Spatial Analysis of Road Traffic Crash Severity in Limassol: A Data-Driven Framework for Urban Road-Safety Management

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Abstract

Road traffic crashes continue to impose significant human and economic costs worldwide, yet traditional approaches to identifying hazardous locations often rely on simple frequency metrics that fail to capture spatial dependence or account for crash severity. This study addresses these limitations by developing a comprehensive spatial analytics framework for assessing crash severity patterns in the greater Limassol area, Cyprus. The methodology integrates severity-weighted crash values and applies a suite of spatial statistical techniques to detect clustering behaviour and identify micro-scale hotspots. Results reveal strong clustering of crash locations based on Average Nearest Neighbour Distance analysis, while Global Moran's *I* shows weak or non-significant global autocorrelation of severity. This pattern indicates that severe crashes do not form broad regional trends but instead appear as highly localized clusters. Local Moran's *I* analysis confirms the presence of small but meaningful High-High severity hotspots and several spatial outliers (High-Low and Low-High), typically located along major arterial corridors, network transition points, and mixed-use zones. A comparison of pre- and post-COVID periods shows a substantial reduction in crash frequency and cluster intensity, suggesting measurable benefits from altered mobility patterns and the introduction of automated speed enforcement. The findings demonstrate the value of localized, severity-sensitive spatial analysis for modern road-safety management. The proposed framework offers actionable insights for black-spot identification, targeted interventions, dangerous goods routing, and integration into digital-twin and ITS decision-support environments, supporting data-driven strategies aligned with Vision Zero objectives.

Keywords:

GIS, ANND, Moran's I, Crash Severity, Spatial Analysis, Hotspots, Cyprus

Introduction

Road traffic crashes remain a persistent global challenge, killing approximately 1.35 million people every year and severely injuring tens of millions more. In many urban contexts, crash events are not spatially random; instead, they exhibit strong clustering tendencies arising from recurring geometric, operational, and behavioral factors [1]. Numerous studies have demonstrated that traffic crashes form spatial point patterns characterised by significant clustering or hot spots that can be detected and analysed using spatial statistical tools [2]. As georeferenced crash datasets have expanded in accuracy and availability, spatial analysis techniques, such as Kernel Density Estimation (KDE), Average Nearest Neighbour Distance (ANND), and Local Indicators of Spatial Association (LISA), have become central to modern road-safety diagnostics, outperforming traditional frequency-based approaches for identifying hazardous locations along the road network.

Despite these advancements, several methodological and policy gaps remain. Traditional black-spot identification practices in many countries, including several EU member states and Cyprus, continue to rely on frequency-based metrics such as crash counts or crash rates, which are known to produce biased results due to random fluctuations and do not account for spatial dependence [3]. These approaches can obscure underlying spatial dynamics and may lead to suboptimal allocation of limited safety resources. Furthermore, despite widespread reliance on KDE-based hotspot maps, several authors have noted that such methods lack statistical significance testing and should be complemented with more rigorous spatial-autocorrelation techniques when prioritising intervention measures [4, 5]. A further gap concerns the treatment of crash severity. Much of the existing hotspot literature either aggregates crashes of varying severity or focuses solely on fatal or injury crashes, potentially overlooking the spatial heterogeneity of different severity types. Recent work highlights the need to explicitly analyse spatial dependencies among fatal, serious, and slight injuries, as distinct severity levels often follow different clustering patterns and may indicate different underlying crash mechanisms [6,7,8]. Considering severity explicitly is also consistent with the ambitions of Vision Zero and the EU Road Safety Policy Framework 2030 [9], which emphasise eliminating fatal and serious injuries rather than merely reducing total crashes.

Spatial autocorrelation techniques, particularly ANND and the Global and Local Moran's *I* statistics, address these limitations by quantifying whether crash severities exhibit significant clustering patterns and by identifying High-High, Low-Low, and spatial outlier clusters. These techniques have been successfully used to examine hotspot morphology, evaluate spatial dependencies, and compare risk patterns, offering valuable support for safety interventions and planning strategies [2, 5]. However, in many jurisdictions, including Cyprus, legislative frameworks for black-spot identification remain outdated. Current practices rarely require spatial significance testing, multi-scale clustering assessment, or severity-weighted metrics, and they are not yet fully integrated with GIS-based analytical workflows or digital-twin platforms. As cities and national authorities increasingly adopt data-driven decision-support systems, there is a pressing need for robust, severity-sensitive, spatially validated methodologies to support risk identification, infrastructure planning, and applications such as routing of dangerous goods.

