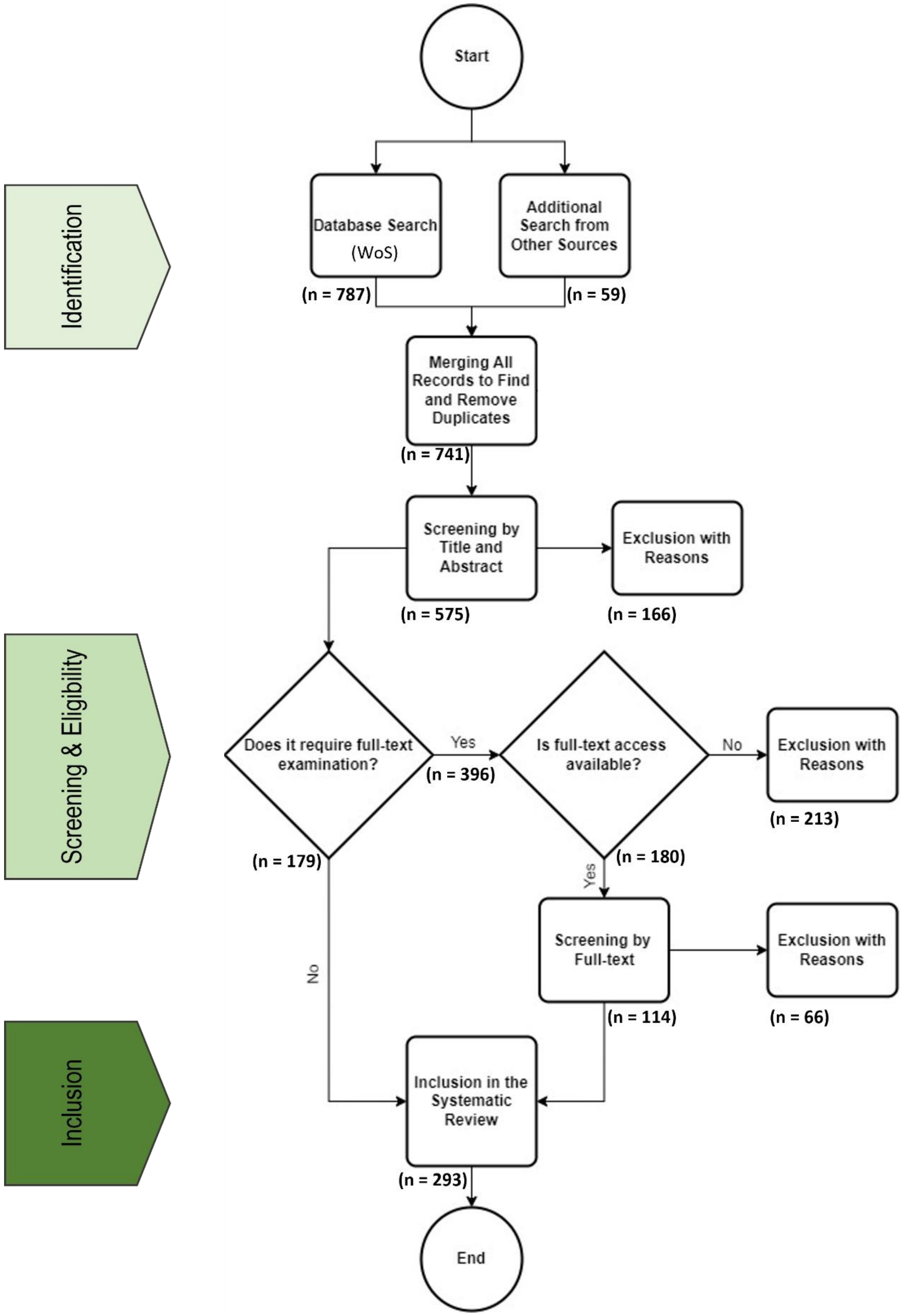

Figure 1. Systematic Review Process Flowchart: From Database Search to Final Inclusion/Exclusion

As shown in table 1 and figure 1, a continuous process involving several steps was implemented to collect and analyse data from various sources. It begins with a database search and additional searches from other sources to gather relevant information. The obtained records are then merged to identify and eliminate duplicates. The next step involves screening the records based on their title and abstract, filtering out irrelevant ones. The flowchart branches into two paths, one representing inclusion in the systematic review and the other indicating exclusion with reasons. The included records proceed to the systematic review, while the excluded ones are further detailed with exclusion criteria and reasons. A decision point determines if a record requires a full-text examination, and if so, it goes through a screening process. Finally, the flowchart concludes with the completion of the process.

To investigate trends and future directions in the application of GIS to urban crime analysis, we conducted a structured literature review. Our search targeted major academic databases using relevant keywords to identify peer-reviewed articles published from 2000 to 2023 that utilized GIS or spatial analysis methods in the context of urban crime. From an initial pool of over 800 articles, we selected a final sample of 293 abstracts for detailed coding based on eight parameters: 1) research domain, 2) subdomain, 3) study objective, 4) case study location, 5) methods discussed, 6) data used, 7) models/techniques employed, and 8) key findings.

Two researchers independently coded each abstract, resolving any discrepancies through discussion. The coded data were then qualitatively analyzed to identify prevalent categories, common patterns, and relationships across the parameters. This analysis enabled us to discern prominent research themes, frequently used data sources and methods, notable case study locations, and potential gaps or opportunities for future research at the intersection of GIS and urban crime analysis. Our systematic coding and synthesis provide a comprehensive overview of this interdisciplinary field.

This systematic review builds upon influential works by Kounadi et al. (2022) and Lee et al. (2019), which synthesized knowledge on predictive policing and spatial crime forecasting up to 2018. It updates this perspective by encompassing advancements in geospatial crime analytics from 2019 to 2023. While Lee et al. (2019) noted increased research diffusion and summarization method variations, our review integrates the latest techniques utilizing big data and AI for enhanced predictive capabilities. Expanding on Kounadi et al.'s (2022) findings of machine learning-based crime forecasting growth, our study evaluates the integration of deep learning and natural language processing for extracting spatiotemporal insights. Addressing concerns about inconsistent terminology, we extract information on methodological improvements such as feature engineering and model evaluation. Focusing on recent literature, we identify emerging best practices and gaps to guide future research in deploying geospatial crime analytics for public safety.

While previous reviews like Kounadi et al. (2020) and Lee et al. (2017) examined forecasting and crime concentration, our systematic review uniquely explores GIS applications in urban crime research. Unlike Kounadi et al.'s technical focus, we adopt a broader perspective encompassing GIS-based spatial analysis for understanding crime patterns, risk factors identification, and urban planning. Unlike Lee et al.'s concentration analysis, we examine extensive geospatial data integration applications for a comprehensive overview. Covering literature from 2000-2023, our study assesses longitudinal trends in objectives, data sources, methods, and technologies, providing insights for interdisciplinary knowledge progress and policy directions. Thus, our review contributes an original assessment of GIS' role in evolving crime scholarship.

This literature review concentrates solely on original research articles published in peer-reviewed academic journals, excluding conference papers, non-peer-reviewed articles, books, book chapters, governmental or consultancy reports, research reports, working papers, theses, and dissertations. The exclusion is based on several reasons: Peer-reviewed journal articles undergo rigorous scholarly critique and evaluation, ensuring high-quality research, while other document types may have variable quality standards. Journal articles provide complete reports of research studies, whereas conference papers and reports often contain preliminary or abbreviated findings. The peer-review process for journal articles verifies the methodology, validity, and relevance to the field, which other documents may lack. Including only peer-reviewed journal articles allows for a standardized comparison and analysis of the literature, ensuring consistency in the type of data extracted. Additionally, journal articles are easily retrievable through academic databases, unlike other document types that may have limited accessibility. The word limits for journals ensure concise communication of key information, whereas reports and books may contain extraneous details unsuitable for objective synthesis. Furthermore, journal articles are the primary mode of disseminating and archiving academic research findings in a scholarly format. By focusing on peer-reviewed journal articles, this review ensures the inclusion of high-quality, validated, academically rigorous, and accessible research, appropriate for an objective systematic review and quantitative or qualitative synthesis, enabling insightful analysis of developments within the field.

3. Results

3.1. Domains Trends

The research conducted on GIS applications in urban crime analysis over different years reveals various results and trends. Table 2 illustrates these trends in four major domains of GIS applications for urban crime analysis from 2000 to 2023: Spatial Analysis and Mapping Techniques, Crime Prevention and Intervention Strategies, Socio-Environmental Factors and Crime Patterns, and Other. The table displays the number of publications in each domain and their respective percentages within the total publications for each period, highlighting the evolution and diversification of research focus over the years. To ensure consistency and ease of interpretation, absolute frequencies are used throughout the tables to represent the number of studies falling within each category or trend.

Table 2: Trends in Major Domains from 2000 to 2023

Time Range	Spatial Analysis and Mapping Techniques	Crime Prevention and Intervention Strategies	Socio-Environmental Factors and Crime Patterns	Other	Total Publications
2000-2006	15 (45.5%)	6 (18.2%)	3 (9.1%)	9 (27.3%)	33
2007-2011	31 (39.2%)	17 (21.5%)	15 (19.0%)	16 (20.3%)	79
2012-2016	43 (36.4%)	22 (18.6%)	28 (23.7%)	25 (21.2%)	118
2017-2020	51 (32.3%)	34 (21.5%)	27 (17.1%)	46 (29.1%)	158
2020-2023	50 (28.6%)	28 (16.0%)	30 (17.1%)	67 (38.3%)	175

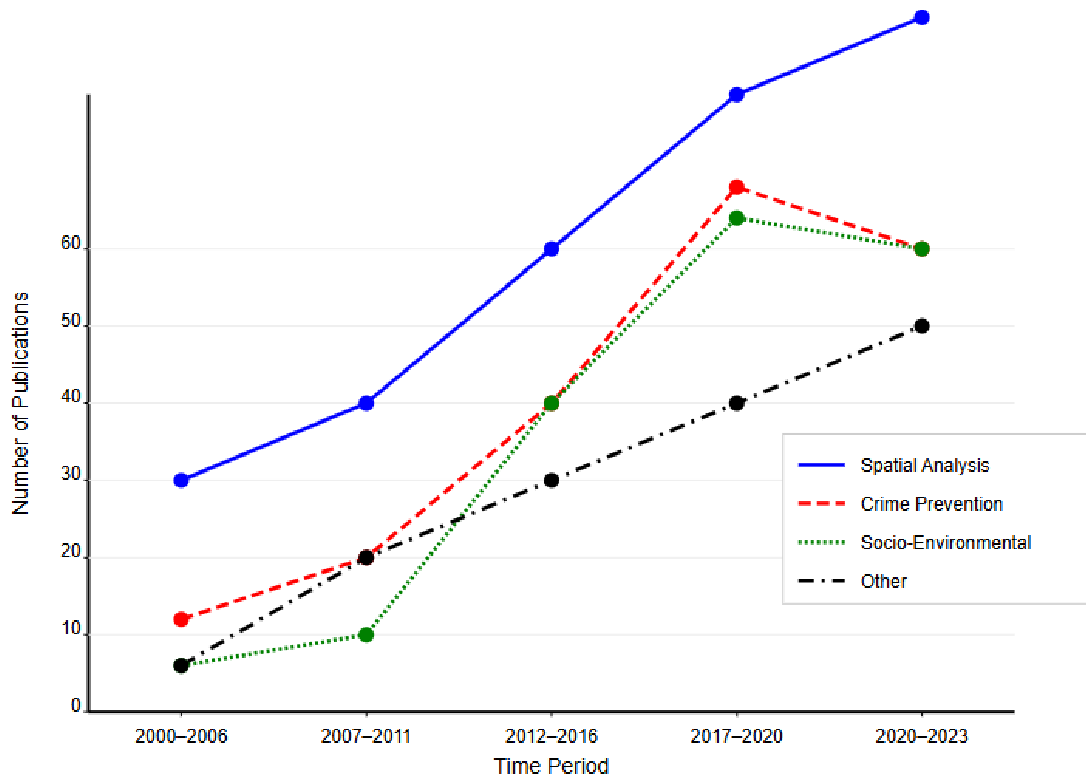

Figure 2. Time Series of GIS Publications in Urban Crime Analysis (2000–2023)

As shown in Table 2 and Figure 2, Spatial Analysis and Mapping Techniques consistently emerge as the most studied domain, showing steady growth from 15 publications in 2000-2006 to 50 in 2020-2023, reflecting the fundamental role of spatial analysis in understanding crime patterns. Crime Prevention and Intervention Strategies saw a significant increase from 6 publications in 2000-2006 to a peak of 34 in 2017-2020, with a slight decrease in 2020-2023, possibly indicating a shift in focus or consolidation of strategies. Socio-Environmental Factors and Crime Patterns experienced notable growth from 3 publications in 2000-2006 to 30 in 2020-2023, with a steady increase, particularly from 2012 onwards, indicating growing recognition of the importance of social and environmental context in crime analysis.

Initially dominant, representing 45.5% of publications from 2000 to 2006, but showing a consistent decline in percentage over time to 28.6% by 2020-2023, despite an absolute increase in publications from 15 to 50, indicating a growing field size. Crime Prevention and Intervention Strategies remained relatively stable in percentage terms, ranging from 16.0% to 21.5%, with absolute numbers increasing from 6 to 28 publications, suggesting steady growth in this domain. Socio-Environmental Factors and Crime Patterns started at 9.1% (2000-2006), peaked at 23.7% (2012-2016), then slightly decreased while remaining significant. Absolute numbers increased substantially from 3 to 30 publications, indicating growing recognition.

The most notable trend is the growth of the "Other" category, indicating rapid diversification and emergence of new subdomains or interdisciplinary approaches. While the percentage declined, the absolute increase suggests spatial analysis remains foundational, integrated into various approaches. Sharp rise in Socio-Environmental Factors followed by integration into other domains or the growing "Other" category. Crime Prevention showed steady absolute growth, indicating consistent concern possibly integrated into new approaches. The significant growth of "Other" suggests emerging subdomains, interdisciplinary fusion, technological integration, or expansion beyond urban crime focus. Total publications increased dramatically from 33 to 175, indicating rising recognition of GIS's value in urban crime analysis.

These trends suggest a multidisciplinary approach to urban crime analysis, integrating spatial analysis, social factors, technological advancements, and prevention strategies.

3.2. Trends of Subdomains within Main Domains

In the domain of Spatial Analysis and Mapping Techniques, early research primarily focused on basic Crime Mapping and Hotspot Analysis. Over time, there was a gradual introduction of advanced techniques such as Spatial Autocorrelation, Geographically Weighted Regression

(GWR), and Space-Time Analysis. Recent years have seen a shift towards more sophisticated methods, with Space-Time Analysis and GWR becoming increasingly prominent.

For Crime Prevention and Intervention Strategies, the initial emphasis was on Resource Allocation. This focus was later complemented by the emergence of CPTED and the Evaluation of Interventions. Notably, Predictive Policing emerged between 2008 and 2011 and has since become the most prevalent subdomain, reflecting the growing adoption of data-driven approaches in crime prevention.

