Journal of Strategic Security

Volume 17 | Number 3 | Article 4

Crimen en la Frontera: Exploring Texas-Mexico Border Crimes using a Geospatial Analysis

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pp. 49-69

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Abstract

Border crimes threaten public safety and security in the United States and the US-Mexico border region. Several evaluations support that data-driven, place-based crime prevention approaches can complement current public safety strategies and help reduce crime. Accordingly, place-based crime prevention may successfully prevent border crimes since these are inherently spatial. However, few studies have analyzed the geographies of Texas-Mexico border crimes, and assessments of data-driven, place-based crime prevention strategies of border crimes still lack a solid empirical foundation – especially in more rural border communities. To address this issue, this study builds police report data (Border Incident Assessment Report (BIAR)), used to record crime information related to cross-border criminal arrests and counter-criminal intelligence collection (2019-2022), for one rural county on the US-Mexico border. Results indicate high degrees of spatial concentrations of human smuggling and drug crimes. This study, moreover, explores how conventional theories of crimes and places (e.g., social disorganization) are able to explain border crimes. Findings indicate that while indicators work reasonably well to explain spatial patterns for drug crimes, more border crime specific indicators and models might have to be developed for human smuggling events.

Acknowledgements

There was no financial support for this study. The authors wish to thank the Zapata County Sheriff's Office, and the Texas Department of Public Safety Sergeant Christopher P. Williams and Raul G. Madrigal, for their valuable contributions.

Introduction

Drug crime, human smuggling, and border security are persistent challenges to federal and local law enforcement agencies along the US Southwest border.[1] For instance, US-Mexico migrant encounters have dramatically increased since 2020.[2] with 536,791 single adult migrant encounters, which later increased to 1,993,694 encounters in 2022.[3] Even more challenging, the number of Unaccompanied Children (UC) migrants in 2020 was 34,126 and increased to 152,880 UC migrants in 2022, drawing attention to children's involvement with migrant smuggling organizations and their endangerment and marginalization.[4] At the same time, drugs smuggled from Mexico into the United States (especially the highly potent fentanyl) continue to contribute to the US overdose epidemic.[5] Moreover, increased migrant encounters and a rise in fentanyl seizures have prompted public safety and border law enforcement mental health concerns.[6]

However, human smuggling and drug crimes have been prevalent along the Texas-Mexico border for a long time, with historically different border towns as the main entry points.[7] Some of the border towns where drug crimes and human smuggling are most prevalent were, in recent years, McAllen (TX), Laredo (TX), and El Paso (TX).[8] Human smuggling and drug trafficking are 'big business,' with intelligence reports indicating that transnational criminal organizations (TCOs) and drug trafficking organizations (DTOs) generate several billions of dollars by selling drugs in the United States.[9] Similarly, it is estimated that there is between 200 million and 2.3 billion dollars of revenue from smuggling migrants from Guatemala, Honduras, and El Salvador.[10]

Human smuggling and drug trafficking as cross-border crimes have an inherent spatial dimension. For example, Greenfield and González describe different international migrant smuggling routes that generate different amounts of criminal revenue.[11] Moreover, Slack and Campbell argued that criminal organizations controlled geographical boundaries, and that drug trafficking and human smuggling activities are deeply intertwined.[12] Like Greenfield, Slack and Campbell found that migrants using the Cartel-owned geography needed to pay tolls (under threats of violence). In some instances, the Cartel solicited migrants to guard the Rio Grande River with promises of money or threats of violence.[13] In short, the

US-Mexico borderland geography is used to generate revenue for drug trafficking and human smuggling organizations, ultimately impacting residents on both sides of the US-Mexico border.[14]

While these border studies underscore the importance of location and geography, they provide few details on the spatial clustering of drug crimes and human smuggling incidences along the border. Crime and place research, in general, has persistently found high levels of crime concentration, leading to descriptions such as the "iron law of troublesome places" or the "law of crime concentration."[15] Since the advancement of geographic information systems (GIS) in the 1980s and 1990s, over 44 studies have assessed crime concentrations in micro-places.[16] Since the earliest studies, high degrees of crime concentration across differing micro-places operationalizations (for example, addresses, street segments, intersections, or blocks) have been established (about 50% of all crimes are concentrated in 5% of places.[17] High levels of spatial concentrations of crime, in turn, highlight the potential of place-based crime prevention strategies, such as hotspot policing, and have successfully prevented crimes without or limited displacement.[18]

However, most of these studies on crime and places have focused on major cities such as New York, Chicago, Los Angeles, Philadelphia, Seattle, or St. Louis and often do not distinguish specific types of crimes or analyze index crimes.[19] Studies that have distinguished drug crimes from other crimes found that drug crimes show exceptionally high degrees of concentration.[20] Studies on smaller cities or more rural areas also suggest higher crime concentrations.[21] Since many areas along the US-Mexico border are rural and drug crimes show higher levels of concentration, spatial concentrations of drug crimes in border regions might be exceptionally high, and place-based crime prevention strategies could show particular promise. But, to date, no study has addressed drug crime concentrations in rural US-Mexico border areas. Moreover, investigations into concentrations of human smuggling are also absent from crime in micro-place research, necessitating the extension of the crime and place research agenda to border crimes and rural areas.

Similarly, spatial criminology has focused on assessing crime concentration and spatial patterning and explaining spatial patterns against an urban backdrop and urban crimes.[22] Understanding the

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DOI: https://doi.org/10.5038/1944-0472.17.3.2207

underlying structures could help predict future crime locations and inform crime prevention strategies if different spatial processes create different crime clusters.[23] Two major theoretical traditions have developed to explain the relations between crimes and places.[24] Social disorganization theory centers on explaining crime by focusing on the types of places encompassing crime and the inability of community structures and residents to maintain adequate social controls.[25] Other approaches have outlined how specific place characteristics, such as crime generators or local guardianship, can impact the spatial patterning of crimes.[26] However, currently, proposed indicators, such as concentrated disadvantage for drug crimes or proximity to bars and nightclubs for robbery, might be far less relevant to predict stash house locations in small border towns or smuggling routes across the Rio Grande.

