Cumulative Crime Environmental Pollution Crime Analysis and Legal Frameworks: A Survey

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Abstract

This survey paper provides an in-depth examination of the interconnected domains of cumulative crime, environmental pollution, crime analysis, and legal frameworks. It highlights the significant impact of urban structures and environmental factors on crime patterns, emphasizing the role of socioeconomic disparities and environmental conditions in shaping crime dynamics. The COVID-19 pandemic is explored as a case study, illustrating how mobility restrictions influenced crime rates globally. Advances in crime analysis techniques, including data collection, statistical methods, and technological innovations like deep learning, are discussed for their potential to enhance crime prediction accuracy. The paper underscores the critical role of legal frameworks in addressing these challenges, advocating for the integration of national sovereignty with international law to manage transnational issues effectively. Interdisciplinary approaches, particularly socio-legal studies, are emphasized as essential for developing comprehensive solutions that address the socio-political dynamics underpinning legal agreements. The survey concludes by advocating for continued research and collaboration across disciplines to tackle the multifaceted challenges posed by cumulative crime and environmental pollution, with a focus on leveraging technological innovations and fostering interdisciplinary cooperation to enhance public safety and promote sustainable urban development.

1 Introduction

1.1 Contextual Background

Understanding the interplay between cumulative crime, environmental pollution, crime analysis, and legal frameworks is crucial, particularly in urban areas characterized by socioeconomic disparities, where environmental factors such as heat significantly influence crime rates [1]. The COVID-19 pandemic further altered urban crime patterns due to global stay-at-home restrictions, with regions like Los Angeles experiencing notable shifts in crime trends as a result of containment policies [2, 3].

The enforcement of national criminal laws, particularly against illegal activities such as foreign fishing, highlights the economic and environmental ramifications of these practices [4]. Local regulatory frameworks, including alcohol licensing policies, illustrate the links between public health, crime rates, and legal structures [5]. Additionally, the rise of Artificial Intelligence Crime (AIC) presents both challenges and opportunities, necessitating a thorough analysis of interdisciplinary literature to address emerging threats [6].

The integration of big urban data with criminological theories enhances our comprehension of urban crime dynamics, thereby improving analysis and intervention strategies [7]. Collectively, these factors underscore the need for a holistic approach to crime analysis and legal frameworks, incorporating environmental and technological dimensions to tackle the complex nature of crime and pollution.

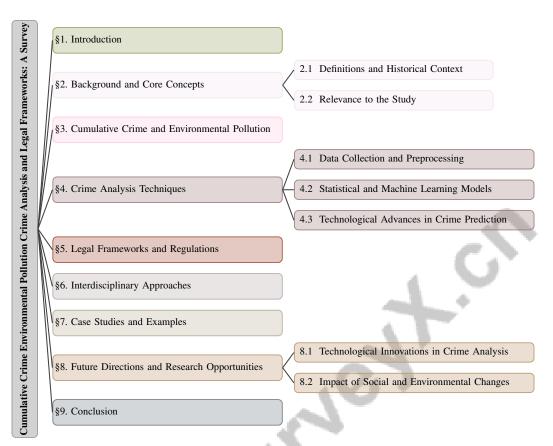


Figure 1: chapter structure

1.2 Structure of the Survey

This survey provides a thorough examination of the interconnected domains of cumulative crime, environmental pollution, crime analysis, and legal frameworks. It begins with an introduction that contextualizes these intertwined issues. The second section addresses foundational concepts, offering definitions and historical context relevant to the study. The relationship between cumulative crime and environmental pollution is explored in the third section, emphasizing the influence of urban structures and environmental factors.

The fourth section centers on crime analysis techniques, detailing data collection, statistical methods, and technological advancements that aid in identifying crime patterns and trends. Legal frameworks and regulations are analyzed in the fifth section, evaluating their efficacy and implementation challenges. The sixth section highlights the importance of interdisciplinary collaboration among criminologists, environmental scientists, and legal experts.

Real-world applications of crime analysis techniques and legal frameworks are illustrated through case studies in the seventh section. The survey concludes by identifying future research directions and opportunities, considering emerging trends and technologies that may impact these fields. The final section encapsulates the key findings and reflects on the interconnectedness of the topics, stressing the need for ongoing research and collaboration. The following sections are organized as shown in Figure 1.