The main objectives of this paper are to: 1) analyse the spatial distribution of road traffic crashes in the greater Limassol area, with an emphasis on understanding the geographic extent and concentration of crash occurrences across the urban transport network; 2) develop a severity-weighted spatial representation of crash risk by integrating crash frequency, severity level and vehicle involvement information into a unified spatial framework; and 3) provide an evidence-based spatial risk assessment that can support targeted road-safety interventions, infrastructure planning and data-driven policy decisions for the city of Limassol.

Method

Data

The dataset used in this study comprises geo-referenced road traffic crashes recorded between 2016 and 2023 within the greater Limassol area. Compared to the other major urban centres of Cyprus, Limassol exhibits the highest number of crashes and the largest proportion of serious injuries (39%), representing the highest severity share among the four cities. As illustrated in Figure 1(A), the spatial distribution of crashes reveals an extensive concentration of incidents along the coastal axis, indicating a prominent linear pattern of risk.

The original dataset contains a broad range of attributes describing each crash, including temporal information, environmental and roadway conditions, contributing factors, vehicle characteristics and detailed crash descriptors. For the purposes of the present spatial analysis, a selected subset of variables was extracted such as crash severity and the number of vehicles involved, as these variables were essential for the spatial processing workflow, grid aggregation scheme and autocorrelation modelling. The remaining attributes, such as lighting conditions, weather, surface state, speed environment and driver-related factors, were not used in the current analysis but remain valuable for future research focused on crash causation and behavioural or environmental influences on road safety in Cyprus.

Crash severity was categorised into four classes: Fatal, Serious Injury, Slight Injury and Damage Only, allowing for quantitative comparisons across the study area. Of the 1,558 crashes recorded, 67 (4.3%) were fatal, 621 (39.8%) resulted in serious injuries, 364 (23.7%) resulted in slight injuries and 506 (32.5%) involved property damage only. Information on vehicle involvement was available for all 1,558 records: two-vehicle collisions were the most frequent, representing 1,048 crashes (67.3%), followed by single-vehicle crashes (348 crashes; 22.3%). Multi-vehicle crashes involving three or more vehicles accounted for 162 incidents (10.4%), forming a relatively small portion of the dataset. These variables formed the foundation of the spatial analytical framework developed for this study, allowing the integration of crash severity, geospatial location and vehicle involvement into a unified structure suitable for spatial aggregation and multiscale autocorrelation assessment.

The criteria used for classifying crash severity follow the WHO definitions, distinguishing between fatal, serious and minor (slight) injury outcomes. A crash is classified as fatal when it results in one or more deaths within 30 days of the incident. A serious injury crash is defined as one requiring hospitalization for at least 24 hours, while crashes involving injuries of shorter duration are classified as slight. The present study relies on official crash records and severity classifications as documented by the Traffic Department of the Cyprus Police. Over the eight-year period, the data reveal consistent severity patterns: serious injury crashes remain relatively stable at approximately 35–45% of all annual crashes, slight injuries represent 20–25%, and damage-only crashes frequently constitute the largest proportion. Fatal crashes remain comparatively low (<7% annually), which, although positive from a safety standpoint, results in small sample sizes that limit the statistical robustness of any standalone spatial analysis for fatal-only events. These trends highlight the importance of severity-weighted indicators, which allow fatal and serious injuries to influence spatial risk patterns even when absolute case numbers are low.

Before conducting the spatial statistical analysis, the crash dataset underwent a series of preprocessing steps to ensure accuracy and analytical consistency. These steps included verification and cleaning of the coordinate fields, transformation of the coordinate reference system where necessary, removal of incomplete or inconsistent records, and extraction of the core variables required for the spatial analysis. Subsequently, the crashes were aggregated using a hexagonal tessellation grid, selected for its geometric efficiency and reduced directional bias compared to square grids. Each hexagon represented a defined spatial unit with a horizontal spacing of 50 m and a vertical spacing of 250 m, providing sufficient spatial resolution to capture intra-urban crash patterns while maintaining computational feasibility. Within each hexagonal cell, crash records were aggregated and assigned a severity-weighted value. The following weights were applied: Fatal = 50, Serious Injury = 30, Slight Injury = 10 and Damage Only = 5. This weighting scheme enabled the identification of areas with elevated severity levels, ensuring that high-risk zones were more prominently represented in the analysis. For the spatial autocorrelation assessment, additional filtering was applied to the hexagonal grid (Figure 1(B)). A drop-NaN procedure was used to exclude empty or non-informative cells, specifically those with no crashes or only a single recorded case, to reduce noise and ensure that autocorrelation indices were calculated only for meaningful spatial units. This step enhanced the robustness of the spatial statistical outputs and improved the interpretability of clustering patterns.