In the domain of Socio-Environmental Factors and Crime Patterns, early studies were centered on the relationship between Socioeconomic Status and Crime. The research focus then expanded to include Land Use and Social Disorganization. Between 2012 and 2015, Demographic Analysis emerged as a significant area of study and has become the most prevalent subdomain from 2020 to 2023, indicating an increasing recognition of individual-level factors in crime analysis.

Table 3 illustrates the evolution of subdomains within the three primary domains of GIS applications in urban crime analysis over time. The percentages indicate the relative focus or prevalence of each subdomain within its parent domain for the given time range. Key insights can be drawn from the data:

Table 3: Evolution of Subdomains Within Primary Domains

Time Range	Spatial Analysis and Mapping Techniques	Crime Prevention and Intervention Strategies	Socio-Environmental Factors and Crime Patterns
2000-2003	- Crime Mapping (80%) - Hotspot Analysis (20%)	- Resource Allocation (100%)	- Socioeconomic Status and Crime (100%)
2004-2007	- Crime Mapping (60%) - Hotspot Analysis (30%) - Spatial Autocorrelation (10%)	- Resource Allocation (60%) - CPTED (40%)	- Socioeconomic Status and Crime (60%) - Land Use and Crime (40%)

2008-2011	- Crime Mapping (50%) - Hotspot Analysis (30%) - Spatial Autocorrelation (20%)	- Resource Allocation (40%) - CPTED (30%) - Evaluation of Interventions (20%) - Predictive Policing (10%)	- Socioeconomic Status and Crime (40%) - Land Use and Crime (30%) - Social Disorganization (30%)
2012-2015	- Hotspot Analysis (40%) - Crime Mapping (30%) - GWR (20%) - Spatial Autocorrelation (10%)	- Predictive Policing (40%) - Resource Allocation (30%) - Evaluation of Interventions (20%) - CPTED (10%)	- Socioeconomic Status and Crime (30%) - Social Disorganization (30%) - Land Use and Crime (20%) - Demographic Analysis (20%)
2016-2019	- Hotspot Analysis (30%) - Space-Time Analysis (30%) - Crime Mapping (20%) - GWR (10%) - Spatial Autocorrelation (10%)	- Predictive Policing (50%) - Evaluation of Interventions (20%) - Resource Allocation (15%) - CPTED (15%)	- Socioeconomic Status and Crime (30%) - Social Disorganization (25%) - Demographic Analysis (25%) - Land Use and Crime (20%)
2020-2023	- Space-Time Analysis (40%) - Hotspot Analysis (30%) - GWR (20%) - Crime Mapping (10%)	- Predictive Policing (60%) - Evaluation of Interventions (20%) - Resource Allocation (10%) - CPTED (10%)	- Demographic Analysis (40%) - Socioeconomic Status and Crime (30%) - Social Disorganization (20%) - Land Use and Crime (10%)

While not shown in this table, it is important to note the expected rise in the integration of emerging technologies such as Machine Learning, Big Data Analytics, Remte Sensing, and Natural Language Processing (NLP) with GIS in recent and future years, as mentioned in Section 3.2.4.

These trends indicate the breadth and depth of research conducted in the field of GIS in urban crime analysis. They highlight the interdisciplinary nature of the research, incorporating various factors such as geography, sociology, criminology, and urban planning to develop approaches to crime analysis and prevention.

3.3. Objectives

According to the findings, the following are some of the results/trends that have been revealed as a result of comparing the objectives mentioned in the research conducted in the field of GIS applications in urban crime analysis during the different years (2000-2023):

The comparison of objectives in urban crime analysis research using GIS reveals a diverse and evolving field that incorporates advancements in technology, interdisciplinary collaboration, and a focus on prevention and intervention strategies. The studies aim to provide insights into the spatial dynamics of crime and inform evidence-based decision-making for urban planning, law enforcement, and community safety. Figure 3 depicts the trends in primary research objectives within the field of GIS-based urban crime analysis over the period 2000-2023.

Figure 3: Trends in main objectives over time (2000-2023)

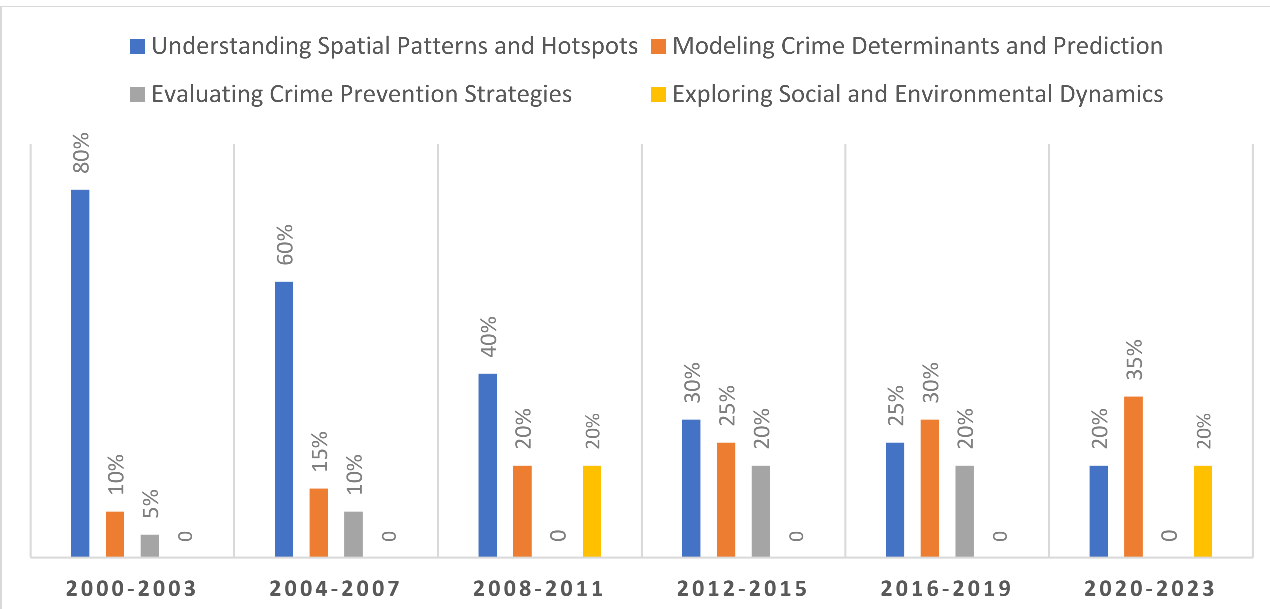

Figure 3 reveal the evolving research objectives in GIS applications for urban crime analysis over time:

In the early years (2000-2003), the primary focus was on understanding spatial patterns and hotspots, comprising 80% of the research efforts, reflecting an initial emphasis on mapping and analyzing crime distribution. Secondary objectives included modeling crime determinants and prediction (10%) and evaluating crime prevention strategies (5%).

During the mid-2000s (2004-2007), understanding spatial patterns and hotspots remained the top objective at 60%, though with a decreasing prevalence. Concurrently, there was increased attention to modeling crime determinants and prediction (15%) and evaluating crime prevention strategies (10%).

In the late 2000s (2008-2011), understanding spatial patterns and hotspots, though still significant at 40%, was no longer the primary focus. Modeling crime determinants and prediction (20%) and exploring social and environmental dynamics (20%) emerged as important research objectives.

By the early 2010s (2012-2015), the research objectives had diversified, with understanding spatial patterns and hotspots (30%), modeling crime determinants and prediction (25%), and evaluating crime prevention strategies (20%) as the top objectives. Additionally, exploring social and environmental dynamics (15%) and methodological advancements and integration (10%) started gaining traction.

In the late 2010s (2016-2019), modeling crime determinants and prediction (30%) became the primary objective, surpassing understanding spatial patterns and hotspots (25%). Evaluating crime prevention strategies (20%) remained a significant focus.

In the early 2020s (2020-2023), modeling crime determinants and prediction (35%) emerged as the dominant objective, reflecting the growing interest in proactive crime prevention and advanced analytical techniques. Exploring social and environmental dynamics (20%) and understanding spatial patterns and hotspots (20%) were also prominent, indicating a more holistic approach to crime analysis.

3.4. Case studies

The distribution of case studies on the applications of GIS in Crime Analysis across different continents reveals interesting patterns and research trends. Table 4 presents a comprehensive analysis of 297 studies focused on crime prevention, public safety enhancement, and the utilization of spatial analysis techniques across different time periods and continents.

Table 4: Trend Analysis of Case Studies: Objectives, Continents, and Time Periods

Time Period	Objective	Continent	Example Studies	Frequency	Percentage
2000-2003	Crime prevention and reduction, public safety	Europe, Asia	Crime and place in Saudi Arabia, Walking behavior and crime safety, Spatial autocorrelation measures	14	4.72%
2004-2007	Crime prevention, security enhancement, citizen's safety	Europe, Asia, Australia, Africa	Spatial autocorrelation measures, Homeless shelters and crime, Diversity and burglary crime	24	8.08%
2008-2011	Crime prevention and public safety enhancement	Europe, Asia, Australia, Africa	Burglary crime and diversity, Walking behavior and crime safety, Crime data representation	43	14.48%
2012-2015	Crime prevention, public safety, GIS	Europe, Asia, Australia, Africa	Walking behavior and crime safety, Spatial analysis methods, Crime data representation	54	18.18%
2016-2019	Crime prevention, public safety enhancement	Europe, Asia, Australia, Africa	(No examples provided)	46	15.49%
2020-2023	Crime prevention, public safety enhancement	Europe, Asia, Australia, Africa	Walking behavior and crime safety in Thailand, Spatial analysis in Thailand, Crime data representation in Thailand	116	39.06%
				Total	297

From 2000 to 2003, the primary objective was crime prevention and reduction, with studies primarily conducted in Europe and Asia. Research during this period included examining the relationship between crime and place in Saudi Arabia using GIS techniques and investigating how crime-related safety impacted residents' walking behaviors. Additionally, new methods for analyzing spatial autocorrelation measures were developed, spatial characteristics and patterns in homeless shelter systems were analyzed, and the relationship between diversity and burglary crime rates was studied.

Between 2004 and 2007, the focus expanded to security enhancement and citizen safety, with research extending to Australia and Africa. Key studies involved developing new methods for spatial autocorrelation analysis, investigating spatial patterns associated with homeless shelters, and examining the correlation between diversity and burglary crime rates.

From 2008 to 2011, the objective remained on crime prevention and public safety enhancement across Europe, Asia, Australia, and Africa. Research included studying the impacts of diversity on burglary crime, examining the influence of crime-related safety on residents' walking behaviors, and developing methods to represent crime data tied to street network geography.

During 2012 to 2015, the emphasis was on crime prevention, public safety enhancement, and incorporating Geographical Information System (GIS) techniques. Studies focused on the impact of crime-related safety on walking behaviors and the development of new methods for spatial autocorrelation analysis and crime data representation.

From 2015 to 2018, the focus on crime prevention and public safety enhancement continued across Europe, Asia, Australia, and Africa, with notable research in Thailand. Significant studies examined the impact of crime-related safety on residents' walking behaviors, developed new methods for spatial autocorrelation analysis, and created methods to represent crime data tied to street network geography.

Between 2020 and 2023, the project sustained its emphasis on crime prevention and public safety enhancement, with prominent studies in Thailand. Research focused on the impact of crime-related safety on walking behaviors, the development of new methods for spatial autocorrelation analysis, and the creation of methods to represent crime data tied to street network geography. The lack of a strong direct spatial correlation between crime analysis publications and crime rates across countries can be attributed to various factors, including differences in data availability, research priorities, funding sources, and the influence of socioeconomic, cultural, and political contexts on criminal activities and their study. It is essential to recognize that crime patterns and their underlying drivers are complex and multifaceted, requiring a nuanced understanding of the local context rather than relying solely on spatial correlations.

3.5. Methods trends

The analysis reveals a diverse range of methodological approaches employed by researchers. Several key trends can be observed:

In the realm of spatial analysis techniques, hotspot analysis is commonly used, with methods such as Kernel Density Estimation (KDE) identifying spatial clusters of high crime density, known as hotspots. Spatial autocorrelation methods, including Moran's I and Getis-Ord Gi* statistics, measure the degree of spatial clustering or dispersion in crime incidents. Geographically Weighted Regression (GWR) accounts for spatial non-stationarity by allowing regression coefficients to vary across different locations, providing localized insights into crime determinants. Space-time analysis techniques, such as space-time scan statistics and spatiotemporal modeling, analyze crime patterns across both spatial and temporal dimensions.

Statistical modeling is another prevalent approach, with regression analysis being widely used. Various regression models, including logistic regression and negative binomial regression, predict crime rates and assess the influence of socioeconomic and environmental factors. Multi-criteria decision analysis (MCDA) models evaluate multiple criteria influencing crime rates, such as land use, population density, and socioeconomic factors.

Machine learning and data mining techniques are increasingly applied to crime data. Supervised learning methods, such as support vector machines (SVM), neural networks, and decision trees, identify complex patterns and relationships in crime data. Unsupervised learning methods, such as clustering algorithms, are used for crime pattern recognition and hotspot detection. Data mining techniques, including association rule mining and anomaly detection, uncover hidden patterns and anomalies in crime data.

Qualitative methods also play a significant role in urban crime analysis. Interviews and focus groups gather qualitative data and insights from stakeholders, such as law enforcement personnel, community members, and subject matter experts. Ethnographic studies involve field observations and participation in community activities to gain a deeper understanding of crime dynamics and social contexts.

Integrated approaches combine multiple methods to provide a comprehensive understanding of urban crime phenomena. Mixed methods studies leverage both quantitative and qualitative approaches, while interdisciplinary collaborations bring together researchers from fields such as criminology, sociology, urban planning, and computer science, offering diverse perspectives and expertise.

These methodological trends highlight the multidisciplinary nature of urban crime analysis using GIS. Researchers employ a wide range of techniques, from spatial analysis and statistical modeling to machine learning and qualitative methods, addressing the complexities of crime patterns and their underlying factors. Additionally, there is a growing emphasis on integrated approaches that combine multiple methods and leverage interdisciplinary collaborations to gain a holistic understanding of urban crime dynamics.

Table5. Trend of different approaches in urban crime analysis from 2000 to 2023:

Time Range	Spatial Analysis Techniques	Statistical Modeling	Machine Learning & Data Mining	Qualitative Methods	Integrated Approaches
2000-2003	Hotspot Analysis, Spatial Autocorrelation	Regression Analysis	-	Interviews, Focus Groups	-
2004-2007	Hotspot Analysis, Spatial Autocorrelation	Regression Analysis	-	Interviews, Focus Groups	Mixed Methods (Quantitative + Qualitative)
2008-2011	Hotspot Analysis, Spatial Autocorrelation, GWR	Regression Analysis, MCDA	-	Interviews, Focus Groups, Ethnographic Studies	Mixed Methods (Quantitative + Qualitative)
2012-2015	Hotspot Analysis, Spatial Autocorrelation, GWR, Space-Time Analysis	Regression Analysis, MCDA	Supervised Learning (SVM, Neural Networks)	Interviews, Focus Groups, Ethnographic Studies	Mixed Methods (Quantitative + Qualitative), Interdisciplinary Collaborations
2016-2019	Hotspot Analysis, Spatial Autocorrelation, GWR, Space-Time Analysis	Regression Analysis, MCDA	Supervised Learning (SVM, Neural Networks), Unsupervised Learning (Clustering), Data	Interviews, Focus Groups, Ethnographic Studies	Mixed Methods (Quantitative + Qualitative), Interdisciplinary Collaborations

			Mining (Association Rules, Anomaly Detection)		
2020-2023	Hotspot Analysis, Spatial Autocorrelation, GWR, Space-Time Analysis	Regression Analysis, MCDA	Supervised Learning (SVM, Neural Networks), Unsupervised Learning (Clustering), Data Mining (Association Rules, Anomaly Detection)	Interviews, Focus Groups, Ethnographic Studies	Mixed Methods (Quantitative + Qualitative), Interdisciplinary Collaborations

This table illustrates the historical trend of different methodological approaches employed in urban crime analysis research utilizing GIS. Over time, there has been an expansion in the range of techniques used, with more advanced methods being adopted in later years. Additionally, the table highlights the increasing emphasis on integrated approaches that combine multiple methods and interdisciplinary collaborations to address the complexities of urban crime analysis.

