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Spatiotemporal Distribution of Road Traffic Crashes and Crash Hotspots in Bamako, Mali: A Retrospective Analysis of Police Registry Data, 2019-2022

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Abstract

Introduction: Road traffic crashes (RTCs) are a leading cause of preventable mortality in low- and middle-income countries. In Bamako, their spatial and temporal distribution remains poorly documented. The objective was to describe the spatiotemporal distribution of reported RTCs and identify areas of high crash concentration using data from the 2nd arrondissement Police registry (2019-2022). **Methodology:** Retrospective descriptive study based on secondary analysis of a police registry. Annual, seasonal, weekly and hourly distributions were compared with uniformity using chi-square tests. The spatial distribution was analysed using retrospectively geocoded coordinates (WGS84): kernel density estimation (KDE), spatial autocorrelation (Moran I) and hotspots (Getis-Ord Gi* on a grid), with analyses performed in Python at a significance level of 0.05. **Results:** A total of 3075 crashes were recorded with complete date, time, and location information and were geocoded from registry descriptions. Monthly crash counts declined by approximately 6% per year after accounting for the number of days in each month (RR = 0.94 per year; $p < 0.001$; not statistically significant after accounting for overdispersion), peaking in 2020, and marked seasonality (about 21% more crashes per day during the rainy season; crude rate ratio 1.21; $p < 0.001$). The daily rhythm was bimodal (peaks 10:00 - 13:00 and 17:00 - 19:00) and the distribution across weekdays was homogeneous ($p = 0.49$). Significant spatial clustering was observed (Mo-

ran's I = 0.24, p = 0.001), with persistent concentrations around Pont Fahd and Nation roundabout. **Conclusion:** Reported crashes concentrate in a few stable spatial foci and follow marked seasonal and hourly rhythms, offering actionable spatial and temporal targets for prevention, and systematic geocoding would strengthen spatial surveillance.

Keywords

Road Traffic Crashes, Spatial Analysis, Spatiotemporal Analysis, Hotspots, Mali, Police Registry

1. Introduction

Traffic crashes are a major global public health problem. The WHO estimated that 1.19 million people died in traffic crashes in 2021. These crashes remain the leading cause of death among people aged 5 to 29 [1].

This burden is disproportionately high in low- and middle-income countries, where vulnerable road users account for a significant proportion of deaths [1]-[4]. Beyond mortality, crashes result in disabilities and impose considerable social and health costs [3] [5].

This burden, which is largely preventable, weighs heavily on sub-Saharan Africa, which has the highest road fatality rate in the world [3]. Systematic reviews from sub-Saharan Africa have reported a high burden of road traffic injuries, with young men and users of motorized two-wheelers frequently represented among those affected [3] [5] [6]. The widespread use of motorcycle taxis as an informal mode of transportation may shape road-safety risks in sub-Saharan African cities [7]. Road safety also requires coordinated action among the transportation, urban planning, law enforcement, and health sectors [8] [9].

In Bamako, the capital of Mali, the proliferation of motorcycles and motorcycle taxis, urban expansion, and the heterogeneity of road infrastructure create conditions in which crash occurrence may vary considerably by location and time.

Previous studies based on police and health facility records have highlighted significant underreporting and emphasized the predominance of motorized two-wheelers among road traffic crash victims [4]. However, georeferenced analysis of routine police data remains limited. Spatial analyses conducted in African cities have revealed a concentration of crashes around major roadways and intersections and have demonstrated the usefulness of police data for identifying black spots [10]-[13]. The present study therefore aimed to describe the annual, seasonal, weekly, and hourly distribution of crashes reported to a police station in Bamako between 2019 and 2022, as well as to identify areas with a high spatial concentration that could be targeted for priority preventive action.

2. Methodology

2.1. Study Type, Setting and Period

We conducted a retrospective descriptive study using the traffic crash registry of the 2nd arrondissement Police Station in Bamako. This registry covers a densely populated urban area traversed by major transportation routes and includes descriptions of crash locations.

2.2. Population and Sampling

The unit of analysis was the reported crash. All records logged between January 1, 2019, and December 31, 2022, were included, totaling 3075 cases. Records from 2018 and 2023 were excluded because they were incomplete.

2.3. Data Management and Variables

Information from the registry was entered into KoBoToolbox, cleaned, and standardized. Variables related to date, time, and location were retained for this analysis.