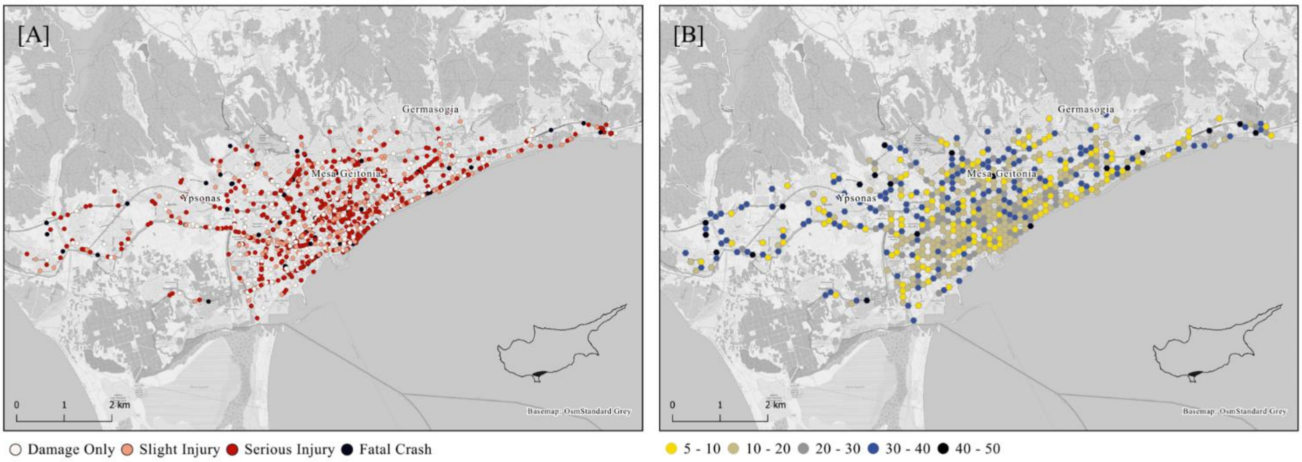

Figure 1 – (A) Crash data in Limassol; (B) Tessellation of the crash data

Framework

The methodological framework employed in this study is based on a set of spatial statistical techniques designed to examine the clustering behaviour and spatial autocorrelation of crashes based on their severity. Initially, crash density and clustering tendencies were assessed using the *ANND* method, which evaluates whether crash locations exhibit statistically significant clustering, dispersion, or approximate spatial randomness. The severity-weighted index, derived from the hexagonal aggregation and weighting scheme, integrates both crash frequency and severity into a unified metric, enabling the identification of areas characterized by recurrent and severe incidents, as opposed to those dominated by minor crashes [5].

Subsequently, the *Global Moran's I* statistic was applied to evaluate the presence and significance of spatial autocorrelation in the severity-weighted crash values. Global Moran's *I* provides a single summary index derived from the cross-product of a variable and its spatial lag, where both are expressed as deviations from their respective means. A positive and statistically significant Moran's I value indicates spatial clustering of similar severity levels, whereas a negative value suggests spatial dispersion. Global Moran's *I* index ranges between -1 and 1, where positive values indicate spatial clustering of similar severity levels, and negative values suggest spatial dispersion or the proximity of dissimilar values. Values close to zero reflect the absence of a meaningful spatial pattern, indicating approximate spatial randomness. The statistical significance of the Moran's *I* value is assessed using the associated Z-score, which is computed under the assumption of a random spatial distribution with an expected mean of zero and a variance of one. A positive Z-score signifies that neighbouring spatial units exhibit similar severity-weighted values, whereas a negative Z-score indicates that a spatial unit is surrounded by dissimilar values [5]