2 Background and Core Concepts

2.1 Definitions and Historical Context

Cumulative crime encompasses the aggregation of criminal activities influenced by social and environmental factors over time and space [8]. This concept reflects the temporal distribution

of crime in urban areas, shaped by socioeconomic disparities and environmental conditions [9]. Methodological challenges arise in analyzing these trends, particularly due to violations in error variance assumptions in regression models for small populations [10]. The COVID-19 pandemic underscored the dynamic nature of crime, necessitating innovative analytical approaches to capture shifts across categories [3]. Additionally, the absence of a universally accepted definition for crime hot spots, as demonstrated in Hungary, calls for a reevaluation of traditional crime analysis methods [11].

Environmental pollution, defined by the introduction of harmful substances into ecosystems, correlates with rising crime rates, particularly in economically disadvantaged urban areas [1]. The link between increasing urban temperatures and crime demands a comprehensive urban planning approach, integrating environmental considerations into crime prevention strategies [7].

Legal frameworks, comprising institutional structures and regulations, are crucial in addressing societal challenges such as crime and environmental degradation. Their evolution reflects adaptability to emerging issues, including the ethical and legal implications of AI-Crime (AIC) [6]. The integration of AI and big data into legal frameworks, especially in disaster risk management, highlights the importance of ethical considerations in technological applications [12]. Historical examples, such as the impact of local alcohol licensing policies on crime rates, illustrate the complex interplay between regulatory measures and public health outcomes [5].

Recent advancements in data analysis, notably deep learning applications to spatio-temporal datasets, present new opportunities for insights and policy decisions [13]. Enhanced sampling methods like Multivariate Virtual Stratified Ranked Set Sampling (MVSR) aid in studying interconnected phenomena such as cumulative crime and environmental pollution [14]. The historical context of these concepts underscores the intricate relationships among urban development, environmental changes, and legal interventions, necessitating a multidisciplinary approach for effective solutions.

2.2 Relevance to the Study

Exploring cumulative crime, environmental pollution, crime analysis, and legal frameworks is vital for understanding broader societal and policy implications. Crime concentration in specific urban areas is crucial for developing legal frameworks that address variations in crime patterns, as demonstrated by Poisson-based regression models enhancing small count handling [10]. The influence of local policies, such as alcohol licensing, on public health and crime emphasizes integrating public health considerations into legal frameworks [5].

The COVID-19 pandemic further highlights the need to analyze crime trends within global health crises, as restrictions significantly altered crime dynamics, necessitating informed public health and safety strategies [2]. Community-specific factors remain pivotal during such events, underscoring the importance of tailored interventions considering local contexts [15].

Moreover, the economic and environmental effects of enforcing national criminal laws against illegal activities, like foreign fishing, demonstrate the interconnectedness of legal frameworks and societal outcomes [4]. Examining policing practices through federal and state investigations provides empirical evidence of legal frameworks' influence on crime rates, informing policy decisions [16].

Advanced methodologies, including sparse tree-based models for density estimation, enhance crime analysis's scalability and interpretability. Utilizing fine-grained urban, mobile, and public service data, these models reveal complex patterns and relationships among crime incidents, improving understanding of criminal behaviors within environmental and social contexts. They outperform traditional high-dimensional histograms, maintaining accuracy across dimensions and facilitating effective visualization, contributing to informed urban crime research and policing strategies [17, 18, 7, 19, 20]. Deep learning applications to spatio-temporal data mining uncover complex patterns informing comprehensive policy frameworks across transportation, climate science, and human mobility.

The survey of Artificial Intelligence Crime (AIC) underscores the ethical implications and potential risks associated with technological advancements in crime, necessitating reevaluation of existing legal frameworks to address these challenges [6]. Clarifying hot spot analysis in crime research addresses critical knowledge gaps, especially in underutilized regions like Hungary, enhancing practical applications of crime analysis techniques [11]. Collectively, these concepts highlight the

necessity for multidisciplinary approaches to tackle cumulative crime and environmental pollution, laying the groundwork for informed policy-making and societal interventions.

In examining the interplay between urban development and societal issues, it is crucial to consider the intricate relationships that define these dynamics. As illustrated in Figure 2, the hierarchical structure of the cumulative crime and environmental pollution dynamics is depicted, emphasizing the impact of urban structures and environmental factors. This figure highlights the interconnectedness of key themes, including crime patterns and pollution challenges, while also showcasing advanced analytical methods that can be employed to better understand these complex interactions. By integrating these visual insights, we can enhance our comprehension of how urban environments influence both crime rates and environmental health.