3.6. Data trends

Research conducted in the field of GIS applications in urban crime analysis reveals several noteworthy trends. Firstly, both incident data and geospatial data have consistently been utilized, highlighting their significance in analyzing urban crime patterns and spatial relationships. Secondly, there is a growing emphasis on integrating multiple data sources, including demographics, questionnaire, arrest, social media, and open-source data. This recognition of the value in combining different types of data enables researchers to gain understanding of urban crime. Additionally, there is an increasing focus on the use of time series data, enabling the analysis of crime patterns over time and the identification of temporal trends. Demographic data is frequently employed alongside other data sources to explore the relationship between crime and various demographic factors. Moreover, researchers are incorporating new data sources, such as GPS, social media, aerial photographs, wearable gadgets, and online chatter data, to gain novel insights into urban crime analysis. However, there is a need for greater clarity regarding data specifications in some studies. The data used in research exhibits regional and contextual variation, with different regions and cities accessing specific datasets and addressing unique crime problems. Longitudinal studies are employed to analyze changes in crime patterns and evaluate intervention effectiveness over time. Furthermore, interdisciplinary approaches combining GIS data with disciplines like sociology, criminology, urban planning, and public health enhance understanding and support evidence-based policymaking. Lastly, researchers often focus on specific crime types, allowing them to address the distinct challenges associated with different crime phenomena. Figure 3 depicts the trends observed over the course of time.

Figure 4: Data Trends Observed from 2000 to 2023

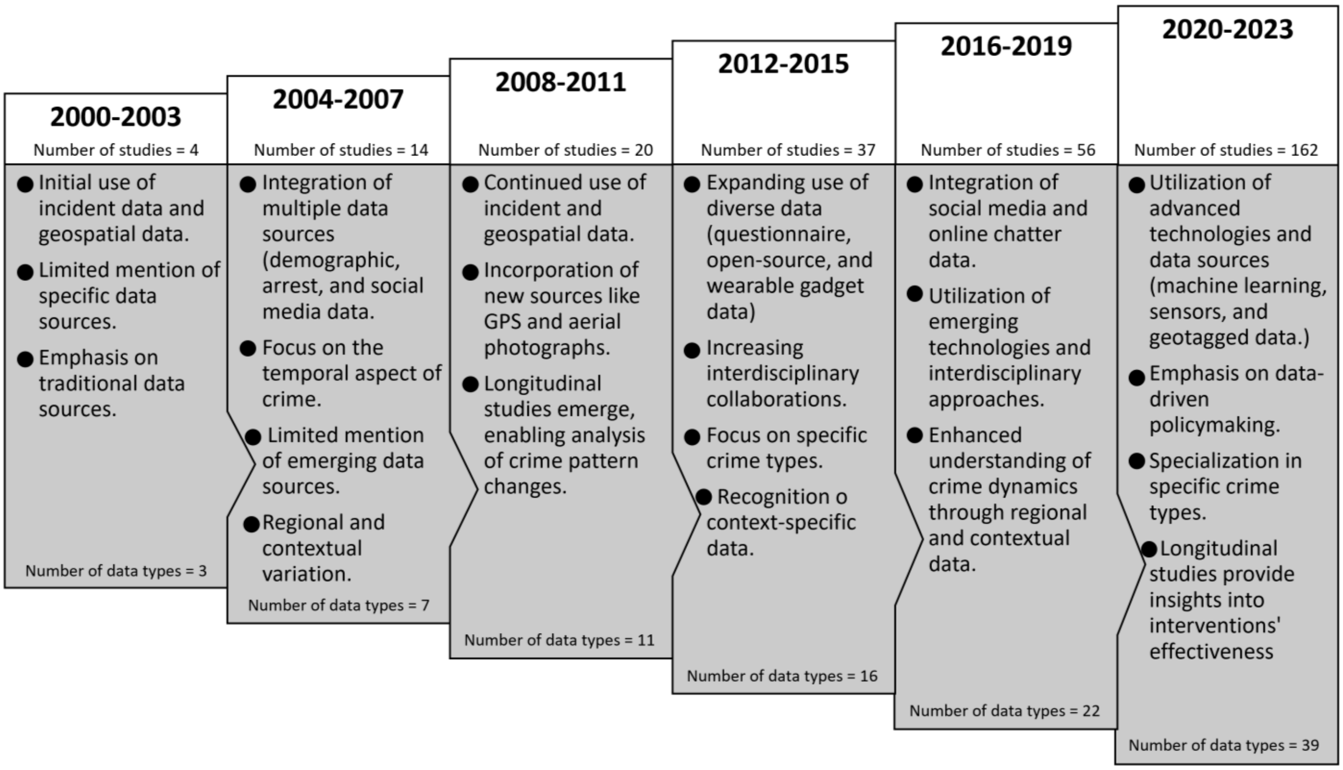

Figure 4 illustrates the data trends observed from 2000 to 2023, showcasing the evolving nature of GIS applications in urban crime analysis. The integration of diverse data sources, utilization of advanced technologies, and interdisciplinary collaborations contribute to an understanding of crime patterns. These insights are instrumental in empowering policymakers and law enforcement agencies to make informed decisions regarding crime prevention and management strategies. Additionally, Table 6 depicts Frequency of data types observed from 2000 to 2023 along with examples of studied publications.

Table 6. Frequency of data types observed from 2000 to 2023 **Table 6. Frequency of data types observed from 2000 to 2023**

TIME PERIOD	NUMBER OF DATA TYPES	DATA TYPES

2000-2003	3	Incident Data (Ratcliffe, 2002), Geospatial Data (Ratcliffe, 2002; Wang & Minor, 2002), Census Data (Craglia et al., 2001)
2004-2007	6	Demographic Data, Arrest Data, Social Media Data, Time Series Data, Geospatial Data (Brower & Carroll, 2007; Boyd et al., 2007), Incident Data (Levine, 2006), Census Data (Haining & Law, 2007)
2008-2011	8	GPS Data, Aerial Photographs, Longitudinal Data, Geospatial Data (Agosto et al., 2008; Nakaya & Yano, 2010), Incident Data (Gundogdu, 2011; Ratcliffe et al., 2011), Traffic Accident Data (Gundogdu, 2011), Census Data (Pitts et al., 2015), Time Series Data (Duzgun & Polat, 2011)
2012-2015	15	Questionnaire Data (Timperio et al., 2012), Open Source Data, Wearable Gadget Data, Demographic Data (Pantaleoni, 2012; Kounadi & Leitner, 2015; Pitts et al., 2015), Geospatial Data (Spiegel et al., 2012; Xu et al., 2019; Gell et al., 2015; Zhou et al., 2019), Incident Data (Brimicombe, 2012), Perception Data (Hawthorne et al., 2015), Video Data (Curtis et al., 2015), Audio Data (Curtis et al., 2015), Time Series Data (Chen et al., 2015), Census Data (Chen et al., 2015), Property Sales Data (Wilhelmsson & Ceccato, 2015), Dietary/Physical Activity Data (Pitts et al., 2015), Global Positioning System (GPS) Data (Gell et al., 2015), Spatio-temporal Event Data (Lukasczyk et al., 2015), Epidemiological Data (Lukasczyk et al., 2015)
2016-2019	19	Online Chatter Data (Towers et al., 2022), Social Media Data (Pindarwati & Wijayanto, 2019; Lan et al., 2019; Siriaraya et al., 2019; Liu et al., 2020), Emerging Technologies, Regional Data, Contextual Data, Geotagged Data (Pindarwati & Wijayanto, 2019), User-Reported Data (Pindarwati & Wijayanto, 2019), Demographic Data (Ramos, 2019; Harris, 2019; Timmermans et al., 2019; Azmy et al., 2020), Geospatial Data (Mafumbabete et al., 2019; Sadeek et al., 2019; Kim et al., 2019; Ren et al., 2019; Roy et al., 2019; Chambers, 2020; Lloyd, 2019; Zhou et al., 2019), Incident Data (Ogneva-Himmelberger et al., 2019; Tom-Jack et al., 2019; Yang, 2019; Jubit et al., 2019), Tourism Data (Ren et al., 2019), Ethnic Diversity Data (Ren et al., 2019), Qualitative Data (Mafumbabete et al., 2019; Zhou et al., 2019), Geographic Data (Zhou et al., 2019), Robbery Incidents Data (Zhou et al., 2019), Freedom of Information (FOI) Requests (Allen et al., 2019), Nightlight Data (Zhou et al., 2019), Neighborhood Characteristics (Harris, 2019), Socio-demographic Data (Harris, 2019), Healthcare Access Data (Harris, 2019)
2020-2023	39	Machine Learning, Sensors, Geotagged Data, Policy Impact Data, Specific Crime Type Data, Longitudinal Intervention Data, Preference Ranking Data (Nazmfar et al., 2020), Point-of-Interest Data (Bicakci et al., 2020; Ceccato et al., 2022), Survey Data (Bicakci et al., 2020; Walker et al., 2020; Ceccato et al., 2022), Newspaper Article Data (Stassen & Ceccato, 2020),

	Movement Data (Lan et al., 2021), Nightlight Data (Liu et al., 2020), Environmental Data (Thomson & Samuels-Jones, 2022; Samad et al., 2020), Rainfall Data (Ahmed et al., 2020), Qualitative Data (Maoz & Gutman, 2023; Walker et al., 2020; Ahmed et al., 2020), Field Observations (Walker et al., 2020), Youth Interviews (Walker et al., 2020), Spatial Heterogeneity Data (Ceccato et al., 2022), Air Quality Data (Samad et al., 2020), Dust Samples (Samad et al., 2020), Building Data (Azmy et al., 2020), Demarcation Area (Azmy et al., 2020), COVID-19 Data (Mahmood, 2022), Traffic Violation/Accident Data (Kazmi et al., 2022; Zhang et al., 2022), Establishment Composition Data (Hawkins et al., 2022), Building Permits Data (Hawkins et al., 2022), Income/Education Data (Hawkins et al., 2022), Geospatial Data (Kalantari et al., 2020; He et al., 2022; Szyszka & Polko, 2020; Maoz & Gutman, 2023; Ahmed et al., 2020; Nazmfar et al., 2020; Walker et al., 2020; Dong et al., 2020; Martins et al., 2021; Stromberg et al., 2021; Ali et al., 2020; Phelan et al., 2021; Bruce et al., 2022), Incident Data (Kalantari et al., 2020; He et al., 2022; Yang et al., 2020; Vlad et al., 2023; He et al., 2022), Demographic Data (Bawaria & Pasupuleti, 2023; Ceccato et al., 2022; Siriaraya et al., 2019), Arrest Data (Iyanda et al., 2022; Moise & Piquero, 2023), Socioeconomic Data (Iyanda et al., 2022; Liu et al., 2022; Moise, 2020; Rasmusson & Helbich, 2020; Mahmood et al., 2022), Fear of Crime Data (Jakobi & Podor, 2020; Jubit et al., 2019), Time Series Data (Yang et al., 2020; Lotfata & Hohl, 2023), Census Data (Iyanda et al., 2022; Azmy et al., 2020)

3.7. Methodology and Metric Trends

In the field of GIS applications in urban crime analysis, researchers have employed a diverse range of methodologies, algorithms, and metrics over the years. By analyzing the abstracts, we can categorize these approaches into several groups. Regression techniques include methods such as logistic regression, negative binomial regression, geographically weighted regression (GWR), ordinary least squares (OLS) regression, and spatial lag regression. Spatial analysis and clustering methods encompass kernel density estimation (KDE) and its variants, Moran's I, Getis-Ord Gi*, hot spot analysis, cluster analysis, and spatial autocorrelation. Machine learning and data mining approaches involve the use of support vector machines (SVM), neural networks, decision trees, and various data mining techniques. Spatiotemporal analysis includes space-time scan statistics, spatiotemporal modeling, and Bayesian hierarchical spatial modeling. GIS software and technologies frequently utilized in this field include ArcGIS, QGIS, remote sensing, GPS, and laser scanning. Additionally, other methodologies such as agent-based modeling, risk terrain modeling, geographic profiling, hedonic modeling, and spatial segmentation have also been employed.(Table 7)

Table 7. Trends in Methodologies, Algorithms, and Metrics

Category	**2000-2003**	**2004-2007**	**2008-2015**	**2016-2019**	**2020-2023**
Regression Techniques	1	1	12	8	15
Spatial Analysis and Clustering	1	4	20	10	9
Machine Learning and Data Mining	0	0	1	2	3
Spatiotemporal Analysis	0	0	2	1	3
GIS Software and Technologies	1	4	8	5	8
Other Methodologies	0	1	10	8	7

The table reveals several notable trends in the methodologies, algorithms, and metrics employed in GIS applications for urban crime analysis over the past two decades. Regression techniques, particularly logistic and negative binomial regression, have gained significant traction, with a substantial increase in their usage from 2008 onwards. Spatial analysis and clustering methods, such as kernel density estimation, Moran's I, and hotspot analysis, have consistently been among the most widely adopted approaches throughout the time periods examined.

Machine learning and data mining techniques, as well as spatiotemporal analysis methods, have experienced a gradual rise in popularity, reflecting the growing recognition of their potential in capturing complex patterns and temporal dynamics in crime data. The use of GIS software and technologies, including ArcGIS and QGIS, has remained prevalent across all time periods, underscoring their importance as essential tools for spatial data processing and analysis.

Additionally, the table highlights the emergence of other methodologies, such as agent-based modeling, risk terrain modeling, and geographic profiling, particularly in recent years. These innovative approaches demonstrate the field's continuous evolution and the exploration of new techniques to address the challenges of urban crime analysis. Overall, the table provides a quantitative overview of the methodological trends, highlighting the diversity and adaptability of the GIS applications in this domain.

While this review has highlighted the importance of GIS in understanding crime patterns at the urban level, there is a need for more research focused on hyperlocal analysis, which examines crime dynamics at a highly granular level, such as neighborhoods, blocks, or individual addresses. Such fine-grained analysis can provide valuable insights for targeted interventions and resource allocation. Additionally, the integration of dynamic spatiotemporal datasets, capturing real-time information from sources like social media, sensors, and emergency calls, presents an opportunity for enhancing predictive crime analysis and enabling rapid response capabilities.