Finally, *Local Moran's I* was applied to identify localized clusters of crash severity, specifically High-High and Low-Low cluster patterns across the study area. Local spatial autocorrelation is essential for detecting crash hot spots and cold spots, as it captures spatial heterogeneity and reveals localized variations that may not be evident through global measures alone. Local Moran's *I* is particularly suitable for this purpose, as it distinguishes both similar local behaviours (e.g., high values surrounded by high values) and contrasting spatial outliers (e.g., high values surrounded by low values) [5]. Unlike the Global Moran's *I* statistic, which provides a single summary measure for the entire study area, Local Moran's *I* offers insight into spatial autocorrelation at the level of individual observations by comparing each spatial unit with its immediate neighbours. The resulting classification highlights four types of spatial associations: high values surrounded by high values (High-High clusters), low values surrounded by low values (Low-Low clusters), high values surrounded by low values (High-Low outliers), and low values surrounded by high values (Low-High outliers). These categories are crucial for identifying localized crash hot spots, safer zones, and abrupt transitions in severity patterns. Moreover, as outlined by [10], the Moran's *I* scatterplot, where the spatially lagged variable is plotted on the y-axis and the original variable on the x-axis, illustrates both global and local spatial relationships. The slope of the regression line corresponds to the Global Moran's *I* value, while the distribution of observations across the four quadrants of the plot reflects the Local Moran's *I* classifications.

Figure 2 presents the workflow diagram used in this study. QGIS™ was employed for the preprocessing of crash data and the execution of geoprocessing tasks, while Python scripting within the QGIS environment was used to implement the ANND, Global Moran's *I*, and Local Moran's *I* analyses.

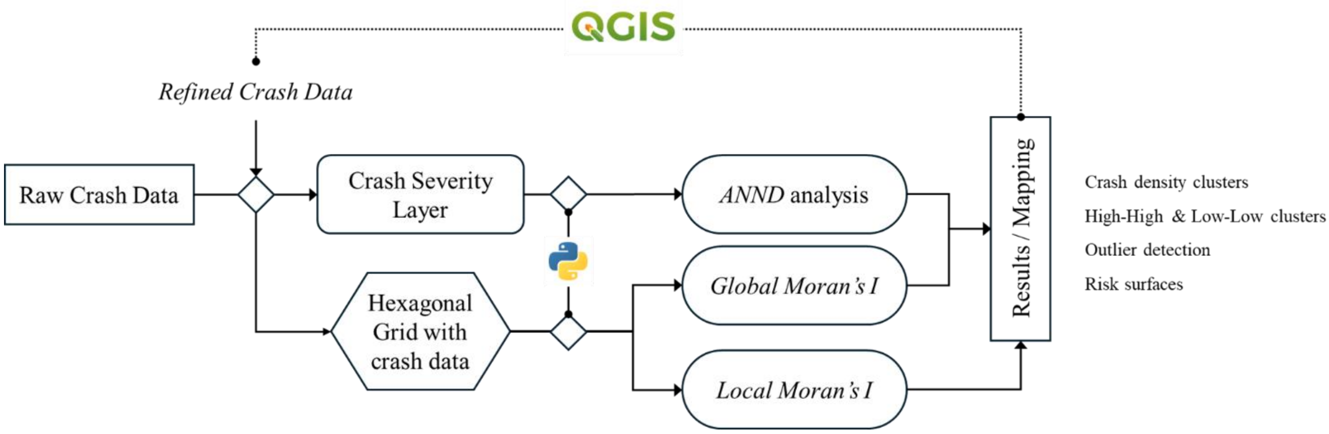

Figure 2 - Workflow diagram

Results and Evaluation

ANND analysis

The ANND results demonstrate a clear and statistically significant clustering of crash locations across all years of analysis. ANND ratios consistently fall between 0.60 and 0.70, with strongly negative z-scores (-7 to -13) and very small p-values (<0.001) (Table 1). These results indicate that crash points are located much closer to one another than expected under spatial randomness, confirming a clustered spatial pattern. This behavior is consistent with findings from previous spatial safety studies [11, 12], where dense urban environments, constrained mobility corridors, and recurring conflict points (junctions, commercial zones, arterial corridors) tend to concentrate crash events. The results affirm that the Limassol crash dataset possesses strong inherent spatial structure, justifying the use of spatial autocorrelation methods for deeper investigation.

