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An Adaptable Framework for Identifying and Prioritising Road Traffic Accident Hotspots

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ABSTRACT

This study introduces a novel, adaptable framework for identifying and prioritising road traffic accident hotspots using the Getis Ord Gi* spatial autocorrelation tool. The framework classifies regions as hotspots or coldspots based on accident severity and frequency. A unique weighting system is developed to compute the Crash Severity Index (CSI), considering the severity of crashes in terms of fatalities and injuries. The identified hotspots are prioritised using the CSI, providing policymakers with a structured approach to allocate resources for crash remedial measures. The main contribution of this work is the development of a flexible framework applicable to various cities, states or countries to improve road safety. The framework's effectiveness is demonstrated through a case study in Punjab, India, revealing that Sangrur, Hoshiarpur and Police Commissionerate Ludhiana are the top three hotspots. The study also offers a detailed analysis of crash statistics in Punjab, emphasising the severity of pedestrian crashes. This approach addresses the current lack of structured hotspot identification and prioritization strategies, marking a significant advancement in road safety management.

KEYWORDS

road traffic accidents; hotspot identification; crash severity; spatial analysis; road safety management; resource allocation.

1. INTRODUCTION

Road accidents are a regrettable fact of life. The severity of the crash determines the level of alarm caused by the number of fatalities and damage. Road accidents cause significant property damage and loss of life. Over 1.3 million lives are lost annually due to road accidents, according to global statistics. 20 to 50 million people experience non-fatal injuries, often resulting in impairments [1]. Road traffic safety analysis aims to prevent fatalities by understanding the causes of accidents and implementing safety measures. Identifying dangerous road regions through accident spatial pattern analysis, collision location comparison and relevant data is the pivotal step in formulating an effective road safety strategy. Spatial analysis is the study of collision occurrence patterns through the examination of their proximate zones or places. Traffic accidents exhibit the key characteristics of geographical variability and spatial dependency of point data. Spatial dependence characterises the influence of neighbouring events on events at a specific location, while geographical variability pertains to the spatial connections between random parameters and recorded occurrences in the model, which are not explicitly defined [2]. The development of GIS is a crucial tool for road safety studies [3]. There are very few signs that collision prevention initiatives are being adopted in low- and middle-income nations, as are other road safety measures [4]. Despite only comprising 60% of the global vehicle population, middle- and low-income countries bear responsibility for a staggering 93% of road crash fatalities [5].

Pedestrians in developing nations experience a disproportionately high number of injuries and fatalities. Vulnerable road users, including pedestrians, cyclists and motorcyclists, account for over 50% of global road traffic fatalities [1]. In 2022, India reported a total of 461,312 road accidents, resulting in 168,491 fatalities and injuries to 443,366 persons. Pedestrian fatalities saw a significant increase of 10.5%, rising from 24,242 in 2021 to 26,797, highlighting the critical need for pedestrian safety measures. Pedestrians accounted for 19.5% of all road user deaths, underscoring their vulnerability compared to other types of road users [6]. The increasing proportion of pedestrians in road accident deaths highlights the urgent necessity for pedestrian safety. Further analysis of hotspot locations reveals that high-speed roadway categories such as National Highways, State Highways and surfaced roads are particularly high-risk areas for pedestrians. Locations with high vehicular densities significantly jeopardise pedestrian safety [7]. Moreover, the design standards for pedestrian crossing facilities in urban areas may not be appropriate for national highways, especially multi-lane highways, thereby increasing their accident proneness [8]. High pedestrian volume and wider minor roads contribute to the risk at unsignalised intersections, resulting in pedestrian fatalities [9]. Factors like high approach speeds, the tendency of vehicles to overtake, high vehicular volumes, encroachment on footpaths and extensive pedestrian-vehicular interactions make intersections particularly hazardous for pedestrians. Additionally, issues such as jaywalking by pedestrians [10, 11], vehicles non yielding right-of-way [12], poor lane discipline, inaccessible pedestrian crosswalks, inadequate sight distances, wider minor carriageways, the absence of pedestrian signal heads and lack of enforcement exacerbate the risks at these junctions. These combined factors contribute to making intersections highly dangerous for pedestrian safety. Similarly, high approach speeds, low pedestrian volumes, wider road widths, on-street parking, insufficient lighting and inadequate pavement markings contribute to making midblock locations dangerous for pedestrians [13]. GIS-based Hotspot Identification (HSID) methods can effectively identify such crash hotspot locations [14]. Thus, it is imperative to consider pedestrians as a distinct category in road safety analysis in India. Pedestrians face unique risks due to infrastructural inadequacies and high vehicular interactions. Prioritising pedestrian safety can lead to more targeted interventions and resource allocations, ultimately reducing the disproportionately high rates of pedestrian injuries and fatalities.

The Ministry of Road Transport and Highways (MoRTH), India, recently incorporated measures to monitor and address severe road accidents. This report focuses on identifying and selecting “accident blackspots,” among other aspects [15]. Analysing the transformation of a crash location into a hotspot, particularly for pedestrian accidents, necessitates a specialised approach. Limited studies in India have incorporated temporal variation in GIS hotspot analysis, despite extensive research on identifying accident hotspots using two-dimensional spatial analysis [16]. While accidents are sporadic occurrences in time and space, they exhibit spatial dependence and autocorrelation, which must be considered when evaluating them [17]. Utilising statistical information gathered at the scene of an accident is among the most popular techniques for analysing traffic accidents. Some studies use straightforward techniques like counting the number of incidents and categorising them according to the severity of the injuries [18]. The limitations of these techniques have become apparent with the advancement of modern spatial analysis tools. Some Limitations include the inability to analyse the correlation between place and time, challenges in identifying and prioritising accident-prone areas and difficulties in considering environmental factors [2]. Furthermore, the tables and charts derived from the accident datasets obtained from the traffic police are intricate and unsuitable for effectively communicating with planners and the general public. Utilising robust spatial-temporal analysis techniques is imperative for enhancing the examination of accident datasets [19]. GIS has been extensively utilised in numerous traffic safety studies. These studies provide a spatiotemporal evaluation of traffic accidents, but most of the results are presented as simple graphs that do not capture the dynamic evolution of accident clusters over time [20]. A deeper understanding of spatial and temporal characteristics of accidents is essential for identifying accident hotspots more comprehensively [2].