Regarding geolocation, coordinates were reconstructed retrospectively based on location descriptions, rather than being recorded by GPS in the field. An operator used KoBoCollect to locate the described site on a map and record approximate WGS84 coordinates. Since the coordinates represented approximate reported locations, the spatial results were interpreted at the scale of zones and corridors rather than at the level of specific crash sites.

2.4. Data Analysis

2.4.1. Statistical Analysis

Frequencies and percentages were used for descriptive analyses. Annual, monthly, day-of-the-week, and hourly distributions were evaluated using chi-square goodness-of-fit tests, where appropriate. Months were classified a priori as rainy (June-October) or dry (November-May), based on the seasonal pattern commonly used for Bamako. Monthly counts were modeled using Poisson regression, accounting for the number of days in the month as well as terms for the annual trend and seasonality. The logarithm of the number of days in each month was included as an offset. The results are presented as rate ratios (RR) with 95% confidence intervals. Hourly results were interpreted descriptively, as no exposure denominator was available.

2.4.2. Spatial Analysis

The spatial distribution was analyzed using geolocated coordinates (WGS84). Kernel density estimation (KDE) was used to visualize the spatial intensity of reported crashes. Geographic coordinates were projected into the WGS84/UTM Zone 29N coordinate reference system, appropriate for the study area, before KDE [14] [15]. A Gaussian kernel was applied, with the bandwidth selected according to Scott's rule. The resulting density surface was evaluated on a regular grid and

expressed as estimated crash density per km^2. Because crash locations were retrospectively geocoded, KDE results were interpreted as areas of concentration rather than as precise crash locations. The bandwidth selected according to Scott's rule was approximately 360 - 450 m.

Global spatial autocorrelation was assessed using Moran's I. The spatial unit of analysis was a regular 300 m grid cell, and the variable analysed was the number of reported crashes per cell; empty cells were assigned a value of zero. Queen contiguity was used to define neighbourhoods, including the eight adjacent cells, with row-standardized spatial weights. No distance threshold or k-nearest-neighbour criterion was applied. Statistical significance was assessed using 999 permutations. Moran's I was 0.24 ($p = 0.001$).

Local hotspots were identified using the Getis-Ord Gi* statistic on a regular 300-m grid, using queen contiguity (eight neighbouring cells) and binary spatial weights. The focal cell was included in its own neighbourhood. Statistical significance was assessed using analytical z-scores; cells with $z > 1.96$ were considered statistically significant at the 5% level and cells with $z > 2.58$ at the 1% level. Overall, 13 cells met the 5% nominal significance criterion; after Benjamini-Hochberg correction for multiple testing, 9 cells remained significant. Sensitivity analyses were conducted using grid cell sizes of 150, 300, and 500 m and by examining potential coordinate duplication. Coordinate duplication was minimal (2974 distinct coordinates, 96.7%; at most four crashes at a single point), and the hotspots were robust across cell sizes (13, 9 and 8 significant cells after correction at 150, 300 and 500 m, respectively).

The analyses were performed in Python using pandas, NumPy, SciPy, statsmodels, libpysal, and esda.

2.5. Ethical Considerations

The study used anonymized administrative registry data, free of any personal identifiers. Administrative authorization to access the registry was obtained from the competent authorities responsible for law enforcement. In accordance with applicable national or institutional requirements, a formal review by an ethics committee was not required.

3. Results

A total of 3075 crashes were recorded and geocoded.

3.1. Annual and Seasonal Distributions

Annual counts were 777 in 2019, 898 in 2020, 756 in 2021 and 644 in 2022. The annual distribution differed significantly ($\chi^2 = 42.3$; df = 3; $p < 0.001$). Monthly Poisson modeling indicated a modest average decline of approximately 6% per year (RR = 0.94; 95% CI: 0.91 - 0.97; $p < 0.001$). However, the monthly counts were overdispersed (Pearson dispersion 3.67) with residual autocorrelation, and after re-estimating the trend with a quasi-Poisson model the decline was no longer

statistically significant (RR = 0.96 per year; 95% CI: 0.90 - 1.02; p = 0.18). The sensitivity analysis excluding 2020 yielded RR = 0.95 (95% CI: 0.92 - 0.98; p = 0.002), although the 2020 peak warrants caution in interpreting the overall trend (Figure 1(a)).