Year	N	Do (m)	De (m)	ANND Ratio	Z - Score	P - value	Interpretation
2016	338	183,34	288,06	0,63	-12,78	<0,001	Strong clustering
2017	316	188,58	297,92	0,63	-12,48	<0,001	Strong clustering
2018	228	208,34	350,73	0,59	-11,72	<0,001	Strong clustering
2019	229	207,94	349,97	0,59	-11,74	<0,001	Strong clustering
2020	157	291,65	422,67	0,69	-7,43	<0,001	Strong clustering
2021	117	426,79	489,61	0,87	-2,65	0,0079	Moderate clustering
2022	91	401,18	555,17	0,72	-5,06	<0,001	Strong clustering
2023	82	463,51	584,85	0,79	-3,59	0,0003	Significant Clustering

Table 1 - ANND results per year for all types of crashes

Global Moran's I

Global Moran's *I* was computed on the severity-weighted hexagonal grid to assess whether crash severity exhibits global spatial autocorrelation across the study region. For the full 2016-2023 dataset, Moran's *I* returned a value of 0.0055, with non-significant z-scores and high p-values, indicating no detectable global autocorrelation. At the yearly level (Table 2), Moran's *I* values ranged from -0.03 to -0.12, also non-significant.

Year	Moran's I	Expected Index	Z - Score	P - value	Interpretation
All	0,005	-0,0007	0,40	0,360	---
2016	-0,038	-0,0014	-1,73	0,042	Weak Significant Dispersion
2017	-0,029	-0,0013	-1,36	0,080	Not Significant
2018	-0,048	-0,0017	-2,00	0,014	Significant Dispersion
2019	-0,074	-0,0016	-3,20	0,001	Strong Dispersion
2020	-0,038	-0,0020	-1,44	0,059	Marginal, Not Significant
2021	-0,113	-0,0022	-4,26	0,001	Strong Dispersion
2022	-0,122	-0,0026	-4,26	0,001	Strong Dispersion
2023	-0,071	-0,0029	-2,32	0,003	Significant Dispersion

Table 2 - Summary of Global Moran's *I* analysis result

While negative Moran's *I* values may suggest spatial dispersion, in this context they reflect the predominance of mixed-severity grid cells and the presence of localized spatial outliers, combined with the conservative nature of global statistics when cluster patterns are small or spatially isolated. This behavior is well documented in urban crash-analysis literature, where Global Moran's *I* tends to flatten toward zero when the study area contains multiple small local clusters spread across a heterogeneous landscape, because these local concentrations do not scale up into a coherent global trend [3, 5]. Thus, the low global values do not imply an absence of spatial patterning; rather, they indicate that spatial clustering of severity is localized, and therefore better detected using Local Moran's *I*.

Figure 3 presents the Moran's *I* scatterplot, where the regression slope approaches zero, further confirming weak global spatial autocorrelation. However, the presence of points in the HH, HL, and LH quadrants highlights localized pockets of clustering and spatial outlier behavior, reinforcing the need for local-level analysis to capture micro-scale variations in crash severity.

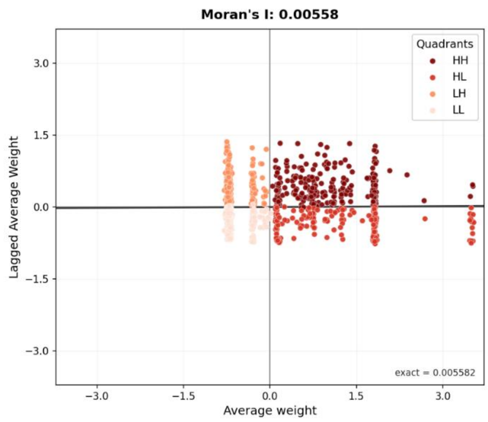

Figure 3 - Global Moran's I scatter plot

Local Moran's I

Local Moran's *I* was applied to detect statistically significant local clusters (High-High and Low-Low) and local spatial outliers (High-Low and Low-High). After filtering out empty and single-crash hexagons, patterns emerged that reflect the complex spatial dynamics of crash severity in Limassol.