2. LITERATURE REVIEW

Road Traffic Crash (RTC) hotspot study aims to identify and highlight road segments needing rapid safety enhancements to attain significant crash diminution through efficient safety alleviation. RTC hotspot zones are determined through a comprehensive analysis that incorporates local knowledge, expert judgment, crash analysis and crash data. To identify hotspots, Cheng et al. [17] used the Systemic approach and thoroughly cross-validated five multivariate models of crash-type-based HSID (hotspot identification) approaches that take into account geographical and temporal random effects [21]. Rear-end, sideswipe, head-on, hit object, broad-side and other crashes were the types of crashes that were gathered for this study. Additionally, the relationships between nearby junctions across crash categories were shown by the spatial random effects. The shortcomings of this study were the small sample size (137 data points) and the variable performance of HSID methods based on the size of crash data. The proposed study uses a sizeable amount of crash data for hotspot analysis to overcome this drawback. By proposing a Time Index (TI) and a Cause Index (CI), respectively, along with the traditional EPDO approach, Barman and Bandyopadhyaya [18] intend to leverage weather and time information to identify a collection of hotspots using a multi-dimensional K-means clustering technique [22]. TI is defined to give different weights to Day and Night-time crashes. In contrast, fog crashes, which are a definite visibility problem, receive the least weightage under CI and crashes caused by faulty geometry receive the greatest weightage. The suggested method's performance was compared to the CF (Crash Frequency) and EPDO (Equivalent Property Damage Only) techniques using road collision data from Patna, India. It was found that the suggested strategy produced the lowest possible false identifications. However, k-means clustering has problems clustering the data when clusters fluctuate in density and size. To address this limitation, Getis Ord *Gi** statistics were used in the current study to identify and prioritise traffic crash hotspots.

Chen et al. [19] introduced a novel HSID approach based on the quantitative risk assessment (QRA) method [23] Accidents likely to occur at a specific location are considered a risk. The empirical Bayesian technique estimates the likelihood of an accident for all exposed vehicles. The potential costs of collisions can be represented as the total of the crash probabilities for all passing vehicles and the accompanying effects of crashes when used as a criterion to rank high-risk areas. However, this study lacks the application of spatial effects [24] and Full Bayesian methods [25], which leaves it open for further improvements. To overcome this shortcoming, the proposed methodology utilises the most recent GIS-based analytical tool for spatiotemporal analysis. Based on a Road Safety Risk Index (RSRI), F. Ouni and M. Belloumi [22] investigated the performance stability of two spatial autocorrelation measures [26]. The ratio of the share of crashes that occur in the detected hotspot to the proportion of the entire study region covered by it is defined as the RSRI. Identifying potential hotspots improves the ability to evaluate a particular route by identifying "hazardous probable lengths," which seeks to predict future traffic accidents. The variety within the areas is addressed by spatial autocorrelation indices, which provide helpful information that can be used to develop safety regulations. The main limitation of this study was the under-reporting of crash data and the small sample size of data. Tola et al. [23] presented a GIS technique for classifying crash hotspots based on a spatial autocorrelation study using four-year crash data throughout Ethiopian regions [27]. The methods utilised in this investigation, which included the crash severity index, Getis Ord *Gi** and Moran's I spatial autocorrelation of collision incidents, successfully located and ranked crash hotspots. The respective crash costs differ from region to region and are used to calculate the severity index of crashes for each level of severity. However, the main drawback of this study was that the severity index created by the Roads and Traffic Authority of NSW (New South Wales) [28] was employed instead of an agreed-upon or specified collision costing equation for certain crash severity levels in Ethiopia.

The inverse network distance-band spatial weights matrix of intersections (INDSWMI) and the k-nearest distance-band spatial weights matrix between crashes and intersections (KDSWMCI) have been developed by Zhang et al. [25] as a new method for immediately detecting crash hotspot intersections (CHIs) [29]. Getis-Ord *Gi** statistic, INDSWMI and KDSWMCI were used in intersection hotspot analysis (IHA) to detect CHIs and evaluate the Intersection Prediction Accuracy Index (IPAI). IPAI is an indicator to measure the prediction accuracy of the IHA. The methodology created by Lee and Khattak [26] allows for quantitative analysis of major geographical clustering patterns defined by crash severity [30].

The current and most frequently used crash hotspot analysis methods can be broadly categorised:

1) Geo-statistical analysis
   - Spatial autocorrelation (Placement of each crash feature value spatially) [31]
   - Density Estimation (Examining the crash units spatially) [32]
2) Non-spatial analysis
   - Full Bayesian [33]
   - Empirical Bayes [34]
   - Regression models [35]

Geo-statistical analysis of crash hotspots is preferred over non-spatial analysis due to its simplified mathematical calculations and reduced data requirements [30]. Furthermore, geo-statistical analysis enables the integration of crash data with geographic factors and the generation of visually comprehensible results. The different methods for geo-statistical analysis are given in *Figure 1*.