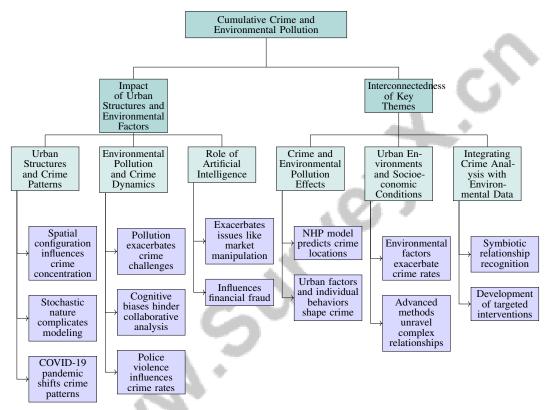


Figure 2: This figure illustrates the hierarchical structure of the cumulative crime and environmental pollution dynamics, emphasizing the impact of urban structures, environmental factors, and their interconnectedness with key themes such as crime patterns, pollution challenges, and advanced analytical methods.

3 Cumulative Crime and Environmental Pollution

3.1 Impact of Urban Structures and Environmental Factors

Urban structures and environmental factors are pivotal in shaping cumulative crime and pollution dynamics. The spatial configuration of urban areas influences crime concentration, as studies demonstrate links between built environments and crime distribution [21]. The stochastic nature of crime data, characterized by spatial and temporal sparsity, complicates modeling and prediction efforts [22]. During the COVID-19 pandemic, shifts in crime patterns due to stay-at-home orders highlighted the impact of community-level interventions [3, 5].

Complex network methodologies provide insights into the connections between urban structures and crime, integrating crime records to reveal underlying distribution patterns [22]. Los Angeles serves as a case study where spatio-temporal data enhances understanding of crime occurrences in relation to environmental factors [21]. Environmental pollution, characterized by harmful substances,

exacerbates urban crime challenges [8]. Cognitive biases further complicate the interplay between environmental degradation and crime, hindering collaborative crime analysis in urban settings.

Moreover, incidents of police violence influence crime rates, underscoring the complex socioenvironmental factors contributing to cumulative crime. The role of artificial intelligence in exacerbating issues like market manipulation and financial fraud illustrates the multifaceted nature of urban crime [5]. These studies collectively emphasize the necessity of integrating urban planning, environmental considerations, and advanced analytical techniques to effectively address the intertwined challenges of crime and pollution.

3.2 Interconnectedness of Key Themes

The interconnectedness of crime and environmental pollution is evident in their combined effects on societal structures and urban environments. The NHP model's capability to predict crime locations based on individual preferences highlights the intricate relationship between crime patterns and urban settings [21]. This model illustrates how urban environmental factors and individual behaviors converge to shape crime distribution, reflecting broader socio-environmental dynamics.

Urban environments, characterized by high population density and diverse socioeconomic conditions, foster complex interactions that significantly influence both crime and pollution levels. Studies indicate that environmental factors, including temperature and pollution, exacerbate crime rates, particularly in low-income neighborhoods. Advanced analytical methods, such as big data integration and deep learning, unravel the complex relationships between urban crime patterns and environmental influences, underscoring the necessity for effective urban governance and targeted crime prevention strategies [17, 1, 8, 7, 9]. The spatial and temporal distribution of crime is often shaped by environmental factors like pollution, which can heighten social tensions and contribute to increased crime rates, especially in economically disadvantaged areas.

Integrating crime analysis with environmental data provides a nuanced perspective on challenges faced by urban planners and policymakers. Recognizing the symbiotic relationship between crime and pollution allows for the development of targeted interventions addressing both environmental and social determinants of crime. A comprehensive approach is essential for promoting sustainable urban development and enhancing community resilience against the interconnected challenges posed by crime and environmental pollution. Leveraging advanced data analytics, including big data techniques and complex network methodologies, can improve understanding of crime patterns and their relationship with environmental factors, ultimately aiding in effective crime prevention strategies and the design of urban environments that mitigate climate change impacts, particularly in vulnerable low-income neighborhoods [7, 1, 8, 17].

4 Crime Analysis Techniques

4.1 Data Collection and Preprocessing

Method Name	Data Sources	Preprocessing Techniques	Computational Challenges	
CACA[23]	Fbi Press Releases	Data Pre-processing	Large Datasets	
RF[24]	Historical Data	Geocoding Incidents	Time Complexity Issues	
CSANRE[25]	Data.gov	R-tree Indexing	Time Complexity	
GBRBM[26]	Atlanta Police Department	Data Cleaning	Real-time Analysis	
ST-ResNet[27]	Los Angeles Data	Spatio-temporal Regularization	Increased Computational Cost	
PRA[10]	Census Data	Poisson Regression	Skewed Error Distributions	
FCA[28]	Xml Format	Data Integration Techniques	Real-time Analysis	

Table 1: The table systematically categorizes various crime analysis methodologies by detailing their respective data sources, preprocessing techniques, and computational challenges. It highlights the diverse origins of crime data, from FBI press releases to census data, and outlines the preprocessing methods such as geocoding and spatio-temporal regularization. Furthermore, the table provides insight into computational complexities encountered in these methodologies, ranging from time complexity issues to challenges in real-time analysis.

Table 1 presents a comprehensive overview of different crime analysis methods, illustrating the interplay between data sources, preprocessing techniques, and computational challenges. Accurate crime analysis and prediction hinge on effective data collection and preprocessing. Sourcing crime

data from diverse platforms, including open data initiatives, is crucial for identifying patterns and trends [23]. Preprocessing often involves geocoding crime incidents, as demonstrated in studies on interpersonal robberies in Dallas that utilized varied datasets for training and testing [24]. The computational complexity of processing large datasets, particularly the $O(n^2)$ time complexity in calculating near-repeat pairs, necessitates more efficient algorithms [25]. Integrating socio-economic and climatic indicators into spatially disaggregated crime datasets, such as those from Los Angeles, enriches the analysis by providing a comprehensive view of crime influences [1].

Advanced preprocessing techniques, like the GBRBM method, enhance pattern extraction from textual data by cleaning, normalizing, and tokenizing narratives into tri-gram terms, and constructing a term-document matrix via TF-IDF [26]. Deep learning architectures, notably residual convolutional networks, improve predictive signal extraction from raw crime data, enhancing multifactor prediction model accuracy [27]. Identifying population sizes alongside offense counts is fundamental for precise statistical analyses [10].

Despite advancements, limitations in current computing systems hinder real-time analysis and visualization of complex crime data [28]. To address this, methodologies that categorize existing methods by spatial settings and temporal spread have been developed, facilitating targeted data processing [11].

4.2 Statistical and Machine Learning Models

Statistical and machine learning models have significantly advanced crime data analysis, enhancing the understanding of crime patterns. Traditional statistical models, such as Poisson-based regression analysis (PRA), provide a foundational framework for examining relationships between crime counts and socio-economic and environmental factors [10]. These models are effective in analyzing crime distributions across urban landscapes.

Machine learning techniques have introduced sophisticated methods for managing complex datasets. The Next Hit Predictor (NHP) model, for instance, employs a self-exciting point process to estimate serial crime risks, accommodating both temporal and spatial dynamics [21]. Random Forests facilitate long-term crime prediction and offer interpretable summaries that deepen understanding of crime trends [24]. Advanced deep learning models use feature-level data fusion to integrate spatial, temporal, and environmental contexts, bolstering prediction capabilities [8].

The Bayesian structural time-series model offers a novel approach for evaluating causal impacts of interventions, such as social distancing, on crime trends by creating counterfactual scenarios [3]. The RIS-STVC method enhances crime data modeling by accounting for constant, spatial, temporal, and spatio-temporal processes, improving understanding of crime dynamics across various dimensions [22].

Integrating statistical and machine learning models equips researchers and policymakers with advanced methodologies that enhance crime prediction and prevention accuracy, addressing urban crime complexities and enabling proactive law enforcement strategies [29, 26, 7, 24, 20]. These models facilitate complex pattern identification, improve prediction accuracy, and inform comprehensive policy frameworks for crime mitigation in urban settings.

4.3 Technological Advances in Crime Prediction

Method Name	Technological Integration	Analytical Techniques	Operational Efficiency	
CFS[29]	Machine Learning	Predictive Models	Expedite Data Analysis	
FCPD[30]	Fuzzy Inference System	Dynamic Segmentation Approach	Computational Efficiency	
CSANRE[25]	R-tree Indexing	Cohesive Subgraph Algorithms	Reduce Computational Complexity	
SMSR[18]	-	Dimension Reduction Techniques	Reduce Computation Time	
FCA[28]	Intelligent Systems	Formal Concept Analysis	Real-time Analysis	
NHP[21]	Self-exciting Risk	Isotronic Kernel	Reduce Computation Time	

Table 2: Comparison of various crime prediction methods highlighting their technological integration, analytical techniques, and operational efficiencies. The table categorizes methods based on their use of machine learning, fuzzy inference systems, R-tree indexing, and other technologies, and evaluates their impact on computational efficiency and data analysis.