Year	Not Significant (NS)	High-High (HH)	Low-Low (LL)	Low-High (LH)	High-Low (HL)
All	976 (77,58%)	77 (6,12%)	69 (5,48%)	82 (6,52%)	54 (4,29%)
2016	566 (80,51%)	22 (3,13%)	9 (1,28%)	62 (8,82%)	44 (6,26%)
2017	604 (83,54%)	19 (2,63%)	9 (1,24%)	66 (9,13%)	25 (3,46%)
2018	482 (83,68%)	13 (2,26%)	0 (0,00%)	47 (8,16%)	34 (5,90%)
2019	545 (91,29%)	5 (0,84%)	1 (0,17%)	43 (7,20%)	3 (0,50%)
2020	411 (85,27%)	10 (2,07%)	0 (0,00%)	28 (5,81%)	33 (6,85%)
2021	353 (78,97%)	7 (1,57%)	8 (1,79%)	36 (8,05%)	43 (9,62%)
2022	312 (81,04%)	1 (0,26%)	0 (0,00%)	38 (9,87%)	34 (8,83%)
2023	268 (78,82%)	3 (0,88%)	0 (0,00%)	41 (12,06%)	28 (8,24%)

Table 3 - Summary of Local Moran's I analysis result

Across all years (Table 3), the clustering patterns revealed by Local Moran's *I* show a consistent structure in the spatial distribution of crash severity. High-High (HH) clusters were relatively limited (0-4%), indicating small pockets of concentrated severe crashes typically located along high-mobility arterial corridors, such as the coastal road and major urban distributors, where exposure and operating speeds are highest. Low-Low (LL) clusters were also modest in prevalence (0-5%) and were mostly found in residential or low-traffic neighbourhoods, reflecting areas with stable low-risk conditions. In contrast, High-Low (HL) and Low-High (LH) spatial outliers frequently exceeded 10%, suggesting the presence of transitional risk zones. These outliers commonly appeared near intersections, speed-environment transitions, or land-use boundaries, locations were relatively minor geometric, operational or behavioural adjustments could substantially reduce crash severity.

Figure 4(A) illustrates the spatial clusters and outliers across the study area, while Figure 4(B) represents statistically significant (p-value<0,005) locations. HL outliers (high-risk cells surrounded by low-risk neighbours) are particularly important for policy because they often indicate emerging hotspots or locations where local geometry or behavior diverges from the surrounding area.

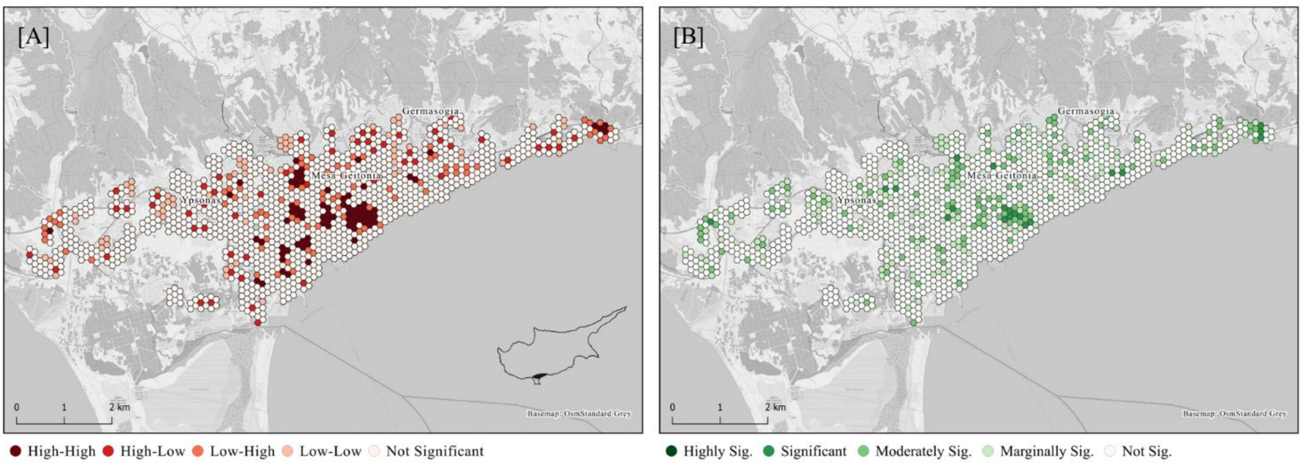

Figure 4 - Cluster and significance maps

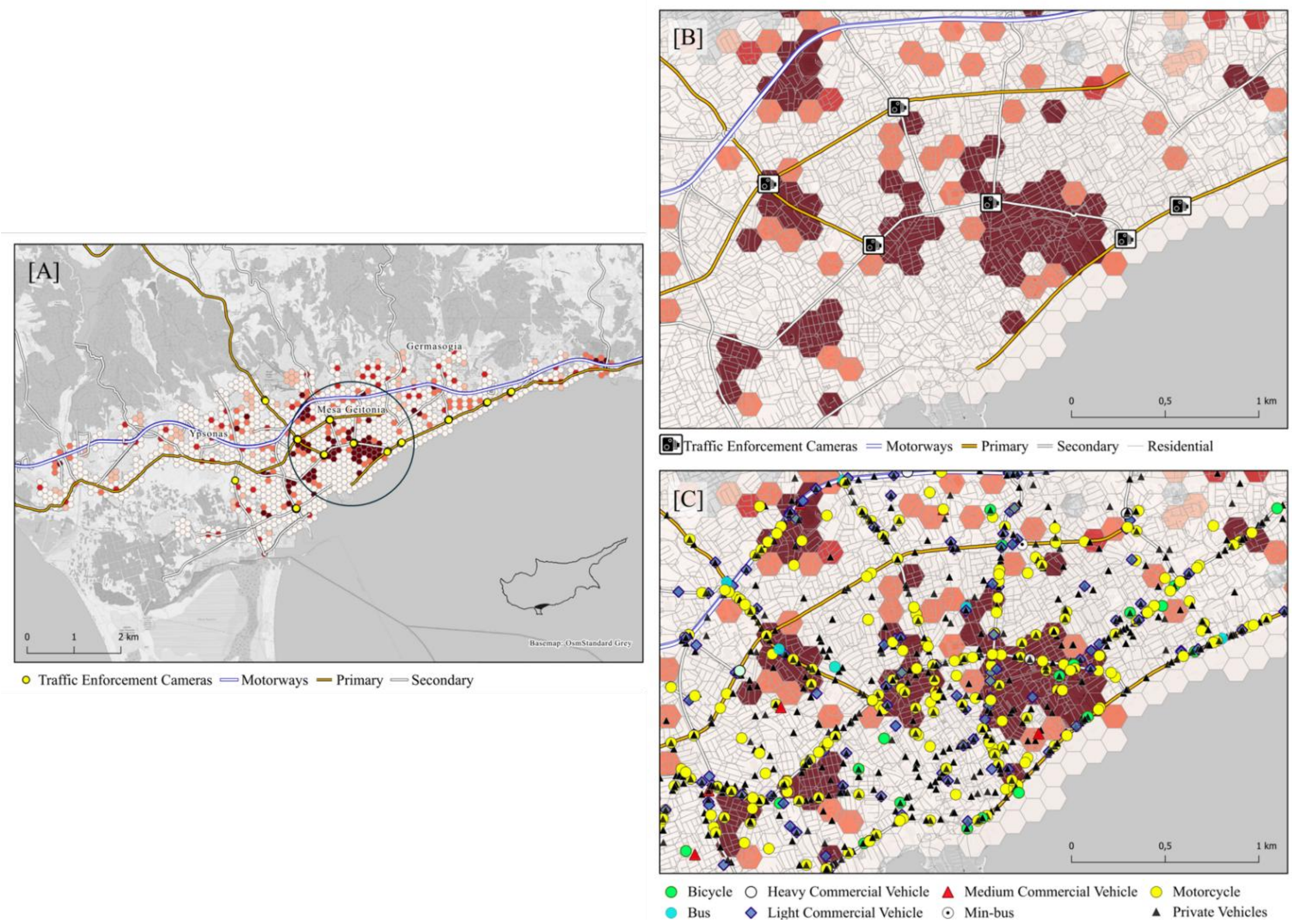

Figure 5 - Cluster maps where: [A] Overlaid information about road network; [B] Zoomed-in view of High-High cluster area; [C] Overlaid information about vehicle type.

Figure 5(A) presents Local Moran's *I* cluster map overlaid with the locations of traffic-enforcement cameras and the primary road network, including motorways and major arterial segments. Figure 5(B) on the other hand, it is a zoomed-in view of a major HH crash-severity hotspot, illustrating the local road geometry and intersection characteristics associated with elevated crash risk. Additionally, Figure 5(C) overlays information on the vehicle types involved in each crash, highlighting the predominance of commercial and private vehicles along the coastal and motorway corridors. In contrast, smaller vehicles such as bicycles and motorcycles appear more sparsely and are mainly concentrated on secondary and residential road segments.

Finally, to explore large-scale temporal changes, Local Moran's *I* outcomes were compared for two periods: 2016-2018 (pre-COVID) and 2021-2023 (post-COVID). The number of crashes declined sharply, representing a 67% reduction in reported crashes. This reduction in cluster intensity aligns with documented changes in post-pandemic mobility patterns and behavioral adjustments. One important local factor is the installation of automated speed enforcement cameras in Limassol after 2021, which may have reduced high-severity crash occurrences and diminished HH cluster formation. The results imply that policy interventions, mobility shifts, and enforcement technologies have measurable spatial effects on crash severity, supporting the integration of spatial statistics into ongoing safety evaluation frameworks.

Possible Applications

The spatial analytics framework developed in this study offers multiple practical applications for road-safety management, transport planning, and Intelligent Transport Systems (ITS). By combining severity-weighted indicators with statistically validated clustering techniques, the methodology provides a more accurate representation of crash risk than traditional frequency-based black-spot identification.

First, the Local Moran's I outputs enable authorities to prioritize interventions at micro-scale High-High (HH) hotspots, where crash severity is both concentrated and statistically significant. These locations often indicate underlying geometric, behavioral, or operational issues that warrant targeted measures such as speed management, redesign of intersections, improved lane configuration, or signal timing modifications. Similarly, High-Low (HL) outliers can reveal emerging or transitional risk zones where safety conditions differ sharply from the surrounding environment locations that would be overlooked by aggregate metrics but are critical for proactive safety monitoring.

Second, the severity-weighted risk surfaces produced by this framework can support safer routing of Dangerous Goods (DG) by steering hazardous-materials transport away from corridors with high-severity crash clusters. This aligns with EU guidance on risk-based DG routing and can be embedded into routing engines used by freight operators or public authorities. Third, the results are directly compatible with Digital Twin platforms such as the evolving Cyprus Digital Twin [13] initiative or GNOSIS ecosystem [14] of the Public Works Department of Cyprus. Integrating LISA-based risk surfaces into a Digital Twin allows real-time monitoring, scenario testing (e.g., evaluating the impact of new enforcement cameras), and predictive analytics for identifying locations where crash severity may increase under changing traffic patterns. This transforms static crash analysis into a continuous, data-driven process that supports evidence-based policy-making and operational decision support for ITS stakeholders.

Finally, the methodology enhances cross-agency data-driven decision-making. Combined with traffic-flow data, enforcement data, or infrastructure inventories, the spatial clusters can help transport authorities to prioritize network upgrades, allocate police resources more efficiently, evaluate speed-camera effectiveness, and monitor progress toward Vision Zero goals. The approach is scalable, transferable to other cities, and well-suited for integration into National Access Points (NAPs) and ITS safety services.

Conclusions

This study developed and applied a comprehensive spatial analytical framework to examine the severity and distribution of road traffic crashes in the greater Limassol. While ANND results confirmed strong overall clustering of crash locations, Global Moran's *I* showed no significant global autocorrelation, indicating that crash severity does not manifest as a broad regional pattern. Instead, Local Moran's *I* revealed that severity clustering is highly localized, forming small but meaningful High-High hotspots and spatial outliers embedded within an otherwise heterogeneous urban environment. These micro-clusters reflect site-specific conditions such as arterial corridors, geometric transitions, and mixed-use areas where exposure and conflict levels increase the likelihood of severe outcomes. The pre- vs post-COVID comparison further revealed a substantial reduction in both crash frequency and cluster formation, likely reflecting shifting mobility patterns and the implementation of targeted enforcement measures such as automated speed cameras. These findings highlight the importance of using spatially sensitive tools to evaluate the effectiveness of policy interventions and monitor evolving road-safety conditions.

Beyond analytical contributions, the study provides a practical, policy-ready methodology for modern road-safety management. The proposed framework enables more accurate black-spot identification, supports targeted infrastructure upgrades, and offers a foundational layer for routing dangerous goods away from high-risk corridors. When integrated into emerging Digital Twin platforms, the severity-weighted spatial outputs can further support real-time monitoring, predictive safety analytics, and evidence-based decision-making for transport authorities.

Overall, the study demonstrates that spatial autocorrelation methods, when integrated with severity-weighted crash modelling, offer a robust and scalable tool for identifying high-risk locations and improving road-safety outcomes.

These insights are particularly relevant for Cyprus and other EU member states pursuing Vision Zero objectives and transitioning toward data-driven, ITS-enabled safety management systems.

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