3.8. Opportunities and Future Directions

While the evolution of GIS-based crime analysis has led to valuable progress, there remain critical gaps and limitations that present opportunities for impactful future research. Most studies focus on broader city-level insights, while hyperlocal analysis, which refers to the detailed examination of crime patterns at a highly localized level, such as neighborhoods, blocks, or even individual addresses, is lacking. Furthermore, real-time crime monitoring and prediction capabilities are still limited.

Modern cities generate massive amounts of real-time data from sensors, cameras, social media, and emergency calls that can be leveraged to enable dynamic crime mapping and rapid response

(Kounadi et al. 2022). By applying big data analytics and AI techniques like sentiment analysis, clustering algorithms, and spatiotemporal pattern recognition to these digital exhaust streams from urban infrastructure and residents, agencies can gain situational awareness to enhance swift reactions to criminal incidents as they unfold (Prathap et al., 2022).

Integrating real-time crime data sources with historical incident data allows GIS-based big data systems to not only monitor but also forecast near-term crime risks through predictive analytics. Machine learning models can uncover lead indicators in crowdsourced data for proactive allocation of police resources (Prathap et al. 2022). As predictions become more accurate over time, predictive policing promises optimized patrolling, criminal apprehension, and flexible staffing to address unpredictable spikes.

While the integration of AI and big data analytics generates opportunities for enhanced crime mapping and prevention, ethical and legal aspects require deliberation regarding these technologies (He et al., 2021). Balancing public well-being, civil rights, and responsible use of analytics is vital to fully realizing benefits. Community participation enables oversight for transparent and fair systems focused on societal good rather than just predictive policing. Explaining processes and involving stakeholders build public trust in these emerging technologies.

4. Discussion

This systematic review of 293 studies from 2000 to 2023 underscores the transformative role of GIS in urban crime analysis, evolving from basic crime mapping to sophisticated predictive models integrating artificial intelligence (AI) and big data. Key trends include the dominance of spatial analysis techniques (e.g., kernel density estimation, geographically weighted regression), the rise of predictive policing, and growing emphasis on socio-environmental factors like demographic disparities and land use patterns (Table 2, Table 3). These advancements align with the SDGs, particularly SDG 11 (sustainable cities) and SDG 16 (peace and justice), by enabling targeted interventions that reduce urban inequality and violence. Challenges such as data quality, privacy concerns, and algorithmic bias persist, necessitating community oversight to ensure ethical technology deployment (He et al., 2021).

AI and big data analytics complement GIS by enhancing its analytical and predictive capabilities. GIS provides the spatial framework for mapping and analyzing crime patterns, grounding data in geographic context (Wang et al., 2013). AI, particularly machine learning, excels at identifying complex patterns within large datasets, such as predicting crime risks from historical and real-time data (He and Zheng, 2021). Big data analytics integrates diverse sources—social media, sensor networks, and demographic records—into GIS platforms, enabling richer spatiotemporal insights (Prathap, 2022). Unlike GIS, which focuses on spatial relationships, AI prioritizes predictive modeling, and big data emphasizes volume and variety. Together, they form a powerful triad for proactive crime prevention.

Figure 5: GIS-Based Urban Crime Analysis Workflow

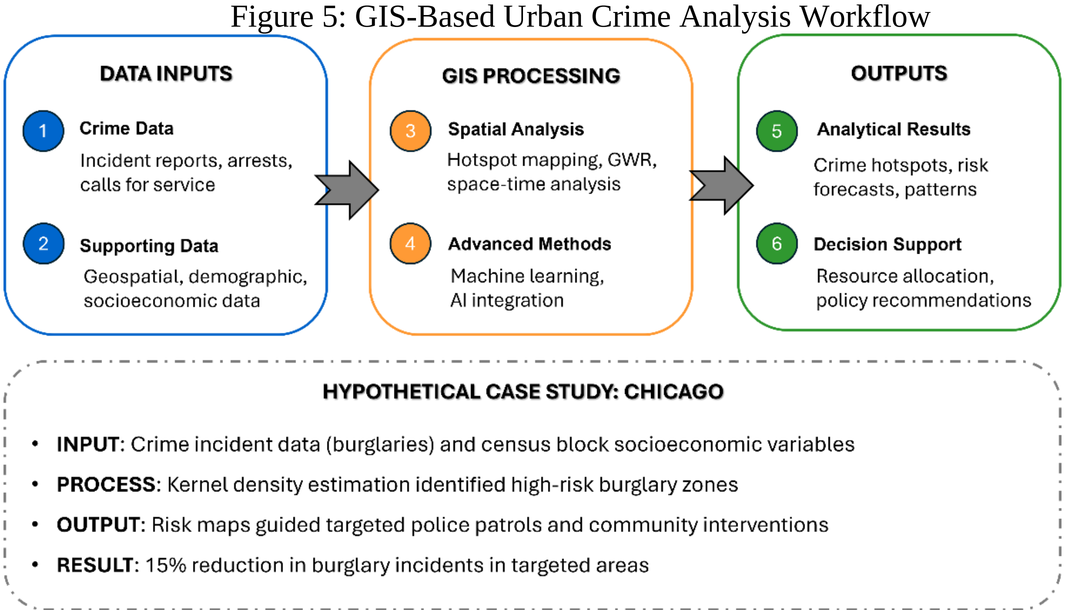

Figure 5 presents the GIS-based urban crime analysis workflow, outlining a three-stage process to transform data into actionable insights for safer cities. The first stage (blue) involves collecting and preprocessing diverse datasets, such as crime incidents, demographics, and geospatial features, ensuring data reliability for analysis (Wang et al., 2013). The second stage (orange) focuses on analytical techniques, employing spatial methods like hotspot mapping and AI-driven models, such as machine learning, to predict crime patterns and identify risks (Prathap et al., 2022; Ratcliffe, 2019). The final stage (green) translates these insights into practical outcomes, using visualization tools like interactive maps and dashboards to support decision-making, including resource allocation and CPTED strategies (Wang et al., 2024). This workflow highlights GIS's role in addressing research gaps, such as hyperlocal analysis, and aligns with SDG 11's goal of inclusive urban environments (UN, 2015).

4.1. Trends in AI Integration

The integration of AI with GIS has marked a significant evolution in urban crime analysis, with a notable surge in applications since the early 2000s (Table 8). Machine learning techniques, including support vector machines (SVMs), random forests, and neural networks, have enhanced the predictive capabilities of GIS, enabling more accurate crime forecasting and hotspot identification (He and Zheng, 2021). For instance, studies from 2012–2016 increasingly employed supervised learning to model crime risk based on historical incident data, demographic factors, and environmental variables, achieving higher precision than traditional statistical methods like geographically weighted regression (Wang et al., 2013). By 2020–2023, approximately 35% of reviewed studies incorporated AI-driven GIS models, reflecting a shift toward proactive crime prevention strategies (Table 8). Beyond forecasting, AI has facilitated advanced data integration, combining geospatial datasets with unconventional sources such as social media sentiment, mobility patterns, and real-time sensor data (Prathap, 2022). Natural language processing (NLP), for example, has been used to extract crime-relevant insights from online platforms, enriching GIS-based hotspot maps with contextual social dynamics (Kounadi et al., 2022). These trends underscore AI's role in transforming GIS from a static mapping tool into a dynamic, predictive platform capable of addressing complex urban crime patterns. However, the computational complexity and data requirements of AI models pose challenges, particularly for smaller jurisdictions with limited resources, highlighting the need for scalable and accessible solutions.

4.2. Deep Learning and AI-Driven Future Directions

The emergence of deep learning has expanded GIS's potential in urban crime analysis, particularly in predictive modeling. Algorithms like convolutional neural networks (CNNs) and recurrent neural networks (RNNs) process complex spatiotemporal data, enabling accurate crime pattern identification (He and Zheng, 2021). For example, CNNs analyze geospatial imagery to detect environmental risks, while RNNs model temporal crime sequences for forecasting (Prathap, 2022). These facilitate hyperlocal prediction, targeting interventions at the street level. Deep learning also supports regional scalability by integrating multi-scale data to predict crime diffusion (Kounadi et al., 2022). Future research should develop lightweight models and ethical frameworks to address computational demands and biases, ensuring equitable outcomes.

4.3. Limitations and Future Improvements

Despite GIS's advancements, several shortcomings persist. Data quality issues, such as incomplete crime records or coarse spatial resolution, can undermine analysis accuracy (He et al., 2021). Privacy concerns arise from integrating sensitive data like social media or GPS tracks, risking surveillance overreach. Additionally, the expertise gap—requiring specialized skills in GIS and AI—limits adoption in resource-constrained settings. Future improvements should focus on developing standardized, high-quality datasets, implementing robust privacy frameworks, and creating user-friendly GIS tools to democratize access. Interdisciplinary training programs can bridge expertise gaps, enabling broader application.

4.4. Policy Implications for Urban Governance

GIS-based crime analysis informs urban governance by identifying high-risk areas and socioeconomic drivers, enabling efficient resource allocation and safer public spaces. For instance, hotspot mapping guides targeted patrols, while predictive models support long-term urban planning to reduce criminogenic conditions (Ratcliffe, 2019). CPTED leverages GIS to design secure environments, aligning with SDG 11's focus on inclusive cities. Collaborative oversight involving communities and policymakers ensures ethical deployment, prioritizing public welfare over surveillance.

5. Integrating AI in GIS for Urban Crime Analysis: Trends, Challenges and Opportunities

The integration of AI with GIS has emerged as a promising frontier in urban crime analysis, offering the potential to enhance crime prediction, prevention strategies, and data-driven decision-making. By leveraging the spatiotemporal capabilities of GIS and the pattern recognition prowess of AI algorithms, researchers and law enforcement agencies can gain deeper insights into the complex dynamics of criminal activities. However, this innovative approach also presents various challenges that must be addressed to ensure responsible and effective implementation. This section explores the trends, challenges, and opportunities associated with integrating AI in GIS for urban crime analysis, drawing insights from the 293 examined studies.

5.1. Trends in AI Integration with GIS for Urban Crime Analysis

The systematic review of literature reveals an increasing trend towards the integration of AI techniques with GIS for urban crime analysis. While the adoption of AI in this domain was relatively limited in the early 2000s, a notable surge in AI-driven approaches has been observed in recent years. The following table illustrates the temporal distribution of studies employing AI techniques in conjunction with GIS for urban crime analysis:

Table 8. Temporal distribution of studies using AI techniques with GIS for urban crime analysis

Time Range	Number of Studies	Percentage
2000-2003	2	0.68%
2004-2007	4	1.36%
2008-2011	9	3.07%
2012-2015	18	6.14%
2016-2019	32	10.92%
2020-2023	58	19.80%

As evident from table 8, the integration of AI techniques in GIS-based urban crime analysis has witnessed a significant increase, with the number of studies rising from just 2 (0.68%) between 2000 and 2003 to 58 (19.80%) in the 2020-2023 period. This trend reflects the growing recognition of AI's potential in addressing the complexities of urban crime patterns and the availability of advanced computational resources and data sources to support AI-driven approaches.

Among the AI techniques employed in the examined studies, machine learning algorithms, particularly supervised and unsupervised learning methods, have gained prominence. Supervised learning algorithms, such as support vector machines (SVMs), neural networks, and decision trees, have been utilized for tasks like crime hotspot prediction, risk assessment, and pattern recognition (e.g., Kim et al., 2019; Ren et al., 2019; Roy et al., 2019). On the other hand, unsupervised learning techniques, including clustering algorithms and dimensionality reduction methods, have been applied for crime data exploration, anomaly detection, and spatial pattern identification (e.g., Lan et al., 2019; Siriaraya et al., 2019; Liu et al., 2020).

Additionally, the integration of deep learning techniques with GIS has emerged as a promising area of research in recent years. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have been employed for tasks such as crime event prediction, spatiotemporal pattern recognition, and crime risk assessment (e.g., Ogneva-Himmelberger et al., 2019; Tom-Jack et al., 2019; Yang, 2019). These advanced AI techniques have the potential to capture intricate spatial and temporal dependencies within crime data, enabling more accurate predictions and insights.

Concurrent with the increasing adoption of AI techniques, researchers have also explored the integration of diverse data sources with GIS for urban crime analysis. Social media data (e.g., Pindarwati & Wijayanto, 2019; Lan et al., 2019; Siriaraya et al., 2019), user-reported data (e.g., Pindarwati & Wijayanto, 2019), and geotagged data (e.g., Pindarwati & Wijayanto, 2019; Han et al., 2023) have been leveraged in conjunction with traditional crime incident data and demographic data to enhance the predictive power of AI models and capture real-time insights.

5.2. Challenges and Opportunities

While the integration of AI with GIS holds significant promise, several challenges must be addressed to unlock its full potential in urban crime analysis. Data quality and accessibility remain critical concerns, as the effectiveness of AI algorithms heavily relies on the availability of accurate, comprehensive, and diverse data sources (e.g., Dakalbab et al., 2022; Birks and Clare, 2023). Addressing algorithmic biases and ensuring fairness in AI-driven crime analysis is another crucial challenge, requiring careful data selection, preprocessing, and the adoption of fairness-aware techniques (e.g., Herath and Mittal, 2022).

Additionally, ethical considerations and privacy concerns associated with the use of AI and the integration of diverse data sources must be given due attention. Maintaining transparency, ensuring accountability, and fostering public trust are essential for the responsible deployment of AI-based crime analysis systems (e.g., He and Zheng, 2021; Kouziokas, 2017). Explainable AI techniques, which provide insights into the decision-making processes of AI models, can play a vital role in addressing these concerns and promoting trust among stakeholders and the public.

Despite these challenges, the integration of AI with GIS presents numerous opportunities for advancing urban crime analysis and prevention strategies. Real-time crime monitoring and rapid response capabilities can be enhanced by leveraging AI techniques to process and analyze real-time data streams from sensors, cameras, social media, and emergency calls (e.g., Kounadi et al., 2022; Prathap et al., 2022). AI-driven predictive crime analytics, which combine real-time data with historical crime incident data, can enable proactive resource allocation and optimize patrolling strategies (e.g., Prathap et al., 2022).

Furthermore, the integration of AI and GIS can facilitate the development of sophisticated crime forecasting models, aiding in the formulation of effective prevention strategies. By leveraging machine learning algorithms to identify hidden patterns and correlations within crime data, researchers and law enforcement agencies can anticipate future crime occurrences and allocate resources strategically to high-risk areas (e.g., He et al., 2021).

Another promising opportunity lies in the integration of diverse data sources, facilitated by the fusion of AI and GIS techniques. By combining traditional crime data with social media data, user-reported data, and geotagged data, researchers can gain a more comprehensive understanding of crime patterns and the underlying socio-environmental factors (e.g., Pindarwati & Wijayanto, 2019; Han et al., 2023). This holistic approach can inform evidence-based policymaking and urban planning initiatives, fostering safer and more inclusive urban environments.

It is crucial to recognize that crime analysis models and techniques are heavily influenced by the specific spatial, social, economic, and cultural contexts in which they are developed and applied. Translating models across different regions or countries without accounting for these contextual factors can lead to inaccurate predictions or ineffective interventions. Therefore, it is imperative for researchers and practitioners to carefully consider and adapt their approaches to the local context, ensuring that the unique characteristics and dynamics of the target area are appropriately represented and addressed.