Technological innovations, particularly in AI and big data, have transformed crime prediction by enhancing complex dataset analysis and improving crime pattern forecast accuracy. The Crime Forecasting System exemplifies the integration of machine learning and computer vision techniques to analyze crime data, yielding predictive insights into future criminal activities [29]. Feature-based Change Point Detection (FCPD) is effective in crime prediction due to its adaptability to time series data shapes, allowing flexible change point detection [30]. Graph representation and cohesive subgraph algorithms enhance understanding of crime dynamics through near-repeat event detection [25].

Advanced computational techniques, such as Murakami's scalable model selection method, expedite spatial data analysis by substituting data matrices with their inner products, significantly reducing computation time [18]. Formal Concept Analysis (FCA) aids in visualizing and analyzing geographical crime patterns, establishing a framework for intelligent systems to better understand and respond to criminal activities [28].

The NHP model further illustrates AI's role in crime prediction by generating risk maps that merge background crime risk with risks triggered by prior offenses, integrating general crime risk with individual criminal behavior [21]. Technological advancements in AI and big data revolutionize crime prediction methodologies, equipping law enforcement agencies with sophisticated tools to forecast and address criminal activities more effectively. Table 2 provides a comprehensive comparison of different technological methods utilized in crime prediction, detailing their integration, analytical techniques, and contributions to operational efficiency. These innovations, including machine learning and computer vision techniques, enable nuanced analyses of complex crime patterns by integrating diverse data sources into predictive models. By leveraging these technologies, agencies can enhance operational efficiency, implement proactive crime prevention strategies, and improve public safety outcomes [29, 8, 7, 6, 27]. Harnessing these innovations allows policymakers and practitioners to develop informed strategies aimed at enhancing public safety and reducing crime.

5 Legal Frameworks and Regulations

5.1 Significance of Legal Frameworks

Legal frameworks play a critical role in addressing crime and environmental pollution, forming the basis for effective interventions and policy development. The integration of urban crime research with environmental and social criminological theories underscores the importance of contextual understanding in crafting legal responses, particularly in urban settings where socioeconomic factors intersect with crime [7]. The COVID-19 pandemic highlighted the need for adaptable legal structures that incorporate public health considerations into crime prevention strategies, maintaining relevance amid shifting societal conditions [3].

In regulating environmental pollution, legal frameworks are vital for controlling activities that threaten ecological integrity. Effective enforcement is essential to protect natural resources and mitigate environmental harm. The advent of advanced crime prediction technologies necessitates legal frameworks that support their integration while safeguarding ethical data use and privacy [8]. Legal frameworks also govern alcohol licensing policies, linking legal, health, and social issues to address urban challenges comprehensively. As urban areas face increasing crime and environmental issues, the demand for adaptive legal frameworks grows, amplified by big data analytics and AI technologies that could foster new criminal activities. Effective legal frameworks must integrate criminology and data science insights to address these complex issues, promoting urban safety and sustainable development [7, 6, 9].

5.2 Gaps in National and Local Legal Frameworks

Current national and local legal frameworks struggle to address the complexities of cumulative crime and environmental pollution. A significant challenge is enforcing laws against foreign vessels involved in illegal activities like unauthorized fishing, hindered by the absence of comprehensive international agreements, necessitating collaborative global legal structures [4]. The rapid evolution of AI technologies has outpaced the development of legal frameworks addressing their ethical and human rights implications, highlighting the need to expand understanding of Artificial Intelligence Crime (AIC) to protect individual rights while leveraging technological advancements [6].

Moreover, existing crime analysis methodologies reveal inadequacies in legal frameworks. Techniques like sparse density estimation, while insightful, struggle with high-dimensional or sparse datasets, potentially compromising prediction accuracy and legal intervention effectiveness [19]. Addressing these gaps requires legal systems to evolve, particularly in illegal fishing and environmental crime enforcement, enhancing governance and societal well-being by ensuring comprehensive, adaptive legal responses informed by interdisciplinary insights [12, 4, 16, 7, 6].

5.3 Integration of National Sovereignty and International Law

Integrating national sovereignty with international law is essential for regulating crime and environmental pollution. National legal systems, operating within sovereign confines, establish laws reflecting local priorities, yet the transboundary nature of many issues requires a collaborative approach beyond national borders [4]. International law facilitates such cooperation, fostering treaties that address global challenges like illegal fishing and pollution across jurisdictions.