Overall, crime research on human smuggling and drug offenses along the Rio Grande River requires further exploration. Therefore, spatial criminological investigations using incident-level border crime data may inform researchers, policymakers, and agencies about the social phenomena behind border crimes. Drawing on four years of current criminal incident data (2019-2022) on human smuggling and drug crimes in a rural border county, we assess three primary research questions:

1. Do border crimes show similarly high degrees of spatial concentration as established for other crimes?

2. Are human smuggling and drug crimes similarly spatially distributed?

3. Are indicators of crime concentrations that have been found predictive for crime in urban areas also predictive for border crimes?

To assess these issues, we first assess local spatial autocorrelations and highlight hotspots for drug crimes and human smuggling in the rural border county. In the second step, we operationalize indicators for social disorganization and assess associations between drug crimes and human smuggling events. Finally, we build on systematic social observations using Google Earth to explore potential other predictors of human smuggling and drug crime locations.

Methods

Study Area and Data

Texas-Mexico border crime arrests and counter-criminal intelligence allow criminal justice practitioners and researchers to understand better the etiology of crime on the border.[27] The criminal behaviors displayed and collected during a thwarted attempt at the Texas-Mexico border are the organized criminal elements that can be studied to comprehend the modus operandi or MO.[28] This study focuses on Zapata County. The Zapata County border towns are near the Rio Grande River, embodying the Texas-Mexico border. Like other Texas border counties, 94 percent of the population is Hispanic, and Zapata (the major town in Zapata County) comprises approximately 13,889 residents.[29] Zapata County's spatial characteristics include interconnecting US and State Highways.[30]

This study used official police reports called the Border Incident Assessment Report (BIAR) provided by the Zapata County Sheriff's Office. Zapata County is a southern Texas-Mexico border town with deputies, or officers, who made the border incident assessment reports during incident responses. The BIAR collected and recorded all criminal characteristics to generate policing strategies along the border. This data was collected from 2019 to 2022, encompassing several border towns within the border county. The data is geocoded with incident locations, allowing for spatial analysis.

Dependent Variable

The dependent variables for this study are human smuggling and drug crime. The official police data provided crime categories, and deputies recorded the outcome, such as whether the incident involved human smuggling, drug crimes, or both. Human smuggling is a dichotomous variable coded (0) Not a human smuggling crime, and (1) Yes, a human smuggling crime. The second dependent variable, drug crime, is also dichotomous, coded (0) Not a drug crime, and (1) Yes, a drug crime. Missing information was compared with accompanying reports and other provided information (for example., types of drugs seized as an indicator for a missing drug crime code) and subsequently imputed (less than 1% of cases). The imputation was conducted by cross-referencing the crime

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categories the deputies missed but were included in the data file. For example, one incident may have been categorized as migrant smuggling but included a criminal charge of possession of cocaine.

Independent Variables

Integrating US Census block characteristics supplements the spatial pattern analysis. 2010 US Census sociodemographic information was applied at the block level (1,765 Census Blocks). This is the smallest geographic unit on which the US Census provides publicly accessible data and has been used in past research on crime in micro places.[31] Demographic block information included Population rate under 18, Population rate of Female Head Household, Urban and Rural Population, Non-White Household Rate, and Vacancy Rates. The population rate under 18 is categorized by areas with a high count of individuals under 18, an average count of under 18, and a lower count of individuals under 18. The vacancy rate is interpreted by the US Census, meaning if there are no individuals currently residing in the household. A high female-headed household rate indicates a higher count of females as the head of the household. These census variables are often used to operationalize social disorganization theory and were assigned to the respective Zapata County blocks.

Since a large part of the county's areas have no population and provide only missing data, we decided to recode the data to create categories that distinguish areas with no population from low levels (bottom 25%), average level (mid 50% of the distribution), and high levels (top 25%) of the respective variable (except for the rural/urban variable which is per Census data either 100% rural or urban). Otherwise, cases without information would have been excluded from spatial regression models, or the information on the absent variable would have to be mixed in with some 'true' 0% of the respective independent variables since we assume that no-population provides a different spatial process than, for example, an actual 0% urban population, we decided on the recoding approach for our exploratory assessment of associations of social disorganization theory and border crimes.

Prior research has also used crime generator indicators to predict crime.[32] While standard information about businesses, bars, nightclubs, and other crime generators is used to predict urban crimes, no list of indicators exists to establish crime generators in rural areas and for border crimes. Building on Sampson and Raudenbush's systematic social observation (SSO) approach, we used Google Earth Pro to explore potential crime generators.[33] Traditional SSOs are resource-intensive and time-consuming. However, using technology such as Google Street View has facilitated the implementation of SSOs.[34] For example, Sytsma studied drug markets and environmental facilitators by combining social observations using Google Street View and camera footage of drug transaction areas.[35] Using Google Street View imagery, Sytsma et al. measured physical disorder, decay, and crime generators and how they affected drug seller actions.[36] Google Earth Pro is a free and advanced geospatial information system that can observe three-dimensional and two-dimensional depictions of the Texas-Mexico Border. Researchers for this study geocoded all segments of the Rio Grande River (Border line) and observed the geographical characteristics Google Earth provided.

A comprehensive search using academic search databases such as EBSCOhost, Google Scholar, and ProQuest yielded no results for Texas-Mexico border research that focused on the geographic factors associated with crime. Therefore, this study uses SSO in an exploratory fashion, building on law enforcement feedback (personal communications of the first author). The developed indicators include businesses, government agencies, and the physical characteristics of the borderline. During the exploratory research stage, deputies advised of the common physical characteristics of the river and their practical knowledge of crime associated with the river. Five crime generators resulted after observing the geographic characteristics of the Rio Grande River: (1) River Proximity, (2) Vehicle Accessibility to the River, (3) Rural Landmarks, (4) Mexico Border Characteristics, and (5) River Vegetation Thickness.

The river proximity variable was geocoded between US Highway 83 and the Rio Grande River border. There are three categories: 0 coded less than 1 mile, 1 coded between 1 to 1.99 miles, and 2 coded two miles or more from the incident to the river. Vehicle accessibility to the river was geocoded based on the number of barriers preventing vehicles from driving in and out from border roads to US Highway 83. The direct path is a straightforward road/path that connects the river border to US Highway 83. The indirect path has some obstacles like mesquite or natural barriers.

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DOI: https://doi.org/10.5038/1944-0472.17.3.2207

No clear path is a barely noticeable trail with natural vegetation. The geocode was based on a 2-mile radius between the incident location and accessibility. Rural landmarks are places distinguished by either private or public access. Public Property includes historical public sites and public parks. Private properties are ranch properties, private lakes, airports, business establishments, or any place with restricted/private access. Picnic sites are rest areas for traveling passengers in public areas off US Highway 83. Rural landmarks were geocoded according to a 2-mile radius between the incident location and the type of landmark.

The geocode Mexico border characteristics variable resulted from borderland characteristics along the countryside in Mexico. Remote areas have no crop fields or houses nearby but thick, green, wet regions. Large open roadways are crop areas with square-shaped lands and dirt roads close to the Mexico riverside. High vegetation is a Land infrastructure that includes buildings, homes, water plants, or any infrastructure. Land infrastructure with open roadways is primarily residential houses with barns and dirt roadways close to the border. A 2-mile radius between the incident location and Mexico border characteristics guided the Mexico border characteristics. The fifth variable is river vegetation thickness, coded based on the vegetation thickness characterized by the number of trees, shrubs, cactuses, and other vegetation types. No vegetation is the absence of trees ample vegetation. Shrubbery is when there are trees or plant life within the vicinity.

Spatial Analysis

We first assessed spatial crime patterns and crime concentrations along the Texas-Mexico border. To conduct the process, the Local Indicator of Spatial Autocorrelation, the LISA method, was used to identify high and low spatial concentrations of drug crimes and human smuggling events.[37] For example, high crime blocks adjacent to high crime blocks will be identified, as well as low crime blocks adjacent to low crime blocks. Alternatively, the number of high-crime blocks adjacent to low-crime blocks is also identified. The LISA spatial technique is a valuable method for understanding rural border towns due to the technique's handling of spatial outliers that might impact global assessments of spatial autocorrelation. A first-order Queens Contiguity Weight Matrix defined spatial relationships among blocks. We use a zonal analysis strategy instead of a point-based analysis of the cases (for example, kernel-density estimation) since this allows for the subsequent combination with US Census data. Subsequently, negative binomial regression is used to analyze crime counts.[38] In other words, the variances within each variable were higher than the mean score, indicating the need to use negative binomial regression analysis over other count-based regression approaches.[39] Due to sample size limitations, we explored only bivariate associations. Finally, we also assessed the bivariate associations among each crime generator indicator we created by the two crime types. We provide chi-square test statistics to explore differences between crime generators for the two crime types.

Results

Assessment of Crime Concentrations

We first assessed global spatial autocorrelations and, subsequently, the local spatial autocorrelations and their patterns. The global spatial autocorrelation indicated that drug crime was significantly concentrated (p=.002, z-score= 6.1842. However, global spatial autocorrelation for human smuggling events was not significant (p= .084, z-score=1.531). However, the local spatial autocorrelation measure identified significant hotspot areas distributed across the County for human smuggling events. Generally, drug crime clusters were mainly located within the inner-city blocks, a differentiating spatial characteristic from human smuggling events (see Figures 1 and 2).

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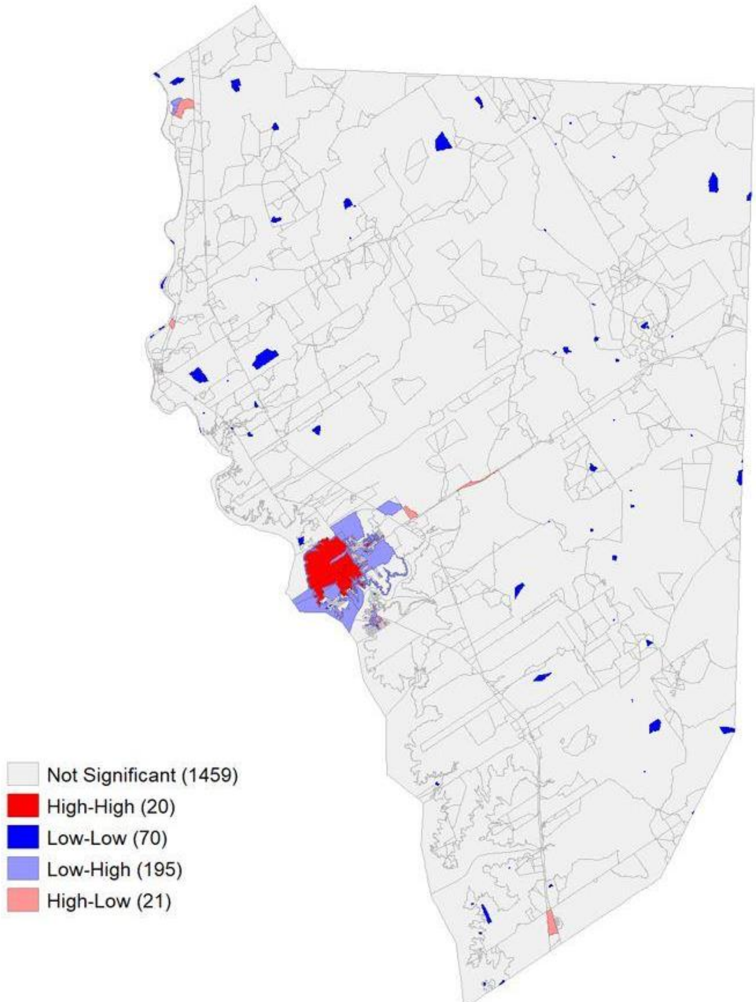
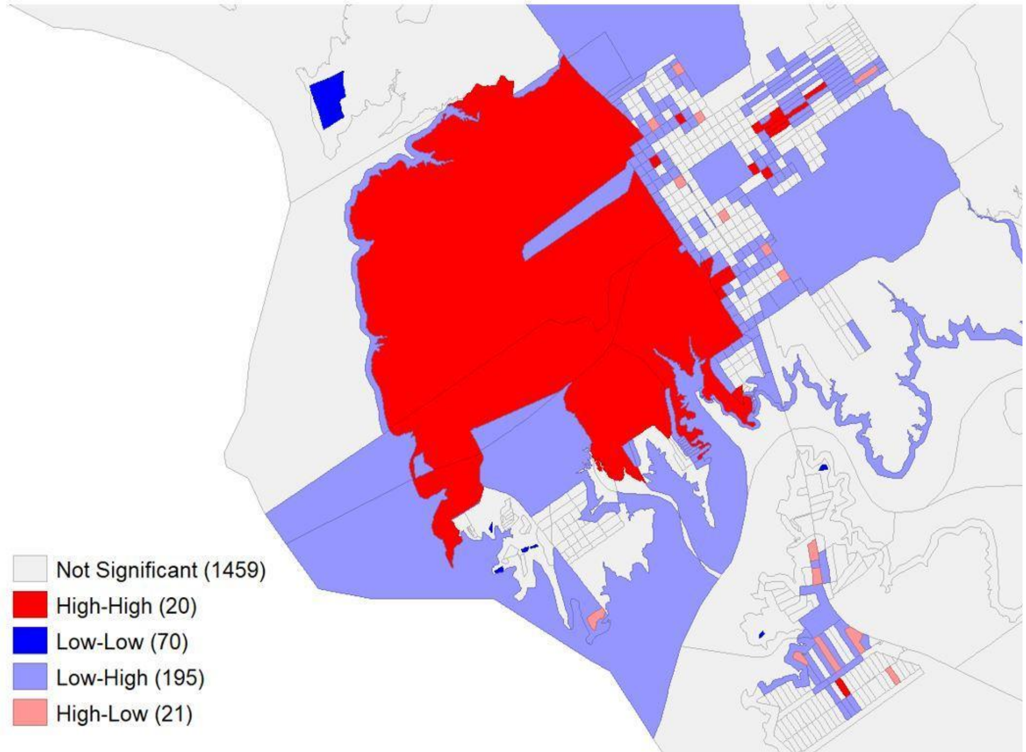
DOI: https://doi.org/10.5038/1944-0472.17.3.2207

Figure 1: Drug Crime Hotspots



Note: High-High indicates the clusters of high crime blocks adjacent to high crime blocks. Low-low indicates low-crime blocks adjacent to low-crime blocks.

Figure 2: Drug Crime Hotspot in Zapata



Note: High-High indicates the clusters of high crime blocks adjacent to high crime blocks. Low-low indicates low-crime blocks adjacent to low-crime blocks.

Accordingly, one of the reasons the human smuggling variable was not found significant when assessing global autocorrelation may be that Zapata is a rural area, with human smuggling cases spread out along highways. In contrast, drug crime cases are more concentrated in small cities (see Figures 1 and 2). In total, twenty blocks were high-high clusters for drug crime incidents. Additionally, twenty-one blocks were high-crime blocks clustering with low-crime blocks, suggesting more isolated drug crime hotspots.

One of the characteristics of drug crime demonstrated by the spatial pattern is that this type of crime is mainly observed within cross streets and more urban areas. One of the highest crime areas is the Medina Addition neighborhood, located close to the center of Zapata in the northeast of the city (see Figure 3). Medina Addition is a small neighborhood interconnecting two major highways with significant high-high blocks, such as high-crime areas neighboring other high-crime areas.

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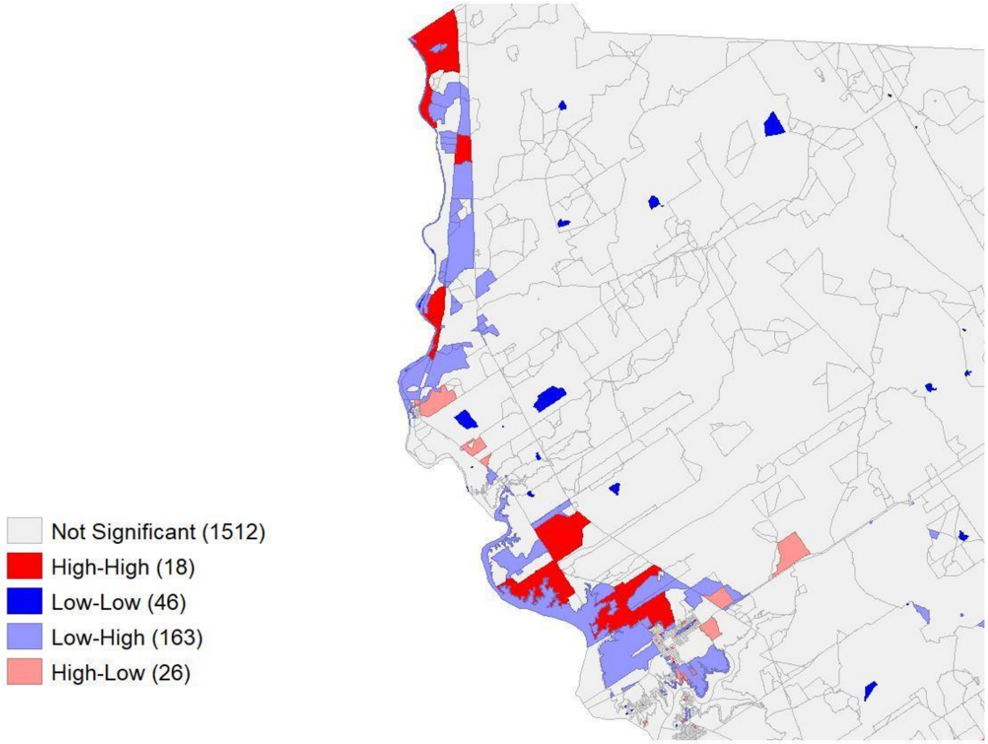
DOI: https://doi.org/10.5038/1944-0472.17.3.2207

Figure 3: Migrant Smuggling Hotspots



Note: High-High indicates the clusters of high crime blocks adjacent to high crime blocks. Low-low indicates low-crime blocks adjacent to low-crime blocks.

Human smuggling hotspots were primarily identified among main highways such as US Highway 83 and State Highway 16 (see Figure 2). 18 High-high block groups were located on the east and west sides of US Highway 83 across the Rio Grande River border. Interestingly, west of US Highway 83 is the Texas-Mexico border, which varies in distance from the highway based on the curvature of the Rio Grande River. Additionally, 26 high-low human smuggling groups were identified along State Highway 16 and US Highway 83. The more significant amounts of high-crime to low-crime incidents with human smuggling cases might indicate specific area features that favor human smuggling activity.

Assessment of Area Characteristics of Hotspots

Several significant relationships existed between social disorganization indicators and both dependent variables. The five social disorganization variables are compared for each indicator category, including the No-Population base category (see Table 1).

Table 1: Negative Binomial Regression Model: Social Disorganization Indicators Associations with Human Smuggling and Drug Crime

		Human Smuggling IRR (95% CI)	Drug Crime IRR (95% CI)
Rural Population (Base: No Population)	Rural	8.2*** (3.0–22.2)	5.9***[b] (2.7–12.6)
	Urban	3.7*** (1.7–8.4)	11.5***[a] (6.1-21.6)
House Vacancy Area (Base: No Houses)	High-Vacancy Rate	4.6** (1.4-15.5)	1.3 [bc] (1.5–2.9)
	Average-Vacancy Rate	6.9*** (2.5–16.6)	9.0***[a] (5.2–17.5)
	High-Occupation Rate	6.7*** (2.5–18.5)	10.6***[a] (5.2-21.4)
Under 18 YOA Rate (Base: No Population)	Low-Rate Under 18	4.0* (1.2–13.1)	3.2*[bc] (1.2-8.7)
	Average-Rate Under 18	7.1*** (2.9–17.6)	11.5***[a] (5.5-23.7)***
	High-Rate Under 18	3.7* (1.2-11.2)	11.4*** (5.5-23.7)
Female-Headed Household Rate (Base: No Population)	Low-Rate Female Head	4.0**[c] (1.6-9.7)	7.1*** (4.0-22.2)
	Average-Rate Female Head	9.7*** (3.6-26.6)	12.7*** (6.3–25.7)
	High-Rate Female Head	1.1[a] (.3-4.3)	9.5*** (4.0-22.2)
Non-White Household Rate (Base: No Population)	Average-Rate Non-White	5.3*** (2.6–11.1)	9.6*** (5.2–17.8)
	High-Rate Non-White	5.6* (1.0–30.1)	8.0*** (2.8–23.1)

Note: Dependent Variable N=1765. *** indicates a P-Value <.001 (compared to the base category), ** indicates a P-Value<.01, *indicates a P-Value<.05. [a] indicates a significant difference (at least p<.05) from the first non-base category, [b] indicates a significant difference (at least p<.05) from the second non-base category, [c] indicates a significant difference (at least p<.05) from the third non-base category.

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For example, human smuggling incidents were 7.2 times more likely in rural areas and 2.7 more in urban neighborhoods compared to the No Population base area (see Table 1). The vacancy rate variable, average vacancy rate, was most closely associated with human smuggling, 6.9 times more likely to spatially co-occur compared to the base category (see Table 1). All other indicators also showed significant differences for human smuggling events, with the average rate categories often showing the strongest associations (albeit mostly not significantly different from the other non-base categories). Interestingly, the average rate of female-headed households was 6.1 times more likely to have a human smuggling incident compared to the base category. Still, in contrast to expectations based on social disorganization theory, the high-rate female-headed households had the smallest difference compared to the base category (see Table 1).

Compared with these human smuggling regression results, drug crimes also had significant but opposite characteristics for the rural and urban variables. Urban areas were 10.5 more likely to have drug crime over the base category (see Table 1). Rural areas were also significantly more likely to be associated with drug crimes, but only at a rate ratio of 4.9. Furthermore, the other social disorganization indicators showed strong, significant associations with drug crimes for the highest categories of each indicator, as expected based on social disorganization theory. The regression results support the spatial analysis result, indicating geographical differences between the commission of drug and migrant smuggling crimes.

Exploring Human Smuggling Crime Generators

Crosstabulation between exploratory crime generators and human smuggling events showed significant differences between human smuggling and other crime locations. For example, large open roadways were associated with 15.2% of smuggling cases and only 5% of non-smuggling cases (see Table 2). Table 2 shows that rural landmarks were also significant indicators (with a Chi-square value of 24.5 and a p-value of <.0001), as were river proximity (Chi-square value of 24.8) and vehicle accessibility (Chi-square value of 24.2). Direct paths to the river, which included public roads with a direct connection to the river and highways, are where 41.7% of migrant smuggling incidents occurred, compared to 34.4% as vehicle accessibility became indirect.

Migrant smuggling incidents were also more prevalent in private properties than in public properties. For example, 72.9% of migrant smuggling occurred within private properties and 20.5% in public properties. These results may be related to rural areas comprising single private properties that are several hundred acres along the Rio Grande River. The border characteristics were also shaped by the river's proximity to main highways such as US Highway 83 and public roads connecting to the Rio Grande River. Vegetation thickness was the only crime generator found not significant, and this may be because migrant smuggling involves two methods of smuggling through the border, walking smuggling routes and vehicle pick-up points which might favor different types of vegetation.

Discussion

In this study, unique police data on border crime incident locations with US Census data and crime generator data collected using SSO via Google Earth were combined. Using this spatial exploratory approach, an overview of the spatial distribution of drug and human smuggling crimes along the rural US-Mexico border is provided. One key research question assessed was whether human smuggling and drug crimes show similar spatial patterns. Migrant smuggling research discusses that this type of crime may constitute a differently organized structure than drug crimes.[40] Moreover, it is common to find human smuggling research studies that provide insight into migrants' perspectives or criminal organizers.[41] However, studies that use official crime data to assess and compare spatial patterning are currently lacking.

Through the recorded accounts from official police data, human smuggling cases were observed to be attributed to federal and state highways. Spatial characteristics demonstrated significant hotspots where the highways were closer to the Rio Grande River. US Highway 83 had clear pathways and curved roadways in several incident clusters. The curved roadways that increased river proximity demonstrated significant hotspots for human smuggling. Through the recorded accounts from official police data, human smuggling cases were observed to be attributed to federal and

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Table 2: Border-Specific Crime Generators and Human Smuggling Events

	MX River Characteristics			**Rural Landmarks**			**River Proximity**			**Vehicle Accessibility River**			**Vegetation Thickness**	
	Non-Smuggling	**Migrant Smuggling**		**Non-Smuggling**	**Migrant Smuggling**		**Non-Smuggling**	**Migrant Smuggling**		**Non-Smuggling**	**Migrant Smuggling**		**Non-Smuggling**	**Migrant Smuggling**
Remote Area	39%	31.2%	Public Property	7.1%	20.5%	Less than 1 Mile	8.5%	26.3%	Direct Path	25.5%	41.7%	Dense Shrubs	88.7%	84%
Large Open Roadways	55.3%	52.8%	Private Property	91.5%	72.9%	Between 1 to 1.99 Miles	14.2%	18.2%	Indirect Path	57.4%	34.4%	Some Vegetation	10.6%	16%
Land Infrastructure	.7%	.9%	Picnic Area	0%	5.8%	2 Miles or More	77.3%	55.6%	No Clear Path	17%	23.9%	No Vegetation	.7%	0%
Land Infrastructure with open roadways	5%	15.2%	Private Property & Other	1.4%	.9%									
Chi-Square	**10.9***			**24.5****			**24.8*****			**24.2*****			**5.7**	

Note: * = <.05, **=<.01, *=<.001**

state highways. Spatial characteristics demonstrated significant hotspots where the highways were closer to the Rio Grande River. US Highway 83 had clear pathways and curved roadways in several incident clusters. The curved roadways that increased river proximity demonstrated significant hotspots for human smuggling.

As such, the spatial findings run concurrent with crime generators' findings, supporting that geographic characteristics matter regarding border crime. Spatial and crime generator results further Gonzalez' research by confirming the use of remote areas away from the highway as illicit migrant journeys.[42] The migrant smuggling modus operandi was significant along the borderlands near the main US Highway and indeed necessitate a smuggling facilitator.[43] Subsequently, human smuggling events are concentrated further north along US Highway 83 since human smuggling not only involves border crossings but also the illicit transportation of migrants to northern cities away from the Texas-Mexico border.

Like Slack and Campbell and Greenfield et al., migrant smuggling and drug crimes were found to be prevalent along the Mexican border, but both crimes have differentiating modus operandi.[44] This study contributed to the pre-existing body of research on Texas-Mexico border crime by identifying the geographic differences between drug crime and the smuggling of migrants. The spatial characteristics associated with drug crimes were contrary to human smuggling cases. Significant drug crime hotspots were located within urban communities in Zapata and several high-crime block groups in specific town neighborhoods. Zapata County has six border towns, including Zapata City; interestingly, this town has all major drug crime hotspots in the county. The Zapata border town is also at the center of US Highway 83 and State Highway 16's intersection.

Moreover, predictors of human smuggling and drug crime locations are at times associated with differing sociodemographic predictors. The most rural areas of Zapata were significantly associated with human smuggling incidents. Areas that had an average rate of subjects under the age of 18 were attributed to human smuggling and drug crime, in line with social disorganization assumptions on the need for informal and formal social controls. The neighborhoods where drug crimes were concentrated were significantly more socially disorganized than neighborhoods without

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DOI: https://doi.org/10.5038/1944-0472.17.3.2207

crimes and human smuggling event locations. This might indicate that while social disorganization theory is appropriate to understand and predict drug crime locations in the borderlands, comparable to the broader United States, it is less valuable to explain human smuggling events. To understand the spatial patterning of human smuggling events, developing and collecting alternative location predictors is necessary.

Limitations

One of the limitations of this study is the reliance on official police data, which often suffers from underreporting of crimes and reflecting policing practices.[45] Here, additional information sources such as qualitative information from interviews might help to assess the quality of the police data.[46] Although police agency criminal law procedures regulate the collection and documentation of official police data, the quality of the data relies on the officer completing the report accurately and completely.[47] Additionally, official police data is subject to the natural change of laws, policies, and police enforcement strategies influencing reporting standards and categorizations of crimes and associated case information.[48] The possibility of human smuggling and drug crime law changes and policing practices affecting arrest numbers and locations is unavoidable. The addition of new police executives or administration can change policy by what their agency's officers can and cannot do. One administration can enforce or prioritize different types of crime; this may influence the officers' decision-making during an incident.[49] The changing policing strategies can also impact police-public contact. The number of police calls in one area can result in the agency changing patrol locations and separating patrol enforcement within areas of the community. There is also an assumption that crime in proximity to the border is border-related, which depends on the reporting officer and grant-related enforcement. This study was also limited to two types of crimes, overshadowing several violent crimes such as robbery, extortion, assault, sexual assault, and many more.

Another limitation of the large border crime research agenda highlighted by this study is the need for new crime indicators for human smuggling. Contemporary human smuggling literature must provide crime indicators that can be tested in quantitative spatial studies. An alternative to the lack of criminal indicators is to employ an SSO approach using public resources such as Google Earth to code spatial characteristics along the Texas-Mexico border. SSO can generate spatial characteristics such as street structure, public parks, businesses, or hotels and assess their spatial relationships to hotspots. The approach here needs to be refined and tested in other border areas.

Conclusion

Overall, the spatial analysis of border crimes demonstrated significant concentrations of human smuggling and drug events in one rural Texas-Mexico border county. Both types of border crimes show spatial patterns that can inform public policy and border law enforcement strategies to counter organized crime, facilitating such events. Two essential takeaways were provided: human smuggling incidents involve main highways transporting undocumented migrants away from the Texas-Mexico border. Drug crime cases were identified at the border within small-town neighborhoods impacted by social disorganization. As a result, law enforcement agencies can allocate patrol enforcement on highways to deter human smuggling events and neighborhood patrols to thwart drug activity as a crime prevention strategy. This study helps to fill a gap in prior research on migrant smuggling and drug trafficking organizations by providing a concrete spatial overview of crime locations and assessing the associated area characteristics. The crime generators forming the borderlands proved to be related to migrant smuggling accounts, and the social disorganization framework further enhanced the concept of social controls related to drug crime areas. Thus, the findings might help to inform policing strategies as well as community crime prevention campaigns by showing that evidence-based spatial crime prevention strategies, such as problem-based hotspot policing, might work for drug crimes in small border towns as well as in major urban areas.

Endnotes

1. Robert M. Lawler, "Border Security," in *The Role of Law Enforcement in Emergency Management and Homeland Security*, vol. 24 (Emerald Publishing Limited, 2021), 89-110, https://doi.org/10.1108/S2040-726220210000024005.

2. John Gramlich, "Monthly Encounters with Migrants at US-Mexico Border Remain Near Record Highs," Pew Research Center, January 13, 2023, https://www.pewresearch.org/short-reads/2023/01/13/monthly-encounters-with-migrants-at-u-s-mexico-border-remain-near-record-

https://digitalcommons.usf.edu/jss/vol17/iss3/4
DOI: https://doi.org/10.5038/1944-0472.17.3.2207

highs/#:~:text=Monthly%20encounters%20between%20U.S.%20Border,the%20latest%20available%20government%20statistics.

3 U.S. Customs and Border Protection, "Nationwide Encounters," United States Government, 2023, https://www.cbp.gov/newsroom/stats/nationwide-encounters.

4 Gabriella Sanchez and Sheldon X. Zhang, "In Their Own Words: Children and the Facilitation of Migrant Journeys on the US-Mexico Border," in *Beyond Drugs, Smuggling and Trafficking* (Routledge, 2021), 80-99, https://doi.org/10.4324/9781003152330.

5 Joseph V. Pergolizzi Jr. et al., "Overdoses Due to Fentanyl and Its Analogues (F/FAs) Push Naloxone to the Limit," *Journal of Clinical Pharmacy and Therapeutics* 46, no. 6 (2021): 1501-1504, https://doi.org/10.1111/jcpt.13462.

6 Mark E. Green, "Border Crisis Startling Stats: Illegal Crossings of the Southwest Border Increased in April Ahead Title 42 End," Homeland Security Republicans, May 2023; S. K. Brooks and N. Greenberg, "Mental Health and Wellbeing of Border Security Personnel: Scoping Review," *Occupational Medicine* 72, no. 9 (2022): 636-640, https://doi.org/10.1093/occmed/kqac108.

7 Drug Enforcement Administration (DEA), *NDTA: National Drug Threat Assessment* (United States Department of Justice, 2021), 1-96; Chad Richardson and Rosalva Resendiz, *On the Edge of the Law: Culture, Labor, and Deviance on the South Texas Border* (University of Texas Press, 2006), https://doi.org/10.7560/713338.

8 Richardson and Resendiz, *On the Edge of the Law*.

9 Drug Enforcement Administration (DEA), *NDTA: National Drug Threat Assessment*.

10 Victoria A. Greenfield et al., *Human Smuggling and Associated Revenues: What Do or Can We Know About Routes from Central America to the United States?* (HSOAC, Homeland Security Operational Analysis Center, 2019), http://dx.doi.org/10.7249/RR2852.

11 Greenfield et al., *Human Smuggling and Associated Revenues*; Yaatsil Guevara Gonzalez, "Navigating with Coyotes: Pathways of Central American Migrants in Mexico's Southern Borders," *The ANNALS of the American Academy of Political and Social Science* 676, no. 1 (2018): 174-193, https://doi.org/10.1177/0002716217750574.

12 Jeremy Slack and Howard Campbell, "On Narco-coyotaje: Illicit Regimes and Their Impacts on the US–Mexico Border," *Antipode* 48, no. 5 (2016): 1380-1399, https://doi.org/10.1111/anti.12242.

13 Greenfield et al., *Human Smuggling and Associated Revenues*; Slack and Campbell, "On Narco-coyotaje."

14 Texas Joint Crime Information Center Intelligence & Counterterrorism Division (TJCIC), *Texas Gang Threat Assessment* (Texas Department of Public Safety, 2018), https://www.dps.texas.gov/section/about-dps/threat-assessments; Office of the Texas Governor (OTG), *Texas Homeland Security Strategic Plan 2021-2025*, 2021, https://gov.texas.gov/uploads/files/press/HSSP_2021-2025.pdf.

15 Pamela Wilcox and John E. Eck, "Criminology of the Unpopular: Implications for Policy Aimed at Payday Lending Facilities," *Criminology & Public Policy* 10 (2011): 473, http://dx.doi.org/10.1111/j.1745-9133.2011.00721.x; David Weisburd, Brian Lawton, and Iustin Ready, "Staking Out the Next Generation of Studies of the Criminology of Place," in *The Future of Criminology*, ed. Rolf Loeber and Brandon C. Welsh (Oxford University Press, 2012), 236, http://dx.doi.org/10.1093/acprof:oso/9780199917938.003.0030.

16 YongJei Lee et al., "How Concentrated Is Crime at Places? A Systematic Review from 1970 to 2015," *Crime Science* 6 (2017): 1-16, https://doi.org/10.1108/S2040-726220210000024005.

17 Weisburd, Lawton, and Ready, "Staking Out the Next Generation."

18 David Weisburd and Cody W. Telep, "Hot Spots Policing: What We Know and What We Need to Know," *Journal of Contemporary Criminal Justice* 30, no. 2 (2014): 200-220.

19 Cory P. Haberman, "Overlapping Hot Spots? Examination of the Spatial Heterogeneity of Hot Spots of Different Crime Types," *Criminology & Public Policy* 16, no. 2 (2017): 633-660.

[20] David Weisburd and Lorraine Green, "Policing Drug Hot Spots: The Jersey City Drug Market Analysis Experiment," *Justice Quarterly* 12, no. 4 (1995): 711-735; Travis A. Taniguchi, Jerry H. Ratcliffe, and Ralph B. Taylor, "Gang Set Space, Drug Markets, and Crime Around Drug Corners in Camden," *Journal of Research in Crime and Delinquency* 48, no. 3 (2011): 327-363; Julie Hibdon, Cody W. Telep, and Elizabeth R. Groff, "The Concentration and Stability of Drug Activity in Seattle, Washington Using Police and Emergency Medical Services Data," *Journal of Quantitative Criminology* 33 (2017): 497-517.

[21] Charlotte Gill, Alese Wooditch, and David Weisburd, "Testing the 'Law of Crime Concentration at Place' in a Suburban Setting: Implications for Research and Practice," *Journal of Quantitative Criminology* 33 (2017): 519-545.

[22] Weisburd and Telep, "Hot Spots Policing."

[23] Weisburd and Telep, "Hot Spots Policing."

[24] John R. Hipp and Seth A. Williams, "Advances in Spatial Criminology: The Spatial Scale of Crime," *Annual Review of Criminology* 3 (2020): 75-95.

[25] Charis E. Kubrin and Ronald Weitzer, "New Directions in Social Disorganization Theory," *Journal of Research in Crime and Delinquency* 40, no. 4 (2003): 374-402, http://dx.doi.org/10.1177/0022427803256238; Roderick W. Jones and William Alex Pridemore, "Toward an Integrated Multilevel Theory of Crime at Place: Routine Activities, Social Disorganization, and the Law of Crime Concentration," *Journal of Quantitative Criminology* 35 (2019): 543-572, https://doi.org/10.1007/s10940-018-9397-6.