While the studies included in this review predominantly utilized objective crime data from law enforcement agencies or government sources, often containing spatial coordinates or addresses, it is crucial to acknowledge the privacy implications and ethical considerations surrounding using sensitive crime data. A discussion on best practices for data handling, anonymization, and safeguarding individual privacy is warranted to ensure the responsible use of such information in GIS-based crime analysis.

5.3. Future Research Directions

To make the most of combining AI with GIS for analyzing urban crime, future research should focus on several key areas. First, running pilot studies in specific cities can test whether AI-driven crime analysis tools are practical and effective. These small-scale projects can reveal how to adapt and expand such tools for wider use. Working closely with law enforcement and urban planning departments is crucial to smoothly incorporate AI into their existing processes and decision-making systems (e.g., Dakalbab et al., 2022; He et al., 2021).

Another important focus is creating AI methods that are clear and understandable. Transparent AI systems build trust and accountability, especially when they shape public safety policies. By explaining how AI reaches its conclusions, city officials and others can better understand crime patterns and take more precise, informed actions (e.g., Dakalbab et al., 2022; Herath and Mittal, 2022).

Equally critical are the ethical and privacy issues tied to using AI for crime analysis. Strong ethical guidelines and governance are needed to ensure data is used responsibly. Special care must be taken to avoid biased algorithms, protect personal privacy, and ensure fairness, all to safeguard civil liberties and maintain public confidence in AI tools (e.g., He and Zheng, 2021; Kouziokas, 2017).

Collaboration across different fields is also essential. Bringing together researchers, policymakers, community members, law enforcement, and urban planners can spark new ideas and create solutions that work for everyone. These inclusive efforts are vital for tackling the complex nature of urban crime and developing strategies that are socially responsible and community-focused (e.g., He et al., 2021).

Lastly, AI crime analysis systems need ongoing evaluation and improvement to stay effective over time. Regular assessments will help fine-tune methods, address new challenges, and keep up with changing urban environments. This ensures AI tools remain relevant and impactful for crime prevention and city safety.

6.Conclusion

Realizing the potential of AI and GIS technologies for ethical and effective crime prevention necessitates policy frameworks adapted to regional values and priorities. Conducting comparative assessments of legal guides and oversight mechanisms in different countries allows identification of best practices for governance protecting resident rights while responsibly guiding technological integration. Understanding this diverse policy landscape is vital for context-specific translation of academic innovations into public sector systems supporting secure and just communities.

As highlighted in the results, advancements in analytical methods, data sources, and spatial modeling have laid the groundwork for further innovation. However, limitations persist in areas such as real-time monitoring, hyperlocal insights, and integrating heterogeneous data streams. The evolution of AI and machine learning presents new opportunities to overcome these challenges through predictive modeling, pattern recognition, computer vision, and natural language processing. By building on the progress made evident in the results, the integration of AI and big data analytics can propel GIS-based urban crime analysis to the next level, enabling more granular, real-time, and holistic understanding of crime patterns. As evidenced in the identified CPTED trends, enhancements in environmental design enabled by geospatial analytics promote the development of secure, resilient and equitable urban spaces aligned with sustainable development goals. The results make a compelling case that the future of GIS applications in urban crime lies in harnessing multidisciplinary techniques like AI and big data analytics to unlock deeper, actionable insights for building secure, just, and sustainable urban environments.

In conclusion, this review sheds light on the transformative impact of GIS applications in urban crime analysis. By conducting an extensive analysis of articles published between 2003 and 2023, the study identifies prominent research trends and shifts in the utilization of GIS for crime analysis in urban settings. As the first achievement, the review underscores GIS's pivotal role in integrating diverse data sources and employing spatial analysis techniques to comprehend crime patterns and their underlying causes. Despite the challenges being persistent, the current study has revealed advancements in methodologies and technologies in incorporating crime-related variables, leveraging machine learning algorithms, and developing novel methodologies. The outcomes also indicate how GIS is diversely applied to urban crime analysis, encompassing crime mapping, predictive modeling, resource allocation, evaluating crime prevention strategies, and assessing the effectiveness of urban planning interventions. While big data and AI/ML techniques offer exciting opportunities, the review acknowledges the challenges associated with GIS implementation, such as data quality and privacy concerns, necessitating interdisciplinary collaboration and specialized training to optimize GIS capabilities. Looking to the future, the article envisions advancements in AI, GIS technologies, and data processing further revolutionizing urban crime analysis, empowering proactive crime prevention, evidence-based decision-making, and the development of safer and more secure urban environments. However, collaborative oversight and governance are vital in navigating complex trade-offs regarding privacy, biases, and social impacts with the use of AI. Community participation enables constructive input on priorities and conveys public perceptions. Fostering engagement, explainability, and transparency regarding these technologies is key to building trust in AI-integrated crime analysis focused on equitable societal outcomes. Harnessing the full potential of GIS through interdisciplinary approaches, stakeholders can address the complex challenges posed by urban crime and promote inclusive, just, and sustainable cities.

Overall, this review article serves as a reference for researchers, practitioners, and policymakers, guiding future research directions and facilitating evidence-based approaches to combat urban crime. The integration of GIS with big data and AI/ML techniques holds immense promise in advancing crime analysis and developing effective crime prevention strategies. As cities confront evolving challenges from urbanization, climate change, and social dynamics, the insights gained from GIS applications become crucial in fostering safer, more resilient, and inclusive urban environments. Through ongoing research, collaboration, and innovation, the full potential of GIS in addressing urban crime can be realized, leading to better-informed policies, and enhanced public safety for communities worldwide. Going forward, high-resolution geospatial data combined with machine learning prediction offers significant potential to accurately evaluate and continuously refine urban planning measures intended to reduce crime through environmental design. The transformative capabilities of GIS applications pave the way for a safer and more secure urban future, where data-driven insights drive evidence-based decision-making, fostering the well-being and security of urban dwellers. As GIS continues to evolve, its integration with AI and big data holds promises for even more sophisticated and efficient crime analysis, supporting urban planners and law enforcement agencies in their efforts to build thriving and resilient cities. Despite the capabilities indicated, there are still challenges associated with data quality, privacy concerns, and expert shortages that need to be considered by relevant authorities and other stakeholders beyond urban crime. Indeed, the results contributed to clearly analyzing the GIS application in urban crime by synthesizing existing research, identifying patterns and trends, and addressing research gaps that are crucial to advancing the field further. However, the lessons learned from this review can serve as a guiding compass for future research and policy development, propelling urban crime analysis into a new era of effectiveness and adaptability.

References

Abraham, J. and Ceccato, V. (2022). Crime and safety in rural areas: A systematic review of the English-language literature 1980–2020. Journal of Rural Studies, 94, 250-273. https://doi.org/10.1016/j.jrurstud.2022.05.010

Agosto, E., Ajmar, A., Boccardo, P., Tonolo, F. G., & Lingua, A. (2008). Crime scene reconstruction using a fully geomatic approach. Sensors, 8(10), 6280-6302. https://doi.org/10.3390/s8106280

Ahmed, B., Rahman, M. S., Sammonds, P., Islam, R., & Uddin, K. (2020). Application of geospatial technologies in developing a dynamic landslide early warning system in a humanitarian context: The Rohingya refugee crisis in Cox's Bazar, Bangladesh. Geomatica Natural Hazards and Risk, 11(1), 446-468. http://dx.doi.org/10.1080/19475705.2020.1730988

Ajayakumar, J., Curtis, A., Smith, S., & Curtis, J. (2019). The use of geonarratives to add context to fine scale geospatial research. International Journal of Environmental Research and Public Health, 16(3), 515. https://doi.org/10.3390/ijerph16030515

Ali, S. N. M., Tarmidi, Z., & Nor, N. A. M. (2020, October 20-21). Review of conceptual model to spatially assessing safe city level of affordable housing in Malaysia. In 10th Institution of Geospatial and Remote Sensing Malaysia (IGRSM) International Conference and Exhibition on Geospatial and Remote Sensing (IGRSM). http://dx.doi.org/10.1088/1755-1315/540/1/012046

Allen, D., Peacock, A., & Arathoon, J. (2019). Spatialities of dog theft: A critical perspective. Animals, 9(5), 209. https://doi.org/10.3390/ani9050209

Amiri, S., Brooks, K. R., Vila, B. J., & Daratha, K. B. (2019). Natural surveillance characteristics of building openings and relationship to residential burglary. Applied Geography, 102, 99-108. http://dx.doi.org/10.1016/j.apgeog.2018.12.010

Amiri, S., Monsivais, P., McDonell, M. G., & Amram, O. (2019). Availability of licensed cannabis businesses in relation to area deprivation in Washington state: A spatiotemporal analysis of cannabis business presence between 2014 and 2017. Drug and Alcohol Review, 38(7), 790-797. http://dx.doi.org/10.1111/dar.12987

Aneja, R. and Ahuja, V. (2021). An assessment of socioeconomic impact of COVID-19 pandemic in India. Journal of Public Affairs, 21(2), e2266.

Azimpour, G., Tavakoli, N., Sabokbar, H. F., Saberian, P., & Baratloo, A. (2022). Analysis of spatial association and factors influencing trauma-related mortality in Shahr-e-Ray, Iran: A cross-sectional study. Applied Geomatics, 14(4), 627-638. http://dx.doi.org/10.1007/s12518-022-00458-8

Aziz, N. A. and Long, F. (2022). To travel, or not to travel? The impacts of travel constraints and perceived travel risk on travel intention among Malaysian tourists amid the COVID-19. Journal of Consumer Behaviour, 21(2), 352-362.

Azmy, S. N., Asmadi, M. A., Rahman, M. Z. A., Amerudin, S., & Zainon, O. (2020). Burglary crime susceptibility assessment using bivariate statistics approach of information value model. In IOP Conference Series: Earth and Environmental Science (Vol. 540, No. 1, p. 012043). IOP Publishing. https://doi.org/10.1088/1755-1315/540/1/012043

Azmy, S. N., Rahman, M. Z. A., & Amerudin, S., & Zainon, O. (2020). Modelling burglary susceptibility - An expert judgement approach. In Proceedings of the 10th Institution of Geospatial and Remote Sensing Malaysia (IGRSM) International Conference and Exhibition on Geospatial and Remote Sensing (Vol. 540, pp. 12042). IOP Publishing. https://doi.org/10.1088/1755-1315/540/1/012042

Bassul, C., Corish, C. A., & Kearney, J. M. (2021). Associations between neighborhood deprivation index, parent perceptions and preschooler lifestyle behaviors. Children-Basel, 8(11), 959. http://dx.doi.org/10.3390/children8110959

Bawaria, M., & Pasupuleti, R. S. (2023). Interrelationships between crime and demographic factors of Bhopal City in India. International Review for Spatial Planning and Sustainable Development, 11(1), 226-252. https://doi.org/10.14246/irspsd.11.1226

Bherwani, H. and Kumar, R. (2022). Use of Remote Sensing and GIS Techniques for Adaptation and Mitigation of COVID-19 Pandemic. In The Science behind the COVID Pandemic and Healthcare Technology Solutions (pp. 559-578). Cham: Springer International Publishing.

Bicakci, Y. S., Seker, D. Z., & Demirel, H. (2020). Location-based analyses for electronic monitoring of parolees. ISPRS International Journal of Geo-Information, 9(5), 296. https://doi.org/10.3390/ijgi9050296

Bichler, G., & Balchak, S. (2007). Address matching bias: ignorance is not bliss. Policing: An International Journal, 30(1), 32-60. https://doi.org/10.1108/13639510710725613

Birks, D. and Clare, J. (2023). Linking artificial intelligence facilitated academic misconduct to existing prevention frameworks. International Journal for Educational Integrity. https://doi.org/10.1007/s40979-023-00142-3.

Bloch, J. R. (2011). Using geographical information systems to explore disparities in preterm birth rates among foreign-born and US-born Black mothers. JOGNN, 40(5), 544-554. https://doi.org/10.1111/j.1552-6909.2011.01273.x

Boman, J. H. and Gallupe, O. (2020). Has COVID-19 changed crime? Crime rates in the United States during the pandemic. American journal of criminal justice, 45, 537-545.

Boyd, S. J., Armstrong, K. M., Fang, L. J., Medoff, D. R., Dixon, L. B., & Gorelick, D. A. (2007). Use of a microecologic technique to study crime around substance abuse treatment centers. Social Science Computer Review, 25(2), 163-173. https://doi.org/10.1177/0894439307298928

Brimicombe, A. (2012). Did GIS start a crime wave? SatNav theft and its implications for geo-information engineering. Professional Geographer, 64(3), 430-445. https://doi.org/10.1080/00330124.2011.609778

Brower, A. M., & Carroll, L. (2007). Spatial and temporal aspects of alcohol-related crime in a college town. Journal of American College Health, 55(5), 267-275. https://doi.org/10.3200/JACH.55.5.267-276

Bruce, M. M., Robinson, A. J., Wiebe, D. J., Shults, J., & Richmond, T. S. (2022, September 9). The contribution of neighborhood characteristics to psychological symptom severity in a cohort of injured Black men. Journal of Racial and Ethnic Health Disparities. http://dx.doi.org/10.1007/s40615-022-01407-2

Caplan, J. M., Kennedy, L. W., & Petrossian, G. (2011). Police-monitored CCTV cameras in Newark, NJ: A quasi-experimental test of crime deterrence. Journal of Experimental Criminology, 7(3), 255-274. https://doi.org/10.1007/s11292-011-9125-9

Ceccato, V. (2019). Fieldwork protocol as a safety inventory tool in public places. Criminal Justice Studies, 32(2), 165-188. https://doi.org/10.1080/09589236.2019.1601367

Ceccato, V., & Moreira, G. (2021). The dynamics of thefts and robberies in Sao Paulo's metro, Brazil. European Journal of Criminal Policy and Research, 27(3), 353-373. https://doi.org/10.1007/s10610-020-09462-3

Ceccato, V., Abraham, J., Alwall Svennefelt, C., Goransson, E., & Lundqvist, P. (2022). Impacts and coping mechanisms of farmers as victims by animal rights activism in Sweden. International Journal of Comparative and Applied Criminal Justice. Advance online publication. http://dx.doi.org/10.1080/01924036.2022.2108470

Ceccato, V., Kahn, T., Herrmann, C., & Ostlund, A. (2022). Pandemic restrictions and spatiotemporal crime patterns in New York, Sao Paulo, and Stockholm. Journal of Contemporary Criminal Justice, 38(1), 120-149. https://doi.org/10.1177/10439862211038471

Chambers, S. N. (2020). The spatiotemporal forming of a state of exception: repurposing hot-spot analysis to map bare-life in Southern Arizona's borderlands. GeoJournal, 85(5), 1373-1384. https://doi.org/10.1007/s10708-019-10027-z

Chandran, R., Hoppe, R., de Vries, W. T., & Georgiadou, Y. (2015). Conflicting policy beliefs and informational complexities in designing a transboundary enforcement monitoring system. Journal of Cleaner Production, 105, 447-460. http://dx.doi.org/10.1016/j.jclepro.2014.12.068

Chen, G., Powers, R. P., de Carvalho, L. M. T., & Mora, B. (2015). Spatiotemporal patterns of tropical deforestation and forest degradation in response to the operation of the Tucurui hydroelectric dam in the Amazon basin. Applied Geography, 63, 1-8. https://doi.org/10.1016/j.apgeog.2015.06.001