Efforts to combat transnational environmental crimes illustrate the interplay between national and international legal frameworks. Treaties like the United Nations Convention on the Law of the Sea provide guidelines for sustainable marine resource management, enabling prosecution of illegal activities by foreign vessels and complementing national laws [4]. The rise of AIC necessitates integrating international legal standards with national regulations, as AI technologies present new challenges requiring a harmonized legal approach to ensure ethical use and human rights protection [6]. Frameworks like the European Union's GDPR model balance technological innovation with privacy and security, guiding national policies in managing AI-related risks.

Aligning national sovereignty with international law is crucial for developing robust legal frameworks addressing crime and pollution. Promoting international collaboration enhances nations' capacity to tackle complex challenges like disaster risk management and illegal activities, advancing sustainable development and global security. This fosters interdisciplinary cooperation among legal, social, and environmental experts, ensuring responsible use of technologies like AI within legal and ethical boundaries, contributing to a resilient global community [12, 4, 11, 6]. Integrating these elements supports national interests and international commitments, promoting comprehensive governance.

6 Interdisciplinary Approaches

6.1 Interdisciplinary Approaches to Crime and Pollution

Addressing the complex relationship between crime and environmental pollution necessitates an interdisciplinary approach, integrating insights from socio-legal studies, computer science, environmental science, and psychology. This is exemplified in research on Artificial Intelligence Crime (AIC), which combines socio-legal evaluations of ethical and legal implications, technological solutions from computer science, and psychological understanding of human behavior and cognitive biases [6]. Environmental science contributes by elucidating socio-environmental dynamics that influence crime patterns. Analyzing spatially disaggregated crime data alongside environmental factors such as pollution and urban heat, researchers have identified conditions that may elevate crime rates, particularly in low-income areas. For instance, studies indicate that extreme heat correlates with a 2.2

The significance of interdisciplinary methods is particularly evident in legal frameworks, where integrating legal expertise with technological advancements can enhance regulatory structures. Incorporating computer science insights enables legal frameworks to adapt to the rapid evolution of AI technologies and their implications for crime and privacy. Socio-legal studies assess the effectiveness of legal interventions by aligning them with empirical evidence and societal values. Research shows that federal and state "Pattern-or-Practice" investigations can significantly impact crime rates based on their initiation context. Specifically, investigations not preceded by high-profile police violence resulted in decreased homicides, while those following such incidents correlated with increased crime, underscoring the importance of understanding broader social implications and community responses to legal actions [11, 16, 31].

Interdisciplinary approaches are crucial for developing comprehensive solutions to the intertwined challenges of crime and environmental pollution. Leveraging diverse fields, policymakers can devise strategies that enhance public safety, promote environmental sustainability, and protect individual rights. This collaborative effort is vital for navigating the complexities of contemporary urban environmental sustainability.

ronments, integrating advanced data analysis from criminology, law, and social sciences, ultimately fostering resilient communities capable of addressing crime and disaster risks [7, 12].

6.2 Socio-Legal Studies and Comprehensive Legal Frameworks

Socio-legal studies play a critical role in developing comprehensive legal frameworks by examining the interplay between law, society, and regulatory mechanisms. This interdisciplinary field provides insights into how legal norms and social contexts influence one another, particularly in areas like disaster risk management, policing, and the implications of artificial intelligence on crime [12, 4, 16, 6, 31]. In the context of environmental pollution and crime, socio-legal studies offer perspectives on formulating and implementing laws that address these interconnected issues.

A significant contribution of socio-legal studies is exploring the intersection of national sovereignty and international law, particularly concerning maritime boundaries and resource management. Legal frameworks must balance national interests with international obligations, and socio-legal analyses help identify potential conflicts and synergies between national and international legal systems, promoting robust frameworks for sustainable resource management [4].

Moreover, socio-legal studies advocate for incorporating empirical research into legal framework development, ensuring laws are theoretically sound and practically applicable. This integration of interdisciplinary insights from artificial intelligence, socio-legal studies, and environmental management enhances the effectiveness of legal interventions in addressing challenges such as AI-driven crime and disaster risk reduction [12, 4, 16, 6]. For instance, socio-legal scholars can analyze the social impacts of environmental regulations to provide evidence-based recommendations for improving legal efficacy in reducing pollution and mitigating its effects on crime.

Integrating socio-legal studies into legal framework design fosters a holistic understanding of law as a social institution, recognizing the multifaceted nature of legal issues and the necessity for interdisciplinary collaboration. By drawing insights from sociology, political science, and environmental studies, socio-legal research shapes responsive legal frameworks adapting to evolving social and environmental dynamics. Such interdisciplinary approaches enhance the adaptability and effectiveness of laws, particularly in disaster risk management and emerging technologies like AI. This collaboration promotes the development of adaptive legal systems prioritizing safety, transparency, fairness, accountability, and contestability, ensuring legal frameworks remain relevant and effective in addressing contemporary challenges. Additionally, it underscores the importance of ongoing dialogue among legal, social, and environmental experts to navigate the implications of AI in disaster management and mitigate potential legal risks related to privacy and liability [12, 16].

7 Case Studies and Examples

7.1 Case Study: Atlanta Police Department Dataset

The Atlanta Police Department dataset serves as a pivotal resource for crime analysis, encompassing over a million crime incidents. A detailed examination of 10,056 burglary and robbery cases utilized spatial-temporal and textual point processes, highlighting the necessity of integrating diverse data dimensions to capture the complexities of crime patterns [20]. Another significant study applied this dataset to evaluate the Gaussian-Bernoulli Restricted Boltzmann Machine (GBRBM) method, embedding 1,096,961 crime incidents into a high-dimensional space to uncover underlying patterns and relationships, thus underscoring the efficacy of advanced machine learning models in enhancing crime analysis [26].

The extensive urban crime datasets underscore the importance of sophisticated data collection and preprocessing methodologies. Traditional demographic-based approaches often fail to encapsulate the dynamic complexities of urban crime. Therefore, advanced data integration techniques that encompass various crime-related sources alongside environmental and social contexts are crucial for comprehensive crime analysis and predictive modeling. By employing robust methodologies, researchers can leverage big data opportunities to improve urban safety, understand offender behaviors, and develop effective crime prevention strategies [7, 8, 17]. The Atlanta Police Department dataset exemplifies the transformative potential of data-driven approaches in addressing urban crime challenges, showcasing the practical applications of cutting-edge methodologies in real-world settings.

7.2 Evaluation of Crime Types Across Geographical Locations

Benchmark	Size	Domain	Task Format	Metric
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Table 3: The table presents a comprehensive overview of representative benchmarks used in the evaluation of crime types across various geographical locations. It details the size, domain, task format, and metric associated with each benchmark, providing a structured framework for understanding the methodologies employed in spatial and temporal crime analysis.

Analyzing crime types across geographical locations requires an understanding of spatial and temporal factors influencing crime patterns. Geographic disparities in crime rates, shaped by socio-economic, environmental, and policy-related factors, necessitate tailored analytical techniques. The Next Hit Predictor (NHP) model, which estimates the risk of serial crimes at various locations, exemplifies the utility of spatial analysis in understanding crime dynamics across urban settings [21]. Its integration of spatial and temporal dependencies aids in identifying high-risk areas and informing targeted interventions.

In Los Angeles, integrating socio-economic indicators and climatic data into spatially disaggregated crime datasets has provided insights into the environmental and social determinants of crime [1]. This contextualization allows for precise identification of crime drivers and the development of localized prevention strategies. Furthermore, advanced machine learning techniques, such as the GBRBM, enhance the detection of related crime series across different locations, deepening the understanding of crime type manifestations in diverse urban environments [26].

The analysis of crime types is further enhanced by employing Formal Concept Analysis (FCA) and cohesive subgraph algorithms, which facilitate the visualization and interpretation of complex geographical crime patterns. FCA categorizes crimes based on shared and distinct attributes, creating a structured framework for geographical crime data analysis. Cohesive subgraph algorithms improve the identification of near-repeat crime events, critical for understanding spatial and temporal correlations in crime incidents [7, 28, 25]. Together, these methodologies inform law enforcement strategies and contribute to targeted crime prevention measures.

A multifaceted approach integrating spatial analysis, machine learning, and socio-economic data is essential for evaluating crime types across geographical locations. By utilizing advanced data mining techniques and incorporating diverse datasets—urban, mobile, and public service—researchers and policymakers can achieve a comprehensive understanding of the factors influencing crime in various urban environments. This nuanced insight facilitates the development of targeted interventions addressing the unique social, environmental, and temporal challenges of each locality, ultimately enhancing urban safety and security. Additionally, integrating criminological theories can illuminate offender behaviors and crime patterns, guiding the creation of computational models that improve crime analysis and inform effective policing strategies [7, 9]. Table 3 provides a detailed overview of the representative benchmarks utilized in the study of crime types across geographical locations, highlighting the diverse methodologies and metrics applied in this field.

8 Future Directions and Research Opportunities

8.1 Technological Innovations in Crime Analysis

The integration of advanced technologies in crime analysis has significantly enhanced predictive accuracy and intervention strategies. Deep learning models, especially those applied to spatial-temporal and textual point processes, have proven effective in capturing complex interactions among crime incidents [20]. Future research should focus on refining these models to handle missing data and incorporate higher-order interactions, thereby enriching the comprehensiveness of crime analysis [27]. Advanced statistical techniques like the Linearization of Geographically Weighted Poisson Regression (L-GWPR) provide robust solutions for managing larger datasets and addressing multicollinearity [32]. Future inquiries should explore Poisson-based models across diverse crime data types and expand methodological frameworks to include nested data structures [10]. Enhancing Bayesian synthetic time-series methodologies and applying them to various public health interventions could further refine crime prediction techniques [5].

Combining complex network tools with deep learning techniques offers a promising avenue for managing high-dimensional datasets and improving performance on intricate crime data [19]. Future studies should assess these technologies in data-scarce regions and utilize transfer learning to enhance prediction accuracy [8]. Developing deep learning models for improved pattern recognition and simulating urban environments for pre-evaluating policing strategies are essential for advancing crime analysis [7]. The adaptability of models like the Next Hit Predictor (NHP) to diverse urban environments, along with the integration of real-time data for dynamic predictions, is pivotal for enhancing crime forecasting capabilities [21]. Incorporating near-repeat crime factors into Random Forest models and validating these methods across different urban settings will further enhance predictive accuracy [24].

In light of global challenges, future research should examine the long-term implications of COVID-19 on crime rates and the effects of ongoing social and economic shifts on criminal behavior [3]. The displacement of crime into online spaces necessitates the establishment of comprehensive legal frameworks and ethical guidelines for AI development to address these emerging issues [6]. By investigating these innovative technologies, researchers can deepen their understanding of crime dynamics and contribute to more effective crime prevention strategies.

8.2 Impact of Social and Environmental Changes

The shifting landscape of social and environmental factors significantly influences future research and policy development in crime analysis and prevention. Urban environments are particularly vulnerable to these changes, where socio-economic dynamics and environmental conditions interact to shape crime patterns. Future studies should explore additional crime types and conduct micro-level analyses to decipher the complexities of crime trends in urban settings [15]. Such investigations can yield insights into how specific social and environmental changes affect crime patterns, facilitating more targeted interventions.

The long-term consequences of federal and state investigations on community trust and police practices represent another critical area for future research. Understanding these impacts is essential for crafting policies that address crime while simultaneously enhancing community relations and trust in law enforcement. Research should examine how policy changes can alleviate potential negative outcomes of such investigations, promoting a more collaborative relationship between communities and law enforcement agencies [16].

Environmental changes, particularly those linked to climate change, necessitate adaptive strategies in urban areas to mitigate their effects on crime rates. Future research could focus on developing comprehensive urban adaptation strategies that address climate-related challenges, such as improving housing conditions and enhancing police responsiveness during extreme weather events, including heatwaves [1]. These strategies are crucial for minimizing the adverse impacts of climate change on urban crime and fostering community resilience.

9 Conclusion

This survey delves into the complex interplay between cumulative crime, environmental pollution, crime analysis, and legal frameworks, underscoring the significant impact of urban environments and socioeconomic disparities on crime dynamics. The COVID-19 pandemic has further illuminated how shifts in mobility and opportunity structures can alter crime rates, with notable declines observed during periods of restricted movement. Advances in crime analysis techniques, particularly through enhanced data collection and the application of statistical and technological innovations, have been pivotal in uncovering crime patterns. Although deep learning models show promise in refining crime predictions, challenges such as model interpretability and the integration of diverse data sources remain critical areas for future exploration.

The role of legal frameworks is paramount in addressing both crime and environmental pollution, highlighting the necessity of integrating national policies with international regulations to tackle transnational challenges effectively. Interdisciplinary approaches, particularly those incorporating socio-legal studies, are essential in crafting robust legal frameworks that consider the socio-political contexts of legal agreements. The survey underscores the imperative of sustained research and cross-disciplinary collaboration to address the multifaceted challenges posed by cumulative crime and

environmental pollution. By leveraging technological advancements and fostering interdisciplinary partnerships, stakeholders can develop more effective strategies to enhance public safety, promote environmental sustainability, and bolster the resilience of urban communities.

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