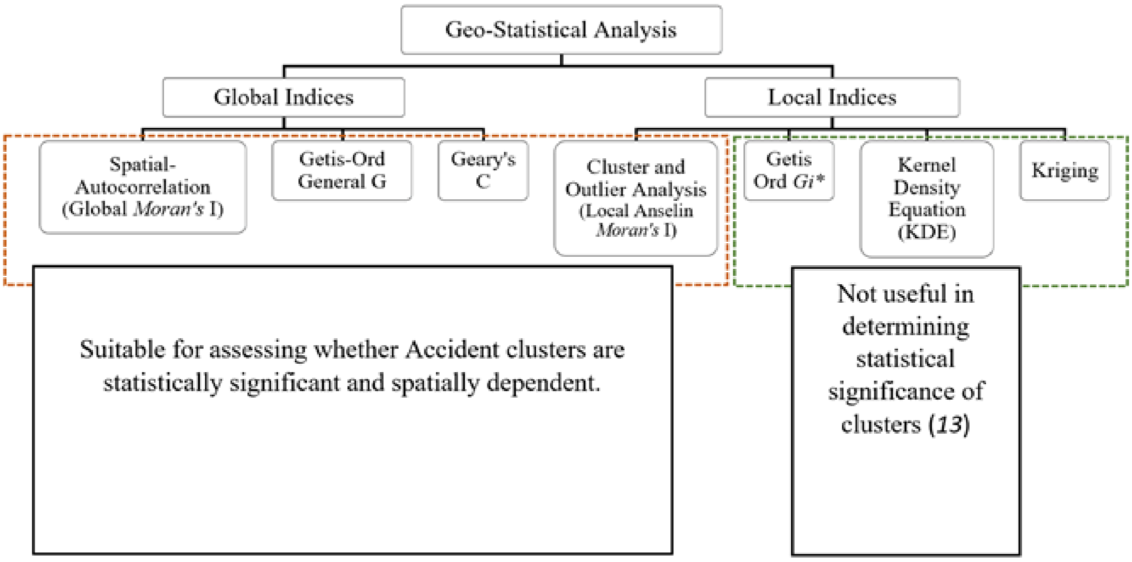


Figure 1 – Different methods for geo-statistical analysis and its significance

The most effective and widely used methods for identifying the precise cluster position (hotspot) within a network or sector are Kernel Density Equation (KDE), Getis Ord *Gi** and Global Moran's I. In a geographic hotspot analysis, the number of events across a unit area at a given position (i.e. first-order attributes) is examined using the KDE. KDE is better suited for visual representation than hotspot detection [36] Compared to the KDE, the level of statistical significance of clustered accidents is assessed by means of Z-Score for both Geary's C and Moran's I [37]. The global statistics technique, which serves as a gauge for the whole research network, is followed by Moran's I and Geary's C. Spatial analysis utilising local indices are preferred for RTC hotspot detection. Local Moran's I is a prominent local spatial analysis method frequently used in hotspot detection of motorised vehicle accidents [38]. The Moran indices family, however, does not distinguish between cold and hotspots. As a result, Getis Ord *Gi** is more suited since it differentiates between clusters of local events with low and high values of feature attributes. When analysing spatial correlation and variance, the local statistics method (such as local Moran's I [39] and Getis-Ord *Gi** statistics [40]) is preferable to the global statistics system. In particular, the Getis-Ord *Gi** statistic is beneficial for detecting statistically significant values of crash hotspots or cold spots [41].

3. METHODOLOGY

This study aims to identify and prioritise accident hotspots in the Indian state of Punjab by examining the severity and spatial pattern of accident occurrences by using the most current GIS-based analytical methods of the Getis Ord *Gi** statistics. This section outlines the comprehensive methodology employed for the hotspot analysis (*Figure 2*).

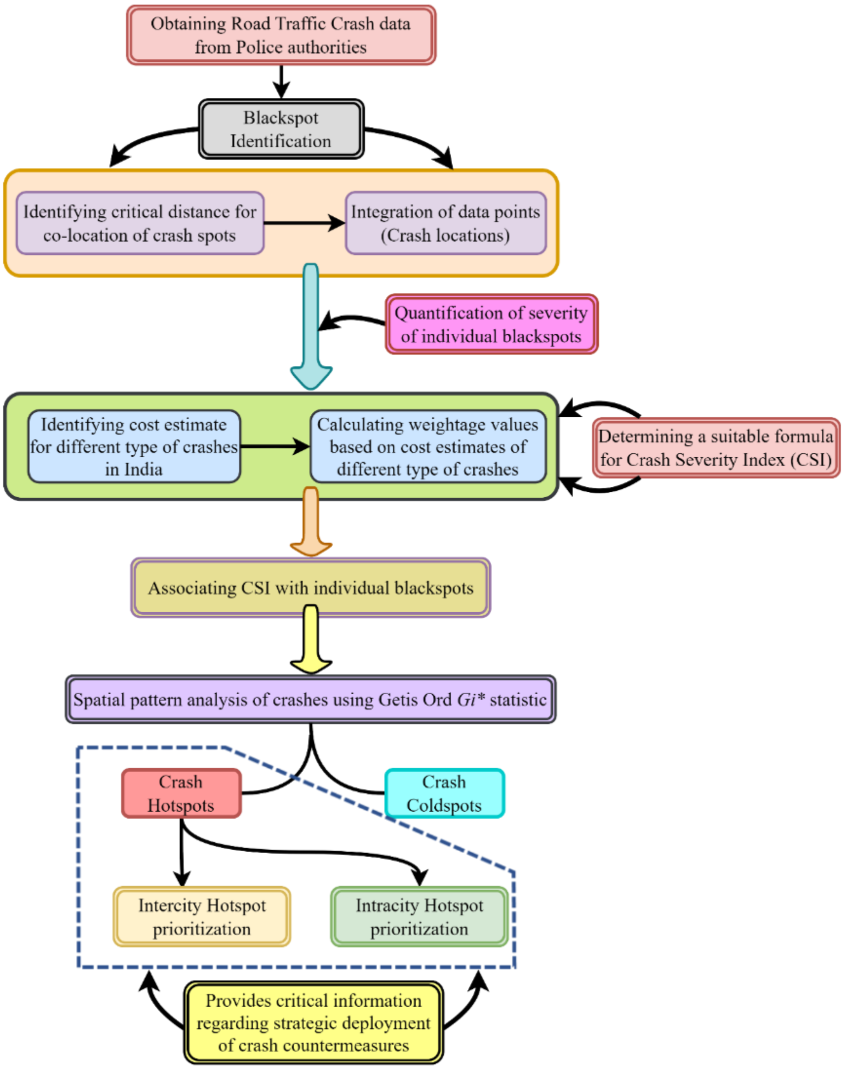


Figure 2 – Proposed methodology to identify Crash hotspots and coldspots

3.1 Black spot identification

A comprehensive and systematic approach to road safety management is necessary to mitigate accidents. The initial stage of road safety management involves identifying accident hotspots or blackspots. Accident blackspots encompass various terms such as "high-risk areas," "dangerous road stretches," "places needing improvement" and "accident-prone situations." In India, a blackspot is defined as a 500-meter stretch that has had five road collisions (involving severe injuries and fatalities) or ten deaths in the previous three calendar years [15]. The crash data consists of latitude and longitude coordinates for each individual crash location. Combining adjacent crash locations within a 500m stretch is essential for identifying blackspots. The integration of data points is crucial for co-locating crash locations. Integration refers to assessing the coordinates of feature vertices in features belonging to single or multiple feature data types. Those close enough to be presumed to represent the same position are given a shared coordinate value. An essential step for data point integration is defining an "x,y tolerance." The shortest distance between the data points before they are deemed equal is referred to as the x,y tolerance. Alternatively, the "x,y tolerance" can also be defined as the distance that establishes the zone in which feature values can concur. Its goal is to incorporate line work and bounds into a correctly configured input feature type spatial reference. For an output geo-dataset, the default "x, y tolerance" is set to 1 mm or its equivalent in map units. If the default value is unsatisfactory, it can be altered. The desired value for "x,y tolerance" in blackspot identification is 500 m. This enables the integration of individual crash locations. Integration is limited to basic feature types such as point, multipoint, line or polygon. Crash locations, being "point" type geo datasets, are integrable. Blackspot identification involves identifying features within a specified x, y tolerance and allocating shared coordinate points for these features.

3.2 Quantification of the severity of individual blackspots

Transport safety practitioners often rely on crash severity and crash count as predictors for assessing the probability of collisions on road sections [42]. The frequency of crashes determines the crash likelihood, while the severity determines the resulting damage. Safety improvement programs primarily prioritise preventing serious and fatal crashes due to their higher per-person costs compared to non-injury and minor injury crashes [43]. Federal road agencies and transport departments strive to decrease crash rates on their road networks. However, to accurately pinpoint high-risk locations (referred to as hotspots or blackspots), it is imperative to consider both crash count and crash severity.

Crash Severity Index

The Crash Severity Index (CSI) is a pivotal component of the proposed framework, designed to quantify the severity of each road traffic crash based on its associated costs and societal impact. The CSI assigns differential weightings to various types of crashes, thereby enhancing the precision and significance of identifying hotspots and coldspots within the studied region.

In this study, we employ a 1:3:5 weighting methodology to differentiate between minor injury crashes (C_3), serious injury crashes (C_2) and fatal crashes (C_1). This weighting scheme is grounded in the study by Geurts et al. (2004), which compared several weighting systems. The chosen system allocates weights of 1, 3 and 5 to minor injuries, serious injuries and fatalities, respectively, reflecting the escalating social and economic costs associated with each level of severity. The 1:3:5 ratio was selected due to its demonstrated effectiveness in accurately representing the severity distribution and impact of road traffic crashes. Geurts et al. [40] found that this ratio resulted in the smallest percentage deviation in predicting hazardous accident sites compared to other tested ratios, such as 1:1:1 and 1:10:10, thereby affirming its robustness in hotspot analysis.

The CSI for a specific crash is computed using the following formula (*Equation 1*):

$$\mathrm{CSI} = 5\mathrm{C}_1 + 3\mathrm{C}_2 + \mathrm{C}_3 \tag{1}$$

where C_1 are the fatal crashes, C_2 are the serious injury crashes and C_3 are the minor injury crashes.

While the 1:3:5 ratio serves as the basis for the current analysis, the CSI framework is inherently adaptable, allowing for the integration of alternative weighting systems as necessitated by regional differences or specific study goals. For instance, other regions or studies might adopt the World Road Association's (PIARC) suggested ratio, which offers a different perspective by placing greater emphasis on the disparity between fatal accidents and less severe injuries. Such adaptability ensures that the CSI remains relevant and applicable across various geographic and operational contexts, enabling tailored approaches to road safety analysis and intervention planning and allowing for an evidence-based, region-specific response to road safety.

3.3 Region-wise prioritization

Accident rates and resulting damages decrease with accurate identification of high-risk areas. Further research is needed to develop a comprehensive and localised strategy for identifying accident hotspots, as there is a lack of local studies and investigations on this topic. The investigation and study of crash hotspots in India are currently insufficient due to the absence of a structured strategy for identifying and prioritising these hotspots, as well as a suitable database for recording and reviewing the nationwide hotspot characterization and the effectiveness of countermeasures. Simultaneously, there is no evaluation of both the scientific identification and ranking of these methods, as well as their effectiveness in reducing accidents, following the investment and acquisition of such measures. Prioritising accident hotspots and tailoring identification techniques can effectively address the problem of traffic crashes. The main objectives of implementing road safety measures are to identify crash hotspots and assess locations with significant potential for reducing accidents. Prioritising regional blackspots/crash hotspots is essential for efficiently allocating safety budgets and promoting faster and more effective improvements in road network safety.

*Getis Ord Gi**

The hotspot analysis can be done either through Global or Local Indexes. Global Indexes test the extent of overall clustering, i.e. the degree to which points nearby have like values to those located further away. Local indexes quantify the degree to which points close to a given point have comparable attribute values within a particular area defined by a specified radius. Hence, spatial autocorrelation analysis through local indexes is better suited for crash hotspot analysis. The local tools include cluster and outlier analysis (Local Anselin Moran's I), Getis Ord *Gi**, Kernel Density Equation and Kriging. Only Local Anselin Moran's I and Getis Ord *Gi** are useful for studying the spatial autocorrelation of road traffic crashes. However, the Moran indices family lacks the ability to differentiate between coldspots and hotspots. Getis Ord *Gi** is the optimal tool for accurately classifying both low-value clusters (coldspots) and high-value clusters (hotspots).