[26] Patricia Brantingham and Paul Brantingham, "Criminality of Place: Crime Generators and Crime Attractors," *European Journal on Criminal Policy and Research* 3 (1995): 5-26, https://www.scirp.org/reference/referencespapers?referenceid=2196342#:~:text=https%3A//doi.org/10.1007/BF02242925; Bryan J. Kinney et al., "Crime Attractors, Generators and Detractors: Land Use and Urban Crime Opportunities," *Built Environment* 34, no. 1 (2008): 62-74, https://doi.org/10.2148/benv.34.1.62.

[27] Victor Manjarrez Jr., *A Border Security Dilemma: The Danger of Chaos and Clutter* (Nova Science Publishers Inc, 2021), 23, 4, 533-543.

[28] Paolo Campana, "Human Smuggling: Structure and Mechanisms," *Crime and Justice* 49, no. 1 (2020): 471-519, https://doi.org/10.17863/CAM.51150.

[29] U.S. Census Bureau. "Zapata County, Texas." Census Bureau Profile. Last modified 2021. https://data.census.gov/profile/Zapata_County,_Texas?g=050XX00US48505

[30] Alicia A. Garza and Christopher Long, "Zapata County," *Handbook of Texas Online*, Texas State Historical Association, 2021, https://www.tshaonline.org/handbook/entries/zapata-county; U.S. Customs and Border Protection (CBP), "U.S. Customs and Border Protection: Zapata Station," *Department of Homeland Security*, 2020, https://www.cbp.gov/border-security/along-us-borders/border-patrol-sectors/laredo-sector-texas/zapata-station.

[31] Jones and Pridemore, "Toward an Integrated Multilevel Theory."

[32] Jones and Pridemore, "Toward an Integrated Multilevel Theory."

[33] Robert J. Sampson and Stephen W. Raudenbush, "Seeing Disorder: Neighborhood Stigma and the Social Construction of 'Broken Windows,'" *Social Psychology Quarterly* 67, no. 4 (2004): 319-342, https://doi.org/10.1177/019027250406700401.

[34] Dana Charles McCoy et al., "Assessing School Communities Using Google Street View: A Virtual Systematic Social Observation Approach," *AERA Open* 8 (2022): 23328584221085247, https://doi.org/10.1177/23328584221085247.

[35] Victoria A. Sytsma, Nathan Connealy, and Eric L. Piza, "Environmental Predictors of a Drug Offender Crime Script: A Systematic Social Observation of Google Street View Images and CCTV Footage," *Crime & Delinquency* 67, no. 1 (2021): 27-57, https://doi.org/10.1177/0011128720910961.

[36] Sytsma, Connealy, and Piza, "Environmental Predictors of a Drug Offender Crime Script."

[37] Luc Anselin, "Local Indicators of Spatial Association—LISA," *Geographical Analysis* 27, no. 2 (1995): 93-115, https://doi.org/10.1111/j.1538-4632.1995.tb00338.x.

https://digitalcommons.usf.edu/jss/vol17/iss3/4
DOI: https://doi.org/10.5038/1944-0472.17.3.2207

---

[38] Joseph M. Hilbe, *Negative Binomial Regression* (Cambridge University Press, 2011); Shaw-Pin Miaou, "The Relationship Between Truck Accidents and Geometric Design of Road Sections: Poisson Versus Negative Binomial Regressions," *Accident Analysis & Prevention* 26, no. 4 (1994): 471-482, https://doi.org/10.1016/0001-4575(94)90038-8.

[39] Kristofer Mansson, "On Ridge Estimators for the Negative Binomial Regression Model," *Economic Modelling* 29, no. 2 (2012): 178-184, https://doi.org/10.1016/j.econmod.2011.09.009; Miaou, "The Relationship Between Truck Accidents and Geometric Design of Road Sections."

[40] Slack and Campbell, "On Narco-coyotaje."

[41] Gabriella Sanchez and Sheldon X. Zhang. "In their own words: children and the facilitation of migrant journeys on the US-Mexico border." In *Beyond Drugs, Smuggling and Trafficking* pp. 80-99. Routledge, 2021. https://doi.org/10.4324/9781003152330

[42] Yaatsil Guevara Gonzalez. "Navigating with coyotes: pathways of central American migrants in Mexico's southern borders." *The ANNALS of the American Academy of Political and Social Science* 676, no. 1 (2018): 174-193. https://doi.org/10.1177/0002716217750574

[43] Gonzalez. "Navigating with coyotes: pathways of central American migrants in Mexico's southern borders."

[44] Victoria A. Greenfield, Ian Mitch Blas Nuñez-Neto, Joseph C. Chang, and Etienne Rosas. Human smuggling and associated revenues: what do or can we know about routes from Central America to the United States? *HSOAC, Homeland Security Operational Analysis Center*, 2019. http://dx.doi.org/10.7249/RR2852; Jeremy Slack and Howard Campbell. "On Narco-coyotaje: Illicit Regimes and Their Impacts on the US–Mexico Border." *Antipode* 48, no. 5 (2016): 1380-1399. https://doi.org/10.1111/anti.12242

[45] Thomas Gotschi, Alberto Castro, Manja Deforth, Luis Miranda-Moreno, and Sohail Zangenehpour. "Towards a comprehensive safety evaluation of cycling infrastructure including objective and subjective measures," *Journal of Transport & Health* 8 (2018): 44-54. https://doi.org/10.1016/j.jth.2017.12.003.

[46] Patrick J. Burke "Examining drug enforcement by specialized police units in Chicago, 2009-2019.," *Journal of Criminal Justice* 81 (2022): 101905. https://doi.org/10.1016/j.jcrimjus.2022.101905.

[47] Burke "Examining drug enforcement by specialized police units in Chicago, 2009-2019."

[48] Thomas Gotschi Alberto Castro, Manja Deforth, Luis Miranda-Moreno, and Sohail Zangenehpour, "Towards a comprehensive safety evaluation of cycling infrastructure including objective and subjective measures."

[49] Peter Bell, Geoff Dean, and Petter Gottschalk. "Information management in law enforcement: The case of police intelligence strategy implementation," *International Journal of Information Management* 30, no. 4 (2010): 343-349. https://doi.org/10.1016/j.ijinfomgt.2010.01.002.