The monthly distribution was highly uneven (chi^2 = 156.0; df = 11; p < 0.001), with the lowest value occurring in February with 139 crashes (4.5%) and the highest in October with 322 crashes (10.5%). Details for the twelve months are shown in Table 1. The rainy season accounted for 46.6% of crashes (1434) compared with 1641 (53.4%) during the dry season. When adjusted for the number of days, the rainy season had approximately 21% more crashes per day than the dry season (2.34 versus 1.93; crude rate ratio 1.21; p < 0.001). Adjustment for annual trend attenuated this association (RR ≈ 1.13; 95% CI: 1.05 - 1.21) (Figure 1(b)).

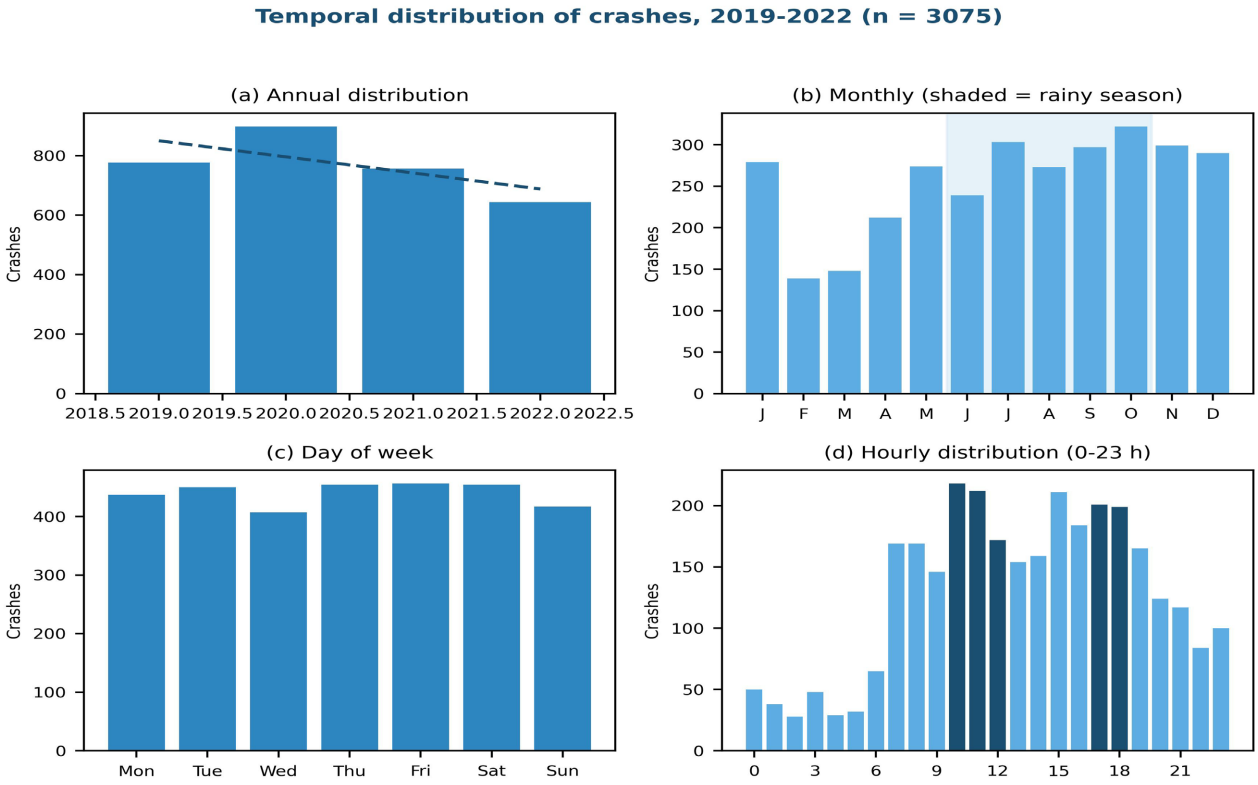


Figure 1. Temporal distribution of crashes, 2019-2022 (n = 3075): (a) annual with trend; (b) monthly and seasonal (shaded area = rainy season June-October); (c) by day of week; (d) hourly (0 - 23 h, peak hours highlighted).

3.2. Weekday and Hourly Distribution of Crashes

The weekday distribution did not differ significantly from uniformity (χ^2 = 5.4; df = 6; p = 0.49) (Figure 1(c)). The hourly distribution was strongly non-uniform descriptively (χ^2 = 785.6; df = 23; p < 0.001), with 7.3% of crashes occurring between midnight and 06:00, 31.8% between 06:00 and 12:00, 35.2% between 12:00 and 18:00 and 25.7% between 18:00 and midnight. The main three-hour concentration was 10:00 - 13:00 (19.6%), followed by a second peak around 17:00 - 19:00 (14.4%) (Figure 1(d)).

3.3. Spatial Distribution and Crash Hotspots

Spatial analysis showed significant positive autocorrelation (Moran's I = 0.24; p = 0.001), indicating marked clustering.

Kernel density identified a primary cluster in the southeast around the Fahd Bridge and Nation/Labor Exchange/Foyer de l'Air roundabouts, and a secondary concentration along the Kati/Sané corridor (Figure 2). On a 300 m grid, 13 cells showed statistically significant Getis-Ord Gi* statistics at the nominal 5% level (9 cells after Benjamini-Hochberg correction; Gi* z > 1.96) (Figure 3). These significant cells formed persistent concentration areas around Pont Fahd and Nation roundabout. The Fahd Bridge and Nation Roundabout had the highest numbers of crashes within individual cells (Table 2). Table 2. Selected 300 m grid cells ranked by number of reported crashes, with corresponding Getis-Ord Gi* statistics, Bamako, 2019-2022. Only cells meeting the statistical significance criterion were classified as hotspots. The main southeastern hotspot persisted across years and remained identifiable when grid size varied from 150 to 500 m; sensitivity to grid-cell size (150 and 500 m) with false-discovery-rate correction is shown in the new Figure A4 (Figures A1-A4).

Table 1. Temporal distribution of Reported Crashes, Bamako, 2019-2022 (N = 3075).

Variables	Number	Percent
Year		
2019	777	25.3
2020	898	29.2
2021	756	24.6
2022	644	20.9
Season		
Rainy season (June-October, 5 months)	1434	46.6
Dry season (November-May, 7 months)	1641	53.4
Month		
January	279	9.1
February	139	4.5
March	148	4.8
April	212	6.9
May	274	8.9
June	239	7.8
July	303	9.9
August	273	8.9
September	297	9.7
October	322	10.5
November	299	9.7

Continued

December	290	9.4
Day of the week		
Business days (Monday-Friday)	2204	71.7
Weekend (Saturday-Sunday)	871	28.3
Time slot		
12 a.m. - 6 a.m. (night)	225	7.3
6 a.m. - 12 p.m. (morning)	979	31.8
12 p.m. - 6 p.m. (afternoon)	1082	35.2
6 p.m. - 12 a.m. (evening)	789	25.7
Peak hour period		
10:00 - 13:00 (3 hours)	602	19.6
17:00 - 19:00	442	14.4

Table 2. Main 300-m grid cells ranked by number of reported crashes, with corresponding Getis-Ord Gi* statistics, Bamako, 2019-2022.

Dominant location of the cell	Number	Gi* (z-score)	p-value
Pont Fahd	228	2.4	$p < 0.05$
Nation roundabout	187	1.8	not significant
Bouteflika boulevard/CICB	161	1.4	not significant
Bourse du travail roundabout	145	1.4	not significant
Nation roundabout (neighbouring cell)	136	2.6	$p < 0.05$
Interchange	136	1.6	not significant
Pont Fahd (neighbouring cell)	130	1.2	not significant
Kati road	96	0.5	not significant

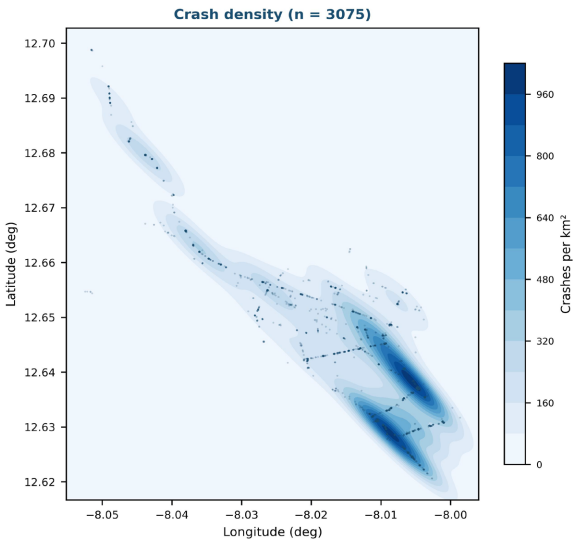


Figure 2. Crash density estimated using kernel density estimation (KDE), Bamako, 2019-2022 (n = 3075 geolocated crashes). Points represent reported crash locations; colour intensity represents estimated crash density (crashes/km²).

The table presents the highest-count cells for readability. Cells are shown for descriptive purposes and ranked by number of reported crashes; only cells meeting the statistical significance criterion were classified as hotspots. Thirteen cells were statistically significant overall.

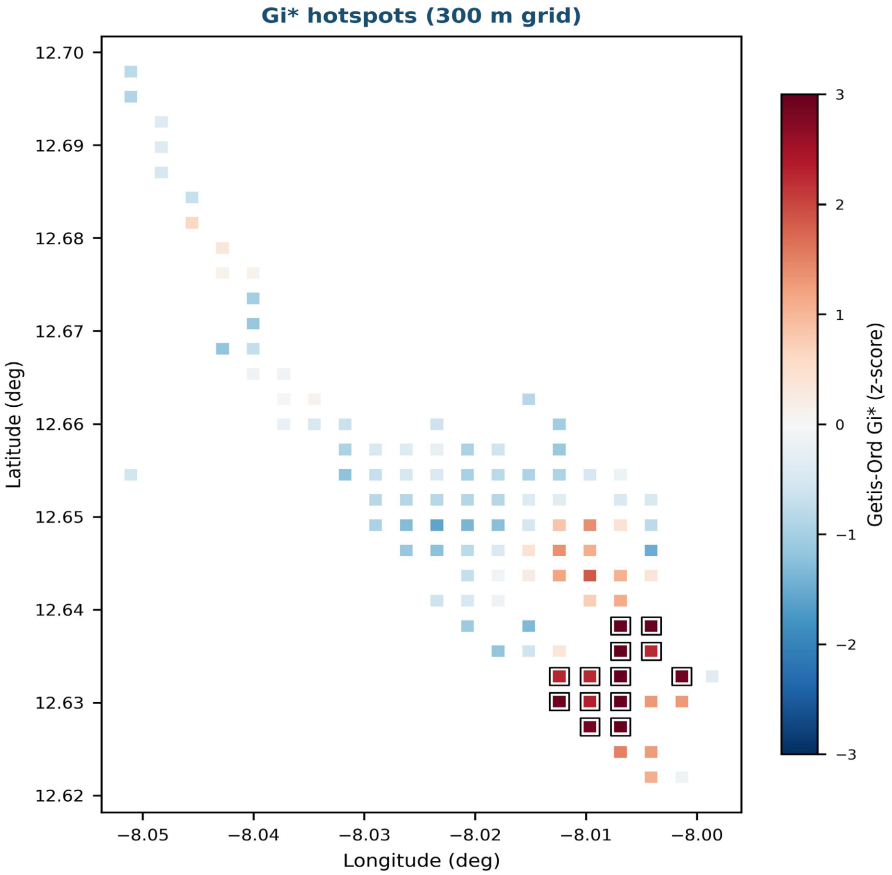


Figure 3. Hotspots identified using the Getis-Ord Gi* statistic on a 300 m grid, Bamako, 2019-2022. Red tones indicate significant local clustering (high z-scores); 13 cells were significant at the 5% level.

4. Discussion

4.1. Key Findings

This four-year analysis identifies three consistent patterns: a concentration of reported crashes in a limited number of urban corridors and intersections; higher daily crash counts during the rainy season; and a bimodal hourly pattern.

4.2. Temporal Patterns

Modeling of the monthly series indicates a slight annual decline (approximately 6% per year), with an unusually high number of reported crashes in 2020. The 2020 peak coincided with the COVID-19 pandemic; however, the available data do not allow its determinants or the role of pandemic-related mobility changes to be established.

The higher daily crash count during the rainy season (approximately 21% higher than during the dry season) suggests a possible contribution of seasonal driving conditions (rain, road conditions, visibility), although it is not possible due to a lack of exposure data to distinguish the contribution of crash occurrence from that of traffic volume. The consistency across days of the week and the bimodal hourly pattern, with peaks in the late morning and late afternoon, are consistent with observations reported elsewhere [16].

4.3. Spatial Patterns and Implications

Crashes were significantly clustered (Moran's I = 0.24; p = 0.001) and concentrated in a few stable clusters, identified using the Getis-Ord Gi* statistic. This spatial concentration is consistent with studies from Kigali and other African cities, including Hawassa and Addis Ababa, showing that police and geospatial data can help identify recurrent crash hotspots around major roads and intersections [10] [12] [13] [17].

The temporal stability of these hotspots suggests that persistent characteristics of the road environment may contribute to the observed spatial pattern, although this hypothesis could not be directly tested in the present study [18]. The rainy-season excess should be interpreted cautiously. Rainfall, road surface conditions and visibility may contribute to crashes, but the absence of traffic-volume denominators prevents separation of increased exposure from increased crash occurrence. The peak observed in 2020 coincided with the COVID-19 pandemic, but the available data do not allow its determinants to be established.

The stability of the principal hotspots across years and grid specifications supports their use as operational targets for road-safety interventions. However, these are locations with high numbers of reported crashes, not necessarily the locations with the highest crash occurrence per vehicle or per kilometer. Combining crash data with traffic volume, road geometry and pedestrian/motorcycle exposure would permit more informative crash occurrence estimates.

This study has several strengths, including four years of continuous police records, a relatively large number of reported crashes, systematic digitization and quality control of the registry data, retrospective geocoding of crash locations, and the use of complementary spatial methods combining KDE, global spatial autocorrelation, and local hotspot analysis.

Public-health perspective: the findings support targeted road-safety audits and corrective measures at recurrent hotspots, combined with intensified enforcement during identified peak periods [8] [19] [20]. The WHO Global Plan for the Decade of Action for Road Safety 2021-2030 emphasizes a systems approach integrating safe roads, safe speeds, safe vehicles, safe road users and post-crash care [8]. For Bamako, systematic geocoding and linkage of police and health-facility records would be an important next step, particularly because previous capture-recapture work demonstrated substantial differences between police and health sources [4].

5. Conclusion

This study described the temporal distribution of reported crashes and identified recurrent spatial concentration areas in the area covered by the 2nd arrondissement Police Station. These results provide actionable spatial and temporal targets for prevention: prioritizing road-safety audits and targeted safety improvements at the identified hotspots, and considering intensified road-safety enforcement and preventive measures during identified peak periods and the rainy season, as part of a safe-system approach. They call for coordinated action among the police, local governments, health authorities, and the national agency responsible for road safety, centered on a small number of high-impact measures. Finally, the continued systematic geocoding of the registry and its integration with hospital data would strengthen spatial surveillance and the measurement of the actual burden; these are prerequisites for an evidence-based road safety policy that can be replicated in other arrondissements of Bamako and in the country's secondary cities.

6. What This Study Contributes

- Provides a four-year spatiotemporal analysis of 3075 police-reported crashes in Bamako's 2nd arrondissement.
- Identifies recurrent spatial concentration areas and statistically significant hotspots.
- Shows the operational value of routine police data combined with systematic geocoding.

What We Already Know on This Topic:

- Road traffic crashes are a major cause of death in low- and middle-income countries, and their spatial and temporal distribution determines the effectiveness of prevention efforts.
- In Bamako, routine traffic crash records are rarely available in a systematically georeferenced format.
- Geospatial analysis of police data can identify recurrent crash hotspots in several African cities.

7. Limitations

The main limitations are the under-reporting inherent in police data, approximate retrospective geocoding, the absence of an exposure denominator, the possible effects of COVID-19-related mobility changes, and the restriction to a single police district. Approximate geocoding may introduce spatial misclassification and affect the identification of fine-scale hotspots. In addition, the use of nominal p-values across multiple grid cells may increase the possibility of false-positive local hotspots. Because the hotspot analysis was exploratory, no formal correction for multiple testing was applied; p-values were therefore considered nominal. Consequently, the findings should not be directly generalized to the whole of Bamako.

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Author Contributions

Fatou Diawara, Fadjiné Soumaïla Diarra, and Siaba Doumbia designed the protocol and coordinated the study's implementation; Siaba Doumbia collected and entered the data; Fadjiné Soumaïla Diarra Ibrahim Terera, and Youssouf Ogodana Dolo conducted the data analysis; Fatou Diawara drafted the manuscript; and Hassan Ibrahim, Brahima Diarra, Fatoumata Sidibé, Mamadou Diepkilé, Ahmadou Sidi Takiou, Faty Haïdara, Fadjiné Soumaïla Diarra, Akory Ag Iknane and Mamadou Sanogo all read and revised the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Appendix

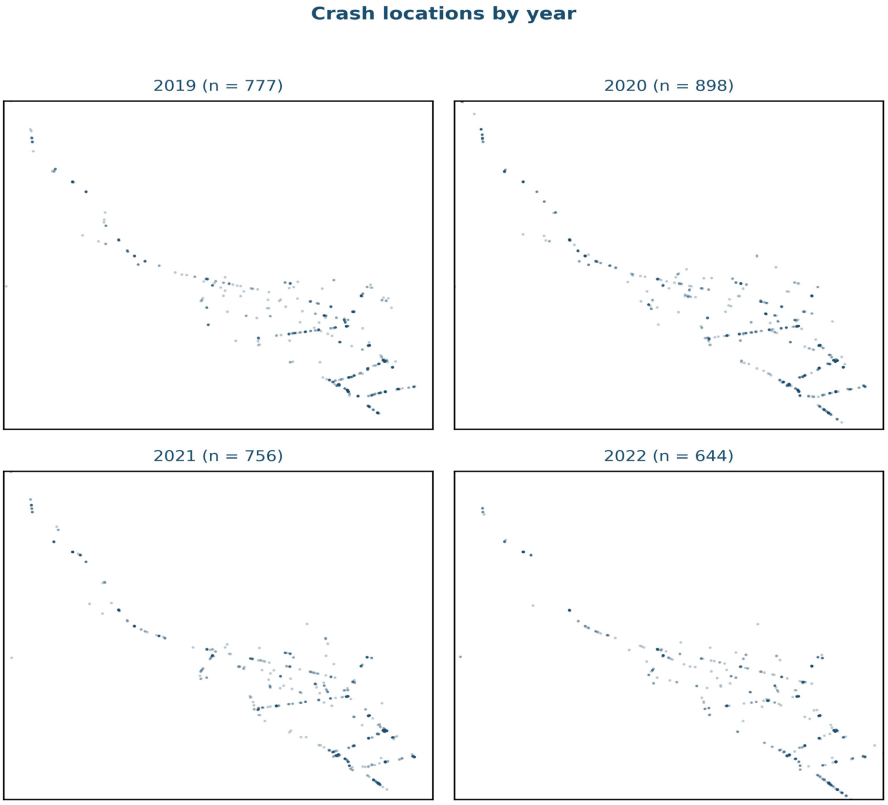


Figure A1. Crash locations by year (point scatter), 2019-2022. Alignment along roads reflects the geocoding of named locations.

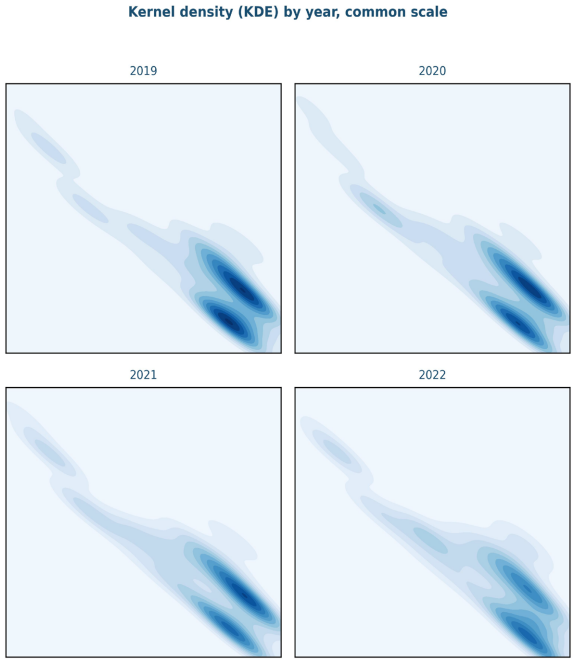


Figure A2. Kernel density (KDE) by year, common scale: the south-east focus (Pont Fahd, Nation roundabout) and the north-west corridor (Kati road) persist each year.