For spatial analysis using Getis Ord *Gi**, an arbitrary variable X is chosen for which *Gi** statistics examine whether some spatial autocorrelation exists. Every data point has an associated event (x_i). The selected variable X is said to have spatial autocorrelation over an area i if x_i bears similar values in contiguous regions. Considering pivotal (central) point i (i = 1, 2, 3, 4, …, n), if the entire study area is split into n regions of indefinite extent, it yields one of the simplest forms of *Gi** statistics as stated below [40] -

$$G_i^* = \frac{\sum_{j=1}^{n} w_{ij} x_i}{\sum_{j=1}^{n} x_j} \tag{2}$$

where *Gi** defines the spatial autocorrelation of feature i, x_j is the value of X at a specified location j. The spatial weight assigned to features i and j is w_{ij}. The value of w_{ij} is calculated using a user-specified threshold distance, d. The choice of d determines the outcome of the *Gi** statistics. The total weights (W_i) can be computed as follows:

$$W_i = \sum_{j=1}^{n} w_{ij} \tag{3}$$

Characteristically, the sample variance (s^2) and sample mean ($\bar{x}$) for a normal asymptotical condition are used to standardise the *Gi** statistics [41].

$$\bar{x} = \frac{\sum_{j=1}^{n} x_j}{n} \tag{4}$$

$$s^2 = \frac{\sum_{j=1}^{n} {x_j}^2}{n} - \bar{x}^2 \tag{5}$$

The expectation value (E) and variance (Var) of *Gi** is given as follows:

$$E(G_i^*) = \frac{W_i}{n} \tag{6}$$

$$Var(G_i^*) = \frac{s^2}{\bar{x}} * \frac{W_i(n - W_i)}{n - 1} \tag{7}$$

where n is the number of occurrences

$$Z(G_i^*) = \frac{\sum_{j=1}^{n} w_{ij} x_i - \bar{x} \sum_{j=1}^{n} {w_{ij}}^2}{s\sqrt{\frac{n \sum_{j=1}^{n} {w_{ij}}^2 - \left(\sum_{j=1}^{n} w_{ij}\right)^2}{n-1}}} \tag{8}$$

Equation 8 gives the Z-score corresponding to the *Gi** statistics. The Z-score indicates the statistical significance of the area of concern; in other words, the Z-score suggests the intensity of clustering within the given data set.

The likelihood that the studied crashes occurred randomly or in a clustered manner is given the p-value for the spatial pattern analysis. The p-value is expressed as a probability; for instance, a p-value of 0.02 indicates a 2% chance that the crashes occurred randomly or arbitrarily. High magnitudes of Z-score and low p-values indicate data clustering. A Z-score in close proximity to zero indicates arbitrarily distributed data. The maximum positive and maximum negative values of Z-scores indicate the cluster of high and low values of feature attributes, respectively. Getis Ord *Gi** method employs the *Gi** statistic to categorise a geographic area as either a hotspot or a coldspot based on the feature attribute values of its neighbours. Hotspots are the regions having high positive, statistically significant values of Z-score and are encompassed by areas having high attribute values. In contrast, coldspots are regions having negative, statistically significant values of Z-score and are encircled by areas having low attribute values. A statistically significant Z-score is generated if the local aggregate of the concerned area and its surrounding values considerably deviates from the likely local value corresponding to a random distribution. The final equation that is used to identify and classify accident hotspots in the Getis Ord *Gi** hotspot analysis tool of ArcGIS is as follows:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{ij} x_j - \frac{\sum_{j=1}^{n} x_j}{n} * \sum_{j=1}^{n} w_{ij}}{\sqrt{\frac{\sum_{j=1}^{n} {x_j}^2 - \sum_{j=1}^{n} x_j}{n} * \sqrt{\frac{n \sum_{j=1}^{n} {w_{ij}}^2 - \left(\sum_{j=1}^{n} w_{ij}\right)^2}{n-1}}}} \tag{9}$$

3.4 Intra-city blackspot prioritization

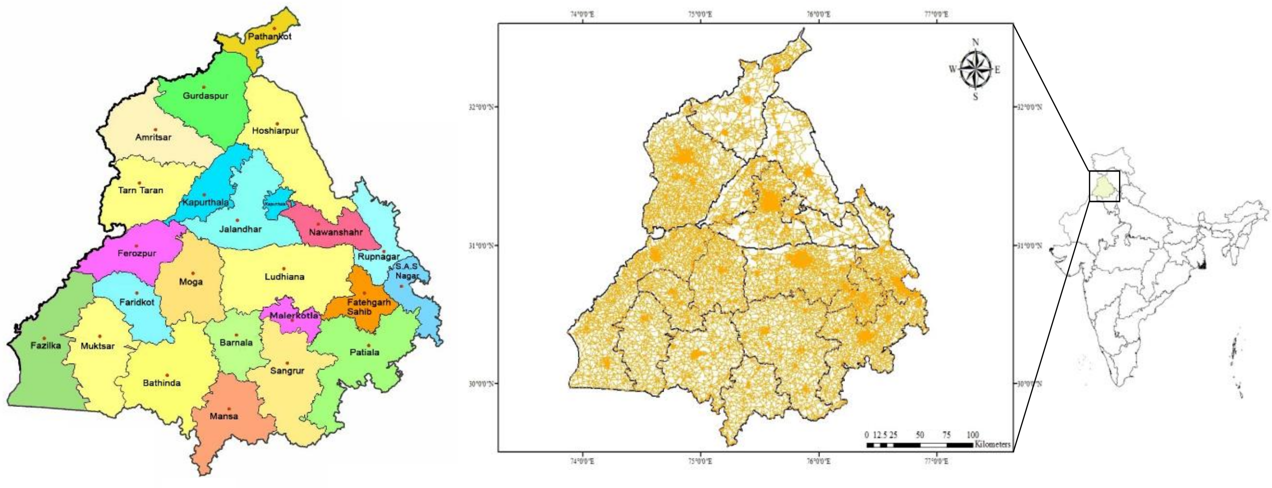
After identifying the crash hotspot regions, it is crucial to prioritise the blackspots within those areas or cities. This will aid policymakers in formulating a systematic plan for crash countermeasures. Blackspots or sites with higher crash severity should be prioritised over others. Prioritising intra-city blackspots will enhance the allocation of resources for crash remedial measures in a more rational and weighted manner.