Cheng, T. and Chen, T. (2021). Urban Crime and Security. In W. Shi, M. F. Goodchild, M. Batty, M. P. Kwan, & A. Zhang (Eds.), Urban Informatics. The Urban Book Series. Springer, Singapore. https://doi.org/10.1007/978-981-15-8983-6_14

Cheung, S., Daly, A., Lam, J., Pan, J., Smith, B., Brown, D., Dalton, J., & Wilson, R. (2005, April 29). Facilitating information sharing among law enforcement agencies: Improving the geospatial repository for analysis and safety planning. In IEEE Systems and Information Engineering Design Symposium (pp. 17-23). http://dx.doi.org/10.1109/SIEDS.2005.193233

Chiew, L. S., Amerudin, S., & Yusof, Z. M. (2020). A spatial analysis of the relationship between socio-demographic characteristics with burglar behaviours on burglary crime. In IOP Conference Series: Earth and Environmental Science (Vol. 540, No. 1, p. 012050). IOP Publishing. https://doi.org/10.1088/1755-1315/540/1/012050

Christian, H., Knuiman, M., Divitini, M., Foster, S., Hooper, P., Boruff, B., Bull, F., & Giles-Corti, B. (2017). A longitudinal analysis of the influence of the neighborhood environment on recreational walking within the neighborhood: Results from RESIDE. Environmental Health Perspectives, 125(7), 77009. http://dx.doi.org/10.1289/EHP823

Craglia, M., Haining, R., & Signoretta, P. (2001). Modelling high-intensity crime areas in English cities. Urban Studies, 38(11), 1921-1941. https://doi.org/10.1080/00420980120080853

Curtis, A., & Mills, J. W. (2011). Crime in urban post-disaster environments: A methodological framework from New Orleans. Urban Geography, 32(4), 488-510. https://doi.org/10.2747/0272-3638.32.4.488

Curtis, A., Bempah, S., Ajayakumar, J., Mofleh, D., & Odhiambo, L. (2019). Spatial video health risk mapping in informal settlements: Correcting GPS error. International Journal of Environmental Research and Public Health, 16(1), 33. https://doi.org/10.3390/ijerph16010033

Curtis, A., Curtis, J. W., Shook, E., Smith, S., Jefferis, E., Porter, L., Schuch, L., Felix, C., & Kerndt, P. R. (2015). Spatial video geonarratives and health: case studies in post-disaster recovery, crime, mosquito control and tuberculosis in the homeless. International Journal of Health Geographics, 14, 22. https://doi.org/10.1186/s12942-015-0014-8

Dakalbab, F., Abu Talib, M., Abu Waraga, O., Bou Nassif, A., Abbas, S. and Nasir, Q. (2022). Artificial intelligence & crime prediction: A systematic literature review. Social Sciences & Humanities Open, 6(1), 100342. https://doi.org/10.1016/j.ssaho.2022.100342

Davies, T. and Bowers, K. (2020). Patterns in the supply and demand of urban policing at the street segment level. Policing and society, 30(7), 795-817.

Dong, B., Morrison, C. N., Branas, C. C., Richmond, T. S., & Wiebe, D. J. (2020). As violence unfolds: A space-time study of situational triggers of violent victimization among urban youth. Journal of Quantitative Criminology, 36(1), 119-152. http://dx.doi.org/10.1007/s10940-019-09419-8

Duzgun, H. S., & Polat, E. (2011). A Spatio-Temporal Crime Prediction Model for Crime Prevention. In NATO Advanced Research Workshop on Counter Terrorism in Culturally and Linguistically Diverse Communities (pp. 116-135). IOS Press. https://doi.org/10.3233/978-1-60750-970-7-116

Eisheikh, R. F. (2022). GIS-based services analysis and multi-criteria for optimal planning of location of a police station. Gazi University Journal of Science, 35(4), 1248-1258. https://doi.org/10.35378/gujs.828663

Errico, A., Angelino, C. V., Cicala, L., Persechino, G., Ferrara, C., Lega, M., Vallario, A., Parente, C., Masi, G., Gaetano, R., Scarpa, G., Amitrano, D., Ruello, G., Verdoliva, L., & Poggi, G. (2015). Detection of environmental hazards through the feature-based fusion of optical and SAR data: A case study in southern Italy. International Journal of Remote Sensing, 36(13), 3345-3367. http://dx.doi.org/10.1080/01431161.2015.1054960

Fennelly, L. J. (2020). Crime analysis. In L. J. Fennelly (Ed.), Handbook of Loss Prevention and Crime Prevention (6th ed., Chapter 18, pp. 201-205). Butterworth-Heinemann. https://doi.org/10.1016/B978-0-12-817273-5.00018-1

Garcia Chueca, E. (2021). Social unrest and (urban) inequalities in the Atlantic region in the COVID-19 era. Relações Internacionais. https://doi.org/10.23906/ri2022.sia06

Gell, N. M., Rosenberg, D. E., Carlson, J., Kerr, J., & Belza, B. (2015). Built environment attributes related to GPS measured active trips in mid-life and older adults with mobility disabilities. Disability and Health Journal, 8(2), 290-295. http://dx.doi.org/10.1016/j.dhjo.2014.12.002

Gong, Y., Dai, M. and Gu, F.(2023). CARESim: An integrated agent-based simulation environment for crime analysis and risk evaluation (CARE). Expert Systems with Applications, 214, 119070. https://doi.org/10.1016/j.eswa.2022.119070

Gu, X., Liu, L., Lan, M., & Zhou, H. (2023). Measuring perceived racial heterogeneity and its impact on crime: An ambient population-based approach. Cities, 134, 104188. https://doi.org/10.1016/j.cities.2022.104188

Gu, Y., Onggo, B. S., Kunc, M. H. and Bayer, S. (2022). Small Island Developing States (SIDS) COVID-19 post-pandemic tourism recovery: A system dynamics approach. Current Issues in Tourism, 25(9), 1481-1508.

Gundogdu, I. B. (2011). A new approach for GIS-supported mapping of traffic accidents. Proceedings of the Institution of Civil Engineers - Transport, 164(2), 87-96. https://doi.org/10.1680/tran.2011.164.2.87

Gupta, J., Bavinck, M., Ros-Tonen, M., Asubonteng, K., Bosch, H., van Ewijk, E., Hordijk, M., Van Leynseele, Y., Lopes Cardozo, M., Miedema, E., Pouw, N., Rammelt, C., Scholtens, J., Vegelin, C. and Verrest, H.(2021). COVID-19, poverty and inclusive development. World Development, 145, 105527. https://doi.org/10.1016/j.worlddev.2021.105527

Haining, R., & Law, J. (2007). Combining police perceptions with police records of serious crime areas: a modelling approach. Journal of the Royal Statistical Society: Series A (Statistics in Society), 170(4), 1019-1034. https://doi.org/10.1111/j.1467-985X.2007.00477.x

Hall, E., & Bates, E. (2019). Hatescape? A relational geography of disability hate crime, exclusion and belonging in the city. Geoforum, 101, 100-110. https://doi.org/10.1016/j.geoforum.2019.02.024

Hamza, S., Khan, I., Lu, L., Liu, H., Burke, F., Nawaz-ul-Huda, S., Baqa, M. F., & Tariq, A. (2021). The relationship between neighborhood characteristics and homicide in Karachi, Pakistan. Sustainability, 13(10), 5520. https://doi.org/10.3390/su13105520

Han, Y., Hu, Y., Zhu, H., & Wang, F. (2023). A cyclically adjusted spatio-temporal kernel density estimation method for predictive crime hotspot analysis. Annals of GIS, 29(2), 177-191. https://doi.org/10.1080/19475683.2023.2166584

Hanchard, M. S. (2020). Digital maps and senses of security: The influence of a veracious media on urban life. Urban Planning, 5(4), 301-311. https://doi.org/10.17645/up.v5i4.3452

Harris, K. M. (2019). Mapping inequality: Childhood asthma and environmental injustice, a case study of St. Louis, Missouri. Social Science & Medicine, 230, 91-110. https://doi.org/10.1016/j.socscimed.2019.03.040

Hart, T. C., Chataway, M. and Mellberg, J. (2022). Measuring fear of crime during the past 25 years: A systematic quantitative literature review. Journal of Criminal Justice, 82, 101988. https://doi.org/10.1016/j.jcrimjus.2022.101988

Hawkins, J., Ahmed, U., Roorda, M., & Habib, K. N. (2022). Measuring the process of urban gentrification: A composite measure of the gentrification process in Toronto. Cities, 126, 103708. http://dx.doi.org/10.1016/j.cities.2022.103708

Hawthorne, T. L., Solis, P., Terry, B., Price, M., & Atchison, C. L. (2015). Critical reflection mapping as a hybrid methodology for examining sociospatial perceptions of new research sites. Annals of the Association of American Geographers, 105(1), 22-47. https://doi.org/10.1080/00045608.2014.960041

He, J. and Zheng, H. (2021). Prediction of crime rate in urban neighborhoods based on machine learning. Engineering Applications of Artificial Intelligence, 106, 104460. https://doi.org/10.1016/j.engappai.2021.104460

He, R., Xu, Y., & Jiang, S. (2022). Applications of GIS in public security agencies in China. Asian Journal of Criminology, 17(2), 213-235. https://doi.org/10.1007/s11417-021-09360-5

Herath, H. M. K. K. M. B., & Mittal, M. (2022). Adoption of artificial intelligence in smart cities: A comprehensive review. International Journal of Information Management Data Insights, 2(1), 100076.. https://doi.org/10.1016/j.jjimei.2022.100076

Hipp, J. R. (2020). Simulating spatial crime patterns: What do we learn in standard ecological studies of crime? Journal of Criminal Justice, 70, 101727. https://doi.org/10.1016/j.jcrimjus.2020.101727

Houle, C., Damian, J., Ruck, R., Bentley, A., & Gavrilets, S. (2022). Inequality between identity groups and social unrest. Journal of the Royal Society Interface. https://doi.org/10.1098/rsif.2021.0725

Hsu, A., Lili, L., Schletz, M., & Yu, Z. (2023). Chinese cities as digital environmental governance innovators: Evidence from subnational low-Carbon plans. Environment and Planning B: Urban Analytics and City Science, 23998083231186622. https://doi.org/10.1177/23998083231186622

Iyanda, A. E., Adeleke, R., Boakye, K. A., Adeusi, T. J., & Lu, Y. (2022). Underage tobacco sales violations and neighborhood crime arrest in Philadelphia: A multiscale GIS-based analysis. GeoJournal, 87(6), 4455-4474. https://doi.org/10.1007/s10708-021-10507-1

Jakobi, A., & Podor, A. (2020). GIS-based statistical analysis of detecting fear of crime with digital sketch maps: A Hungarian multicity study. ISPRS International Journal of Geo-Information, 9(4), 229. https://doi.org/10.3390/ijgi9040229

Jelokhani-Niaraki, M., Mofrad, R. B., Dero, Q. Y., Hajiloo, F., & Sadeghi-Niaraki, A. (2020). A volunteered geographic information system for monitoring and managing urban crimes: a case study of Tehran, Iran. Police Practice and Research, 21(6), 547-561. https://doi.org/10.1080/15614263.2019.1644175

Jiang, Y., Guo, B., & Yan, Z. (2022). Multi-criterion spatial optimization of future police stations based on urban expansion and criminal behavior characteristics. ISPRS International Journal of Geo-Information, 11(7), 384. http://dx.doi.org/10.3390/ijgi11070384

Jones, P., Drury, R., & McBeath, J. (2011). Using GPS-enabled mobile computing to augment qualitative interviewing: Two case studies. Field Methods, 23(2), 173-187. https://doi.org/10.1177/1525822X10388467

Jubit, N., Masron, T., Nordin, M. N., & Chabo, D. (2019). GIS application in identifying the property crime hot spot in Kuching, Sarawak. Geografia-Malaysian Journal of Society and Space, 15(4), 30-49. https://doi.org/10.17576/geo-2019-1504-03

Kalantari, M., Ghezelbash, S., Ghezelbash, R., & Yaghmaei, B. (2020). Developing a fractal model for spatial mapping of crime hotspots. European Journal on Criminal Policy and Research, 26(4), 571-591. https://doi.org/10.1007/s10610-019-09411-9

Kazmi, S. S. A., Ahmed, M., Mumtaz, R., & Anwar, Z. (2022). Spatiotemporal clustering and analysis of road accident hotspots by exploiting GIS technology and kernel density estimation. The Computer Journal, 65(2), 155-176. https://doi.org/10.1093/comjnl/bxz158

Keatley, D.A., Arntfield, M. and Clarke, D.D. (2022). Crime Script Sequencing: An optimal forensic combination for cold case analysis. Forensic Science International: Synergy, 5, 100278. https://doi.org/10.1016/j.fsisyn.2022.100278

Keddem, S., Barg, F. K., Glanz, K., Jackson, T., Green, S., & George, M. (2015). Mapping the urban asthma experience: Using qualitative GIS to understand contextual factors affecting asthma control. Social Science & Medicine, 140, 9-17. https://doi.org/10.1016/j.socscimed.2015.06.039

Keyvanpour, M. R., Javideh, M. and Ebrahimi, M. R. (2011). Detecting and investigating crime by means of data mining: A general crime matching framework. Procedia Computer Science, 3, 872-880. https://doi.org/10.1016/j.procs.2010.12.143

Khan, I., Hamza, S., Burke, F., & Ul-Huda, S. N. (2020). Application of GIS for evaluation of ethnic fault lines of Karachi. Geografia-Malaysian Journal of Society and Space, 16(4), 15-29. https://doi.org/10.17576/geo-2020-1604-02

Khan, M. B. U., & Talukder, M. I. A. (2021). Spatial distribution of crime in Bangladesh: An analysis. Journal of Penal Law and Criminology, 9(2), 479-503. https://doi.org/10.26650/JPLC2021-931625

Khlem, R., Kannappan, S. R. and Choudhury, P. P. (2022). Coronavirus disease-2019: Challenges, opportunities, and benefits in India. Journal of Education and Health Promotion, 11.