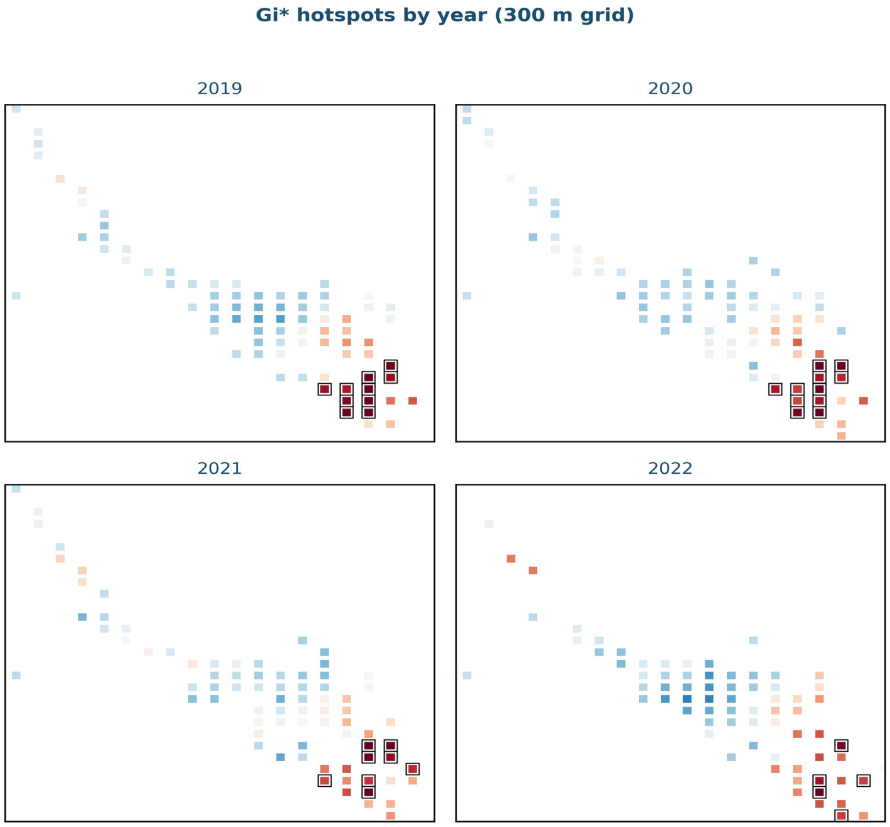


Figure A3. Gi* hotspots (300 m grid) by year: the main foci (Pont Fahd, Nation roundabout) persist each year.

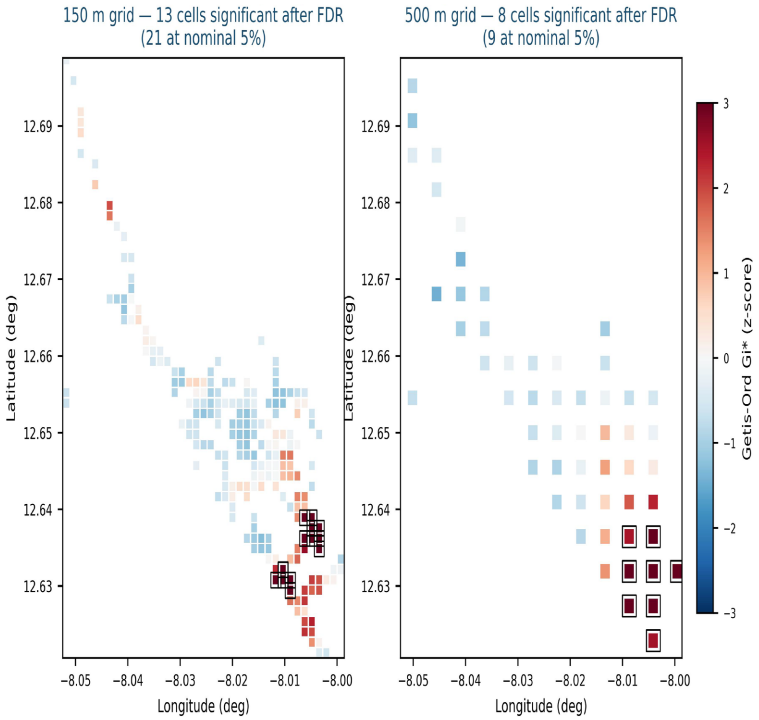


Figure A4. Getis-Ord Gi* hotspots—sensitivity to grid-cell size (150 and 500 m) with Benjamini-Hochberg false-discovery-rate correction, Bamako, 2019-2022.