4. CASE STUDY

The proposed methodology is exemplified by identifying and prioritising accident hotspots (based on severity) within Punjab, India.

4.1 Study area and data collection

The study was carried out in the Indian state of Punjab to identify and prioritise blackspots based on the crash hotspots detected. The map of India, including its states and union territories, as well as Punjab with its districts and road networks, was acquired by BHUVAN, the Indian Geo-Platform of the Indian Space Research Organisation (ISRO), in the form of various shape files (*Figure 3*). Crash data was collected from the Punjab police. Hotspot and crash severity analysis was performed using crash data spanning three consecutive years (2019–2021). The analysis included all types of recorded crashes, such as vehicle-vehicle crashes, pedestrian-vehicle crashes and others.



(a) (b)

Figure 3 – Punjab state boundary (a) and its road network (b)

4.2 Analysis

Blackspot identification and quantification of the severity of individual blackspots

This study utilised the spatial statistics toolkit of ArcGIS 10.5 for blackspot identification and crash hotspot analysis. The stepwise procedure adopted for blackspot identification and severity quantification is summarised below:

1) Plotting the map of the Punjab state showing all its district boundaries.
2) Calculating Crash Severity Index (CSI) associated with each crash (as per Eq. (1)).
3) Integrating neighbouring crashes within a 500-metre range to identify blackspots. This is done by setting the "x,y tolerance" at 500 metres.

The output obtained is given in *Figure 4*, which illustrates the blackspots with diameters proportional to the crash frequency. Additionally, the colour intensity of a blackspot corresponds to the severity of crashes occurring within it. A smaller diameter, dark red blackspot suggests a lower number of highly severe crashes.

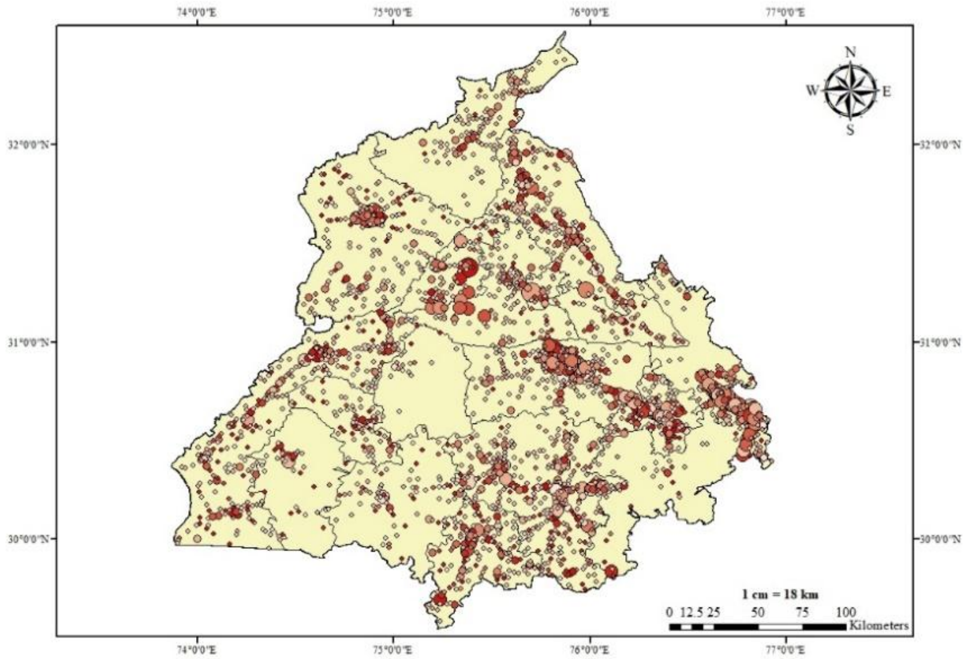


Figure 4 – Blackspots within Punjab

Spatial pattern analysis of crashes

After identifying blackspots, it is imperative to analyse the spatial relationship of the crashes. The Euclidean distance method was employed for spatial pattern analysis. The following methods can be used to conceptualise spatial association:

1) Fixed distance,
2) Inverse distance,
3) Inverse squared distance,
4) K-nearest neighbours,
5) The zone of indifference,
6) The space-time window method, and
7) Contiguity edges and corners.

This study employed the fixed distance method, where crashes within a threshold distance of 500 metres were assigned a weightage value of 1, while those outside this distance were assigned a weightage value of 0. The spatial autocorrelation report (*Figure 5*) provides information about the nature of the data, specifically whether it is dispersed, random or clustered. The obtained results for this study include a z-score of 32.312, a p-value of 0.00 and a Moran's Index of 0.1335, which indicates that there is less than 1% likelihood that the clustered pattern could be the result of random choice, or in simpler words, the data is clustered in nature.