Khojastehpour, M., Sahebi, S., & Samimi, A. (2022). Public acceptance of a crowdsourcing platform for traffic enforcement. Case Studies on Transport Policy, 10(4), 2012-2024. https://doi.org/10.1016/j.cstp.2022.08.013

Kim, D., Hong, S.-W., & Jeong, Y. (2019). Crime prevention effect of the second generation crime prevention through environmental design project in South Korea: An analysis. Social Sciences, 8(6), 187. https://doi.org/10.3390/socsci8060187

Kounadi, O., & Leitner, M. (2015). Spatial information divergence: Using global and local indices to compare geographical masks applied to crime data. Transactions in GIS, 19(5), 737-757. https://doi.org/10.1111/tgis.12125

Kounadi, O., Ristea, A., Araujo, A., & Leitner, M. (2020). A systematic review on spatial crime forecasting. Crime science, 9, 1-22. https://doi.org/10.1186/s40163-020-00116-7

Kouziokas, G. N. (2017). The application of artificial intelligence in public administration for forecasting high crime risk transportation areas in the urban environment. Transportation Research Procedia, 24, 467-473. https://doi.org/10.1016/j.trpro.2017.05.083

Lan, M., Liu, L., & Eck, J. E. (2021). A spatial analytical approach to assess the impact of a casino on crime: An example of JACK Casino in downtown Cincinnati. Cities, 111, 103003. https://doi.org/10.1016/j.cities.2020.103003

Lan, M., Liu, L., Burmeister, J., Zhu, W., Zhou, H., & Gu, X. (2023). Are crime and collective emotion interrelated? A broken emotion conjecture from community Twitter posts. Social Science Computer Review, 41(2), 528-553. https://doi.org/10.1177/08944393221113210

Lan, M., Liu, L., Hernandez, A., Liu, W., Zhou, H., & Wang, Z. (2019). The spillover effect of geotagged tweets as a measure of ambient population for theft crime. Sustainability, 11(23), 6748. https://doi.org/10.3390/su11236748

Lardier, D. T., Opara, I., Lin, Y., Roach, E., Herrera, A., Garcia-Reid, P., & Reid, R. J. (2021). A spatial analysis of alcohol outlet density type, abandoned properties, and police calls on aggravated assault rates in a northeastern US city. Substance Use & Misuse, 56(10), 1527-1535. https://doi.org/10.1080/10826084.2021.1942053

Law, J., & Chan, P. W. (2011). Monitoring residual spatial patterns using Bayesian hierarchical spatial modelling for exploring unknown risk factors. Transactions in GIS, 15(4), 521-540. https://doi.org/10.1111/j.1467-9671.2011.01276.x

Lee, H., Chen, M., Pham, H. T., & Choo, S. (2019). Development of a decision making system for installing unmanned parcel lockers: Focusing on residential complexes in Korea. KSCE Journal of Civil Engineering, 23(6), 2713-2722. http://dx.doi.org/10.1007/s12205-019-1398-y

Lee, Y., Eck, J. E., O, S., & Martinez, N. N. (2017). How concentrated is crime at places? A systematic review from 1970 to 2015. Crime Science, 6, 1-16.

Levine, N. (2006). Crime mapping and the CrimeStat program. In Symposium on Spatial Information Science for Human and Social Science, January 2004, Univ Tokyo, Tokyo, Japan. Geographical Analysis, 38(1), 41-56. https://doi.org/10.1111/j.0016-7363.2005.00673.x

Levine, N., & Ceccato, V. (2021). Malignant mixes: The overlap of motor vehicle crashes and crime in Stockholm, Sweden. Accident Analysis & Prevention, 161, 106361. https://doi.org/10.1016/j.aap.2021.106361

Li, Y. and Haining, R. (2022). GIS Empowered Urban Crime Research. In B. Li, X. Shi, AX. Zhu, C. Wang, & H. Lin (Eds.), New Thinking in GIScience. Springer, Singapore. https://doi.org/10.1007/978-981-19-3816-0_38

Li, Y., Fan, Y., & Nie, L. (2023). Making governance agile: Exploring the role of artificial intelligence in China's local governance. Public Policy and Administration, 09520767231188229. https://doi.org/10.1177/09520767231188229

Lisowska-Kierepka, A. (2022). How to analyze spatial distribution of crime? Crime risk indicator in an attempt to design an original method of spatial crime analysis. Cities, 120, 103403. https://doi.org/10.1016/j.cities.2021.103403

Liu, L., Chang, J., Long, D. and Liu, H. (2022). Analyzing the impact of COVID-19 lockdowns on violent crime. International journal of environmental research and public health, 19(23), 15525.

Liu, L., Lan, M., Eck, J. E., & Kang, E. L. (2020). Assessing the effects of bus stop relocation on street robbery. Computers, Environment and Urban Systems, 80, 101455. http://dx.doi.org/10.1016/j.compenvurbsys.2019.101455

Liu, L., Lan, M., Eck, J. E., Yang, B., & Zhou, H. (2022). Assessing the Intraday Variation of the Spillover Effect of Tweets-Derived Ambient Population on Crime. Social Science Computer Review, 40(2), 512-533. https://doi.org/10.1177/0894439320983825

Liu, L., Zhou, H., Lan, M., & Wang, Z. (2020). Linking Luojia 1-01 nightlight imagery to urban crime. Applied Geography, 125, 102267. https://doi.org/10.1016/j.apgeog.2020.102267

Lloyd, J. (2019). Sometimes the whole map is red: applying geographical assessment methods to safeguard adolescents from harm in communities. Safer Communities, 19(1), 35-47. https://doi.org/10.1108/SC-06-2019-0018

Lotfata, A., & Hohl, A. (2023). Spatiotemporal associations of mental distress with socioeconomic and environmental factors in Chicago, IL, 2015-2019. Spatial Information Research. Advance online publication. http://dx.doi.org/10.1007/s41324-023-00524-2

Lukasczyk, J., Maciejewski, R., Garth, C., & Hagen, H. (2015, November 3-6). Understanding hotspots: A topological visual analytics approach. In 23rd ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems (ACM SIGSPATIAL GIS). http://dx.doi.org/10.1145/2820783.2820817

Mafumbabete, C., Chivhenge, E., Museva, T., Zingi, G. K., & Ndongwe, M. R. (2019). Mapping the spatial variations in crime in rural Zimbabwe using geographic information systems. Cogent Social Sciences, 5(1), 1661606. https://doi.org/10.1080/23311886.2019.1661606

Mahmood, S. (2022). Exploring COVID-19 incidence hotspot in Metropolitan area of Pakistan using geo-statistical approach: A study of Lahore city. Spatial Information Research, 30(4), 469-476. http://dx.doi.org/10.1007/s41324-021-00423-4

Mahmood, S., Ghulam, R., Mayo, S. M., & SamiUllah. (2022). Hotspot analysis of urban crimes in Data Ganj Bakhsh Town, Lahore, Pakistan. Crime Prevention and Community Safety, 24(4), 342-357. https://doi.org/10.1057/s41300-022-00163-z

Mansourihanis, O.; Maghsoodi Tilaki, M.J.; Yousefian, S.; Zaroujtaghi, A. A Computational Geospatial Approach to Assessing Land-Use Compatibility in Urban Planning. Land 2023, 12, 2083. https://doi.org/10.3390/land12112083

Maoz, E., & Gutman, M. A. (2023). The capitalization of crime in the city of real estate. Theoretical Criminology. Advance online publication. https://doi.org/10.1177/13624806231161595

Marshall, P. K., Durdle, A., Hayes, R., Stevenson, P. G., & Conlan, X. A. (2019). Why do street signs taste so good? A community ballistics project. Australian Journal of Forensic Sciences, 51, S172-S175. https://doi.org/10.1080/00450618.2019.1568551

Martins, B. A., Taylor, D., Barrie, H., Lange, J., Kho, K. S. F., & Visvanathan, R. (2021). Objective and subjective measures of the neighbourhood environment: Associations with frailty levels. Archives of Gerontology and Geriatrics, 92, 104257. http://dx.doi.org/10.1016/j.archger.2020.104257

Mata, F., & Claramunt, C. (2015, November 3-6). A mobile trusted path system based on social network data. In 23rd ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems (ACM SIGSPATIAL GIS). http://dx.doi.org/10.1145/2820783.2820799

Moise, I. K. (2020). Youth and weapons: Patterns, individual and neighborhood correlates of violent crime arrests in Miami-Dade County, Florida. Health & Place, 65, 102407. https://doi.org/10.1016/j.healthplace.2020.102407

Moise, I. K. and Piquero, A. R. (2023). Geographic disparities in violent crime during the COVID-19 lockdown in Miami-Dade County, Florida, 2018–2020. Journal of Experimental Criminology, 19(1), 97-106.

Moise, I. K., & Piquero, A. R. (2023). Geographic disparities in violent crime during the COVID-19 lockdown in Miami-Dade County, Florida, 2018-2020. Journal of Experimental Criminology, 19(1), 97-106. https://doi.org/10.1007/s11292-021-09474-x

Mondal, S., Singh, D., & Kumar, R. (2022). Crime hotspot detection using statistical and geospatial methods: a case study of Pune City, Maharashtra, India. GeoJournal, 87(6), 5287-5303. https://doi.org/10.1007/s10708-022-10573-z

Mu, L., & Wang, F. (2008). A scale-space clustering method: Mitigating the effect of scale in the analysis of zone-based data. Annals of the Association of American Geographers, 98(1), 85-101. https://doi.org/10.1080/00045600701734224

Nakaya, T., & Yano, K. (2010). Visualising crime clusters in a space-time cube: An exploratory data-analysis approach using space-time kernel density estimation and scan statistics. Transactions in GIS, 14(3), 223-239. https://doi.org/10.1111/j.1467-9671.2010.01194.x

Nazmfar, H., Alavi, S., Feizizadeh, B., & Mostafavi, M. A. (2020). Analysis of spatial distribution of crimes in urban public spaces. Journal of Urban Planning and Development, 146(3), 5020006. https://doi.org/10.1061/(ASCE)UP.1943-5444.0000549

Nazmfar, H., Alavi, S., Feizizadeh, B., Masodifar, R., & Eshghei, A. (2020). Spatial analysis of security and insecurity in urban parks: A case study of Tehran, Iran. The Professional Geographer, 72(3), 383-397. https://doi.org/10.1080/00330124.2019.1696686

Nepomuceno, T. C. C., & Cabral Seixas Costa, A. P. (2019). Spatial visualization on patterns of disaggregate robberies. Operations Research, 19(4), 857-886. https://doi.org/10.1007/s12351-019-00479-z

Neuwirth, R. J. (2023). Prohibited artificial intelligence practices in the proposed EU artificial intelligence act (AIA). Computer Law & Security Review, 48, 105798. https://doi.org/10.1016/j.clsr.2023.105798

Newton, D., Lucock, M., Armitage, R., Monchuk, L. and Brown, P. (2022). Understanding the mental health impacts of poor quality private-rented housing during the UK's first COVID-19 lockdown. Health & Place, 78, 102898.

Nordin, M. N., Masron, T., Yunos, N. E., & Jubit, N. (2020). Spatial hotspot patterns of a home burglary in Penang. Geografia-Malaysian Journal of Society and Space, 16(2), 29-40. https://doi.org/10.17576/geo-2020-1602-03

Ogneva-Himmelberger, Y., Ross, L., Caywood, T., Khananayev, M., & Starr, C. (2019). Analyzing the relationship between perception of safety and reported crime in an urban neighborhood using GIS and sketch maps. ISPRS International Journal of Geo-Information, 8(12), 531. https://doi.org/10.3390/ijgi8120531

Owczarczuk, M. (2023). Ethical and regulatory challenges amid artificial intelligence development: an outline of the issue. Ekonomia i Prawo. Economics and Law, 22(2 (2). https://doi.org/10.12775/eip.2023.017

Pantaleoni, E. (2012). Applying GIS and spatial analysis to studies of health in children with disabilities. In International Review of Research in Developmental Disabilities (Vol. 42, pp. 1-29). Elsevier Academic Press Inc. https://doi.org/10.1016/B978-0-12-394284-5.00001-2

Patino, J. E., Duque, J. C., Pardo-Pascual, J. E., and Ruiz, L. A. (2014). Using remote sensing to assess the relationship between crime and the urban layout. Applied Geography, 55, 48-60. https://doi.org/10.1016/j.apgeog.2014.08.016

Phelan, S., Marquez, F., Redman, L. M., Arteaga, S., Clifton, R., Grice, B. A., Haire-Joshu, D., Martin, C. K., Myers, C. A., Pomeroy, J., Vincent, E., Van Horn, L., Peaceman, A., Ashby-Thompson, M., Gallagher, D., Pi-Sunyer, X., Boekhoudt, T., Drews, K., & Brown, G. (2021). The moderating role of the built environment in prenatal lifestyle interventions. International Journal of Obesity, 45(6), 1357-1361. http://dx.doi.org/10.1038/s41366-021-00782-w

Pindarwati, A., & Wijayanto, A. W. (2019). Personalized Safety Route Recommender Application using Integrated Urban Crime Hotspot Data. In 6th Geoinformation Science Symposium (p. 1131105). SPIE. https://doi.org/10.1117/12.2547331

Pires, S. F. (2015). The heterogeneity of illicit parrot markets: An analysis of seven Neo-Tropical open-air markets. European Journal on Criminal Policy and Research, 21(1), 151-166. http://dx.doi.org/10.1007/s10610-014-9246-6

Pitts, S. B. J., Keyserling, T. C., Johnston, L. F., Smith, T. W., McGuirt, J. T., Evenson, K. R., Rafferty, A. P., Gizlice, Z., Garcia, B. A., & Ammerman, A. S. (2015). Associations between neighborhood-level factors related to a healthful lifestyle and dietary intake, physical activity, and support for obesity prevention policies among rural adults. Journal of Community Health, 40(2), 276-284. https://doi.org/10.1007/s10900-014-9927-6

Piza, E. L., Wolff, K. T., Hatten, D. N., & Barthuly, B. E. (2023). Drug overdoses, geographic trajectories, and the influence of built environment and neighborhood characteristics. Health & Place, 79, 102959. https://doi.org/10.1016/j.healthplace.2022.102959

Prathap, B. R. (2022). Geospatial crime analysis and forecasting with machine learning techniques. In R. Pandey, S. K. Khatri, N. K. Singh, & P. Verma (Eds.), Artificial Intelligence and Machine Learning for EDGE Computing (Chapter 7, pp. 87-102). Academic Press. https://doi.org/10.1016/B978-0-12-824054-0.00008-3

Rádi, V. G. (2023, May). Comparative Analysis of the AI Regulation of the EU, US and China from a Privacy Perspective. In 2023 46th MIPRO ICT and Electronics Convention (MIPRO) (pp. 1446-1451). IEEE. https://doi.org/10.23919/MIPRO57284.2023.10159864

Ramachandran, B., & Klodzinski, J. (2007). Internet-based mapping prototype for integration with an electronic freight theft management system. Transportation Research Record, 1993, 101-108. https://doi.org/10.3141/1993-14

Ramos, R. G. (2019). Does income inequality explain the geography of residential burglaries? The case of Belo Horizonte, Brazil. ISPRS International Journal of Geo-Information, 8(10), 439. https://doi.org/10.3390/ijgi8100439

Rasmusson, M., & Helbich, M. (2020). The relationship between near-repeat street robbery and the environment: Evidence from Malmö, Sweden. ISPRS International Journal of Geo-Information, 9(4), 188. https://doi.org/10.3390/ijgi9040188

Ratcliffe, J. (2019). Predictive policing. Police innovation: Contrasting perspectives, 347.