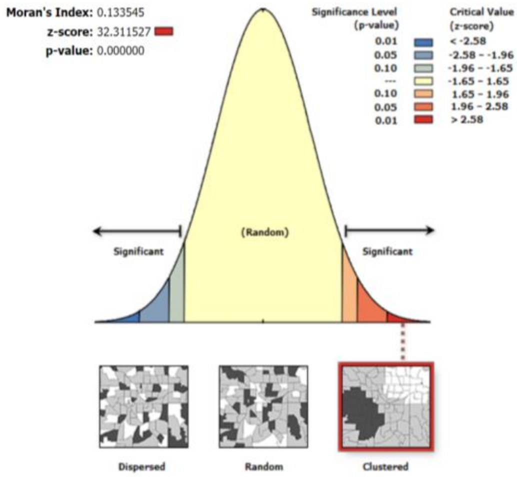


Figure 5 – Spatial autocorrelation report

Hotspot identification

Crash spatial pattern analysis reveals clustering, enabling hotspot identification. CSI values are assigned to all crashes. A threshold distance value of 500 metres, specifically chosen to represent the accident blackspot stretch in India, was utilised for hotspot analysis by employing the Getis Ord *Gi** statistics. The output identifies the crash hotspot, coldspot and randomly distributed regions within the geographic boundaries of the Punjab state (*Figure 6*).

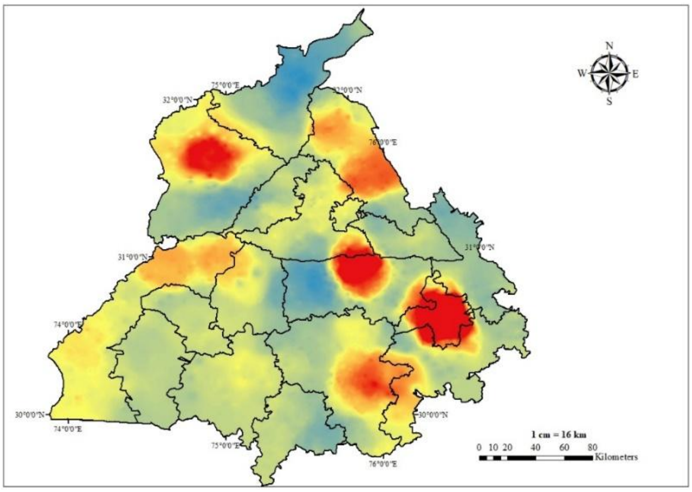


Figure 6 – Crash hotspot and coldspot distribution

4.3 Descriptive crash statistics of Punjab

All crashes

Descriptive statistics of all the crashes that occurred in the state of Punjab are summarised in *Table 1*, which shows that the most severe crashes occurred in the year 2020, followed by 2019 crashes, although 2019 reported 85.8% more total crashes, 5.8% more fatal injury crashes and 16.6% more minor injury crashes, respectively, compared to 2020. This can be attributed to the fact that in 2019, the total number of crashes was reduced in the year 2020 at the expense of a very slight decrease in the number of fatal crashes and a marked increase in cases of serious injury crashes. Crashes that occurred in 2021 accounted for the least amount of damage. Friday witnessed the most severe crashes of all days a week, with Wednesday accounting for the least. Monday and Thursday saw the greatest and least number of crashes reported, respectively, whereas the highest sum of fatal crashes occurred on Sunday. Crashes occurring in winter had the highest value of CSI, along with a greater amount of total, fatal, serious and minor injury crashes than the summer and monsoon crashes. The period 06:00 p.m.–09:00 p.m. witnessed by far the highest severity of all crashes occurring throughout the day, although a 6.1% more crash frequency was observed between 12:00 a.m. and 03:00 a.m. compared to 06:00

p.m.–09:00 p.m. "Hit from back" type of crashes caused the most significant damage compared to all other collision types. However, 40.8% more "hit and run" cases than "hit from back" collisions were observed.

Table 1 – Descriptive crash statistics of all crashes in Punjab

Parameter		Crash frequency	Crashes			Crash Severity Index (CSI)
			Total fatal	**Total serious**	**Total minor**	
Year	2019	3722	675	835	316	6196
	2020	2003	638	984	271	**6413**
	2021	1620	437	593	329	4293
Day of the week	Monday	1098	255	342	156	2457
	Tuesday	1045	257	334	117	2404
	Wednesday	1041	243	294	127	2224
	Thursday	1017	233	352	125	2346
	Friday	1074	261	395	142	**2632**
	Saturday	1048	232	348	124	2328
	Sunday	1022	269	347	125	2511
Season	Summer	2530	558	775	284	5399
	Monsoon	2257	545	727	283	5189
	Winter	2558	647	910	349	**6314**
Time of offence	12:00 a.m.–03:00 a.m.	1579	132	200	68	1328
	03:00 a.m.–06:00 a.m.	268	60	90	38	608
	06:00 a.m.–09:00 a.m.	680	156	207	98	1499
	09:00 a.m.–12:00 p.m.	851	252	391	125	2558
	12:00 p.m.–03:00 p.m.	941	236	354	138	2380
	03:00 p.m.–06:00 p.m.	884	275	397	161	2727
	06:00 p.m.–09:00 p.m.	1488	463	551	219	**4187**
	09:00 p.m.–12:00 a.m.	654	176	222	69	1615
Type of collision	Fixed/stationary object	31	7	31	5	133
	Head on collision	779	314	437	123	3004
	Hit and run	2551	437	376	205	3518
	Hit from back	1812	493	769	305	**5077**
	Hit from side	1395	354	594	213	3765
	Pedestrian	235	40	20	12	272
	Run off road	168	11	36	8	171
	Vehicle overturn	84	16	47	12	233
	With animal	19	5	1	0	28
	With parked vehicle	104	43	62	23	424
	Others	167	30	39	10	277

Pedestrian crashes

Vulnerable road users comprise pedestrians, two-wheelers and bicycles, of which pedestrians have the second highest share of total road accident fatalities caused in India. In India, pedestrian road users accounted for 17.8% of road crash fatalities in 2020; in 2021, this number rose to 18.9%. Moreover, Punjab is the only Indian state to have witnessed more casualties in lesser instances of pedestrian crashes [15]. This proves that pedestrian crashes in Punjab have a high degree of severity, necessitating its study. The descriptive crash statistics of pedestrian crashes in Punjab are given in *Table 2*.

Table 2 – Descriptive crash statistics of pedestrian crashes in Punjab

Parameter		Crash frequency	Crashes			Crash Severity Index (CSI)
			Total fatal	Total serious	Total minor	
Year	2019	233	28	21	4	207
	2020	232	51	51	19	**427**
	2021	146	42	32	35	341
Day of the week	Monday	85	19	13	9	143
	Tuesday	103	16	21	7	150
	Wednesday	102	17	13	11	135
	Thursday	82	21	10	8	143
	Friday	98	21	17	14	**170**
	Saturday	78	10	19	6	113
	Sunday	63	17	11	3	121
Season	**Summer**	194	44	39	17	**354**
	Monsoon	178	35	32	20	291
	Winter	239	42	33	21	330
Time of offence	12:00 a.m.–03:00 a.m.	47	3	9	5	47
	03:00 a.m.–06:00 a.m.	26	4	6	3	41
	06:00 a.m.–09:00 a.m.	61	18	6	6	114
	09:00 a.m.–12:00 p.m.	75	13	14	9	116
	12:00 p.m.–03:00 p.m.	74	16	15	12	137
	03:00 p.m.–06:00 p.m.	83	16	10	8	118
	06:00 p.m.–09:00 p.m.	170	37	34	14	**301**
	09:00 p.m.–12:00 a.m.	75	14	10	1	101
Vehicles involved	Auto rickshaw	1	0	0	0	0
	Bicycle	1	0	0	0	0
	Bus	29	2	3	6	25
	Light motorised vehicle	223	49	31	23	**361**
	Cycle rickshaw	1	0	0	0	0
	Heavy articulated vehicle	8	4	0	0	20
	Motorised two-wheeler	116	18	40	11	221
	Mid-size passenger vehicle	41	6	14	6	78
	Mid-size goods vehicle	67	16	8	8	112
	Others	122	26	6	4	152
Type of Section	**Intersection**	437	86	62	41	**657**
	Midblock	174	35	42	17	318

From *Table 2*, it can be observed that the year 2020 experienced the most severe pedestrian crashes in Punjab. In 2019 and 2020, a similar number of total pedestrian-related crashes were reported. The day-wise trend in pedestrian crashes was similar to that of all crashes, with Fridays being the most severe. However, the highest crash frequency was observed on Tuesday and Wednesday. The summer season had the highest severity of pedestrian crashes, despite the winter season having more frequent crashes. Similar to all types of crashes, pedestrian crashes were observed to be most severe between 06:00 p.m.–09:00 p.m. The light motorised vehicle category, which includes cars, jeeps, vans and taxis, was determined to cause the highest amount of damage in pedestrian accidents. A compelling analysis revealed that approximately 71.5% of pedestrian crashes took place at intersections, resulting in significantly greater severity than midblock pedestrian crashes.

5. RESULTS AND DISCUSSION

5.1 Region-wise hotspot prioritization

The utilization of state-wide hotspots allows for the prioritization of districts within the state for crash remedial action. The severity values of various districts in Punjab can be used to establish a ranking system (*Table 3*). The hotspot analysis reveals that Sangrur, Hoshiarpur and Police Commissionerate Ludhiana form the top three hotspots (high clusters) within Punjab, whereas Gurdaspur, Pathankot and Rupnagar form significant coldspots (low clusters). Furthermore, it is interesting to note that though the number of crashes for Kapurthala (247) is greater than that of SAS Nagar (230), SAS Nagar is a region of more significant concern due to its higher number of fatal crashes and consequently, a higher Crash Severity Index (CSI). The districts in Punjab featured in the Crash Severity Index (CSI) rankings present a nuanced landscape of road safety challenges, each shaped by local factors ranging from infrastructure quality to traffic behaviour and enforcement practices. For instance, Sangrur, which leads the rankings, may struggle with the dual burden of high vehicular traffic and potentially inadequate road infrastructure, exacerbating the risks associated with high-speed travel and commercial transportation. Issues such as unmarked rural roads and intersections commonly found in this district further increase the likelihood of road crashes. Hoshiarpur, with its significant number of serious crashes, possibly suffers from the challenges typical of rural areas, such as limited street lighting, poor road signage and a culture of high-speed driving with inconsistent enforcement of traffic regulations. Ludhiana, as an industrial epicentre, deals with heavy traffic congestion compounded by the frequent intermingling of heavy-duty industrial vehicles and standard commuter traffic. This interaction, combined with possibly overstressed and poorly maintained urban roads, creates a fertile ground for traffic crashes. In districts like Fatehgarh Sahib and Ferozepur, the mix of agricultural and urban traffic during peak seasons, coupled with insufficient pedestrian pathways, likely contributes to their high CSI scores. Mansa, though lower on the list, faces its unique challenges, such as narrow roads and limited visibility, which are symptomatic of smaller, less urbanised regions. These conditions underscore the pressing need for region-specific interventions that not only enhance physical road conditions through better infrastructure but also improve traffic safety through stringent enforcement and localised educational campaigns aimed at promoting safe driving practices.

Table 3 – Crash hotspots ranked according to crash severity index

Rank	Crash frequency	District	Crashes			Crash Severity Index (CSI)
			Total fatal	Total serious	Total minor	
1	785	Sangrur	210	361	214	2347
2	599	Hoshiarpur	195	281	123	1941
3	577	Police Commissionerate Ludhiana	163	297	117	1823
4	502	Fatehgarh Sahib	191	269	42	1804
5	439	Ferozepur	150	187	102	1413
6	278	Fazilka	123	137	18	1044
7	230	SAS Nagar	87	109	34	796
8	247	Kapurthala	69	126	52	775
9	197	Police Commissionerate Amritsar	86	96	15	733
10	208	Mansa	84	90	34	724

Addressing these challenges effectively demands a holistic approach that integrates enhanced road design, improved enforcement mechanisms and community engagement to educate and alter driving behaviours. Such efforts