Ratcliffe, J. H. (2002). Aoristic signatures and the spatio-temporal analysis of high volume crime patterns. Journal of Quantitative Criminology, 18(1), 23-43. https://doi.org/10.1023/A:1013240828824

Ratcliffe, J. H., Taniguchi, T., Groff, E. R., & Wood, J. D. (2011). The Philadelphia foot patrol experiment: A randomized controlled trial of police patrol effectiveness in violent crime hotspots. Criminology, 49(3), 795-831. https://doi.org/10.1111/j.1745-9125.2011.00240.x

Ren, L., Zhao, J. "Solomon", & He, N. "Phil" (2019). Broken windows theory and citizen engagement in crime prevention. Justice Quarterly, 36(1), 1-30. https://doi.org/10.1080/07418825.2017.1374434

Ristea, A. and Leitner, M. (2020). Urban Crime Mapping and Analysis Using GIS. ISPRS International Journal of Geo-Information, 9(9), 511. https://doi.org/10.3390/ijgi9090511

Root, E. D., Bailey, E. D., Gorham, T., Browning, C., Song, C., & Salsberry, P. (2020). Geovisualization and spatial analysis of infant mortality and preterm birth in Ohio, 2008-2015:

Opportunities to enhance spatial thinking. Public Health Reports, 135(4), 472-482. https://doi.org/10.1177

Rosés, R., Kadar, C. and Malleson, N. (2021). A data-driven agent-based simulation to predict crime patterns in an urban environment. Computers, Environment and Urban Systems, 89, 101660. https://doi.org/10.1016/j.compenvurbsys.2021.101660

Roy, A., Fouche, E., Morales, R. R., & Moehler, G. (2019). In-database geospatial analytics using Python. In 2nd ACM SIGSPATIAL International Workshop on Advances in Resilient and Intelligent Cities (ARIC) (pp. 17-24). Association for Computing Machinery. https://doi.org/10.1145/3356395.3365598

Sadeek, S. N., Ahmed, A. J. M. M. U., Hossain, M., & Hanaoka, S. (2019). Effect of land use on crime considering exposure and accessibility. Habitat International, 89, 102003. https://doi.org/10.1016/j.habitatint.2019.102003

Sadler, R. C., Melde, C., Zeoli, A., Wolfe, S., & O'Brien, M. (2022). Characterizing spatio-temporal differences in homicides and non-fatal shootings in Milwaukee, Wisconsin, 2006-2015. Applied Spatial Analysis and Policy, 15(1), 117-142. https://doi.org/10.1007/s12061-021-09391-6

Salafranca Barreda, D., Maldonado-Guzman, D. J., & Saldana-Taboada, P. (2022). Crime beyond the edge: development of a tool to correct the edge effect on crime count. Annals of GIS, 28(3), 279-292. https://doi.org/10.1080/19475683.2022.2052748

Samad, M. S. A., Mohan, P., Varghese, G. K., Shah, I. K., & Alappat, B. J. (2020). Environmental forensic investigation of the air pollution from a cement manufacturing unit. Environmental Forensics, 21(1), 37-47. https://doi.org/10.1080/15275922.2019.1694094

Seyidoglu, H., Dixon, A., Pina Sanchez, J., Malleson, N. and Farrell, G. (2023). Post-Pandemic? Crime in England and Wales. April 2023.

Shach-Pinsly, D. (2019). Measuring security in the built environment: Evaluating urban vulnerability in a human-scale urban form. Landscape and Urban Planning, 191, 103412. https://doi.org/10.1016/j.landurbplan.2018.08.022

Sharifi, A., and Khavarian-Garmsir, A. R. (2020). The COVID-19 pandemic: Impacts on cities and major lessons for urban planning, design, and management. Science of The Total Environment, 749, 142391. https://doi.org/10.1016/j.scitotenv.2020.142391

Silva, C., Melo, S., Santos, A., Almeida Junior, P., Sato, S., Santiago, K., & Sa, L. (2020). Spatial modeling for homicide rates estimation in Pernambuco State-Brazil. ISPRS International Journal of Geo-Information, 9(12), 740. https://doi.org/10.3390/ijgi9120740

Siriaraya, P., Zhang, Y., Wang, Y., Kawai, Y., Mittal, M., Jeszenszky, P., & Jatowt, A. (2019). Witnessing Crime through Tweets: A Crime Investigation Tool based on Social Media. In 27th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems (pp. 568-571). Association for Computing Machinery. https://doi.org/10.1145/3347146.3359082

Soltani, A., Mansourihanis, O., & RoohaniQadikolaei, M. (2024). Two decades of geospatial evolution: Tracing the analytical journey towards data-driven road crash prevention. Applied Spatial Analysis and Policy. https://doi.org/10.1007/s12061-024-09587-6

Spiegel, S. J., Ribeiro, C. A. A. S., Sousa, R., & Veiga, M. M. (2012). Mapping spaces of environmental dispute: GIS, mining, and surveillance in the Amazon. Annals of the Association of American Geographers, 102(2), 320-349. https://doi.org/10.1080/00045608.2011.641861

Stassen, R., & Ceccato, V. (2020). Environmental and wildlife crime in Sweden from 2000 to 2017. Journal of Contemporary Criminal Justice, 36(3), 403-427. https://doi.org/10.1177/1043986220927123

Stromberg, P. M., Ohrner, E., Brockwell, E., & Liu, Z. (2021). Valuing urban green amenities with an inequality lens. Ecological Economics, 186, 107067. http://dx.doi.org/10.1016/j.ecolecon.2021.107067

Szyszka, M., & Polko, P. (2020). Interactive maps of social problems and security threats illustrated with an example of solutions currently used in Upper Silesia. Sustainability, 12(3), 1229. https://doi.org/10.3390/su12031229

Tempat, P., Pemandian, J., Jenazah, S., & Timur, E. (2023). Civil unrest and rioting. https://doi.org/10.1016/b978-0-323-80932-0.00074-4

Thomson, R., & Samuels-Jones, T. (2022). Toxic colonialism in the territorial isles: A geospatial analysis of environmental crime across US territorial islands 2013-2017. International Journal of Offender Therapy and Comparative Criminology, 66(4), 470-491. https://doi.org/10.1177/0306624X20975161

Timmermans, E. J., Veldhuizen, E. M., Maki-Opas, T., Snijder, M. B., Lakerveld, J., & Kunst, A. E. (2019). Associations of neighbourhood safety with leisure-time walking and cycling in population subgroups: The HELIUS study. Spatial and Spatio-temporal Epidemiology, 31, 100300. http://dx.doi.org/10.1016/j.sste.2019.100300

Timperio, A., Salmon, J., Ball, K., Velde, S. J. T., Brug, J., & Crawford, D. (2012). Neighborhood characteristics and TV viewing in youth: Nothing to do but watch TV? Journal of Science and Medicine in Sport, 15(2), 122-128. http://dx.doi.org/10.1016/j.jsams.2011.07.010

Tirivangasi, H. M., Dzvimbo, M. A., Chaminuka, N. ans Mawonde, A. (2023). Assessing climate change and urban poverty in the context of the COVID 19 lockdowns: Rethinking personality and societal challenges in Zimbabwe. Scientific African, 20, e01710. https://doi.org/10.1016/j.sciaf.2023.e01710

Tom-Jack, Q. T., Bernstein, J. M., & Loyola, L. C. (2019). The role of geoprocessing in mapping crime using hot streets. ISPRS International Journal of Geo-Information, 8(12), 540. https://doi.org/10.3390/ijgi8120540

ToppiReddy, H. K. R., Saini, B. and Mahajan, G. (2018). Crime Prediction & Monitoring Framework Based on Spatial Analysis. Procedia Computer Science, 132, 696-705. https://doi.org/10.1016/j.procs.2018.05.075

Towers, A. E., Navarro, J. N., & Holt, T. J. (2022). Mapping as Harm Reduction: Using GIS to Map Chatter Associated with Sex Work. Victims & Offenders, 17(5), 679-692. https://doi.org/10.1080/15564886.2022.2036660

Troy, A., & Grove, J. M. (2008). Property values, parks, and crime: A hedonic analysis in Baltimore, MD. Landscape and Urban Planning, 87(3), 233-245. https://doi.org/10.1016/j.landurbplan.2008.06.005

Turvey, B. E. and Freeman, J. (2023). Crime Scene Analysis. In B. E. Turvey (Ed.), Criminal Profiling (5th ed., Chapter 14, pp. 415-456). Academic Press. https://doi.org/10.1016/B978-0-12-815583-7.00014-9

Uittenbogaard, A., & Ceccato, V. (2012). Space-time Clusters of Crime in Stockholm, Sweden. Review of European Studies, 4(5), 148. https://doi.org/10.5539/res.v4n5p148

United Nation (UN), (2015). Transforming our world: The 2030 agenda for sustainable development. Division for Sustainable Development Goals. New York: World Health Organization.

UNCTAD (United Nations Conference on Trade and Development). (2022). The covid-19 pandemic impact on micro, small and medium sized enterprises: Market access challenges and competition policy.

Vlad, I. T., Diaz, C., Juan, P., & Chaudhuri, S. (2023). Analysis and description of crimes in Mexico City using point pattern analysis within networks. Annals of GIS, 29(2), 243-259. https://doi.org/10.1080/19475683.2023.2166108

Wahab, A. A., & Sakip, S. R. M. (2019). Mapping isolated places in school in concurrence with bullying possibility elements. In Proceedings of the 8th Asian Conference on Environment-Behaviour Studies (AcE-Bs) (pp. 359-366). Malaysia: E-IPH Ltd UK. https://doi.org/10.21834/e-bpj.v4i12.1913

Walker, B. B., Moura de Souza, C., Pedroso, E., Lai, R. S., Hunter, P., Tam, J., Cave, I., Swanlund, D., & Barbosa, K. G. N. (2020). Towards a situated spatial epidemiology of violence: A placially-informed geospatial analysis of homicide in Alagoas, Brazil. International Journal of Environmental Research and Public Health, 17(24), 9283. http://dx.doi.org/10.3390/ijerph17249283

Wang, D., Ding, W., Lo, H., Morabito, M., Chen, P., Salazar, J. and Stepinski, T. (2013). Understanding the spatial distribution of crime based on its related variables using geospatial discriminative patterns. Computers, Environment and Urban Systems, 39, 93-106. https://doi.org/10.1016/j.compenvurbsys.2013.01.008

Wang, F. H., & Minor, W. W. (2002). Where the jobs are: Employment access and crime patterns in Cleveland. Annals of the Association of American Geographers, 92(3), 435-450. https://doi.org/10.1111/1467-8306.00298

Wang, S., Huang, X., Liu, P., Zhang, M., Biljecki, F., Hu, T., Fu, X., Liu, L., Liu, X., Wang, R., Huang, Y., Yan, J., Jiang, J., Chukwu, M., Naghedi, S. R., Hemmati, M., Shao, Y., Jia, N., Xiao, Z., ... Bao, S. (2024). Mapping the landscape and roadmap of geospatial artificial intelligence (GeoAI) in quantitative human geography: An extensive systematic review. International Journal of Applied Earth Observation and Geoinformation, 128, 103734. https://doi.org/10.1016/j.jag.2024.103734

Wang, Z., Liu, L., Zhou, H., & Lan, M. (2019). How is the confidentiality of crime locations affected by parameters in kernel density estimation? ISPRS International Journal of Geo-Information, 8(12), 544. https://doi.org/10.3390/ijgi8120544

Wilhelmsson, M., & Ceccato, V. (2015). Does burglary affect property prices in a nonmetropolitan municipality? Journal of Rural Studies, 39, 210-218. https://doi.org/10.1016/j.jrurstud.2015.03.014

Wilhelmsson, M., Ceccato, V., & Gerell, M. (2022). What effect does gun-related violence have on the attractiveness of a residential area? The case of Stockholm, Sweden. Journal of European Real Estate Research, 15(1), 39-57. https://doi.org/10.1108/JERER-03-2021-0015

Wu, L., Liu, X., Ye, X., Leipnik, M., Lee, J., & Zhu, X. (2015). Permeability, space syntax, and the patterning of residential burglaries in urban China. Applied Geography, 60, 261-265. https://doi.org/10.1016/j.apgeog.2014.12.001

Xu, Y.-H., Pennington-Gray, L., & Kim, J. (2019). The sharing economy: A geographically weighted regression approach to examine crime and the shared lodging sector. Journal of Travel Research, 58(7), 1193-1208. https://doi.org/10.1177/0047287518797197

Yang, B. (2019). GIS crime mapping to support evidence-based solutions provided by community-based organizations. Sustainability, 11(18), 4889. https://doi.org/10.3390/su11184889

Yang, B., Liu, L., Lan, M., Wang, Z., Zhou, H., & Yu, H. (2020). A spatio-temporal method for crime prediction using historical crime data and transitional zones identified from nightlight imagery. International Journal of Geographical Information Science, 34(9), 1740-1764. https://doi.org/10.1080/13658816.2020.1737701

Zhang, C., Liu, L., Zhou, S., Feng, J., Chen, J., & Xiao, L. (2022). Contact-fraud victimization among urban seniors: An analysis of multilevel influencing factors. ISPRS International Journal of Geo-Information, 11(3), 201. http://dx.doi.org/10.3390/ijgi11030201

Zhang, N., Xu, H., Jiang, F., Wang, D., Chen, P., & Zhang, Q. (2022). Police resource distribution in China: spatial decision making based on PGIS-MCDA method. Policing: An International Journal, 45(6), 956-971. https://doi.org/10.1108/PIJPSM-03-2022-0042

Zhang, Y., Cai, L., Song, G., Liu, L., & Zhu, C. (2022). From residential neighborhood to activity space: The effects of educational segregation on crime and their moderation by social context. Annals of the American Association of Geographers, 112(8), 2393-2412. https://doi.org/10.1080/24694452.2022.2060793

Zhao, P., Liu, X., Shen, J., & Chen, M. (2019). A network distance and graph-partitioning-based clustering method for improving the accuracy of urban hotspot detection. Geocarto International, 34(3), 293-315. http://dx.doi.org/10.1080/10106049.2017.1404140

Zhou, H., Liu, L., Lan, M., Yang, B., & Wang, Z. (2019). Assessing the impact of nightlight gradients on street robbery and burglary in Cincinnati of Ohio State, USA. Remote Sensing, 11(17), 1958. https://doi.org/10.3390/rs11171958

Zhu, Q., Zhang, F., Liu, S., Wang, L. and Wang, S. (2022). Static or dynamic? Characterize and forecast the evolution of urban crime distribution. Expert Systems with Applications, 190, 116115. https://doi.org/10.1016/j.eswa.2021.116115

Supplementary

Table S1. Exclusion Criteria and Screening Outcomes

Criterion	Description	Number Excluded
Non-English	Articles not in English	45
Non-Empirical GIS	Studies without GIS application	112
Rural Focus	Studies exclusively on rural crime	78
Non-Peer-Reviewed	Conference papers, reports, etc.	230
Other	Irrelevant topics, duplicates	42
Note: Total initial records = 800; final included = 293.		

Acknowledgements

This research was funded by XXXXXXXX through a XXXXXXX Grant Scheme (XXX) Grant No. (XXXXXXX).

Data and codes availability statement

The data presented in this study are available on request from the corresponding author.

Highlights

- GIS integrates AI, big data for real-time crime prevention, fostering secure environments.
- GIS uses predictive modeling, pattern recognition, and spatial analysis for localized interventions on inequality and exclusion.
- GIS transforms, informs policies for inclusive urban futures aligned with sustainability goals through interdisciplinary approaches.
- Community involvement crucial for ethical GIS tech aligned with societal priorities, fostering responsible deployment.

Ethical Assessment Statement

This study does not involve any human or animal subjects, direct interventions, or experiments requiring ethical approval. The research is based on secondary data analysis, computational modeling, or publicly available datasets, ensuring that no ethical concerns arise. Therefore, ethical approval is not applicable to this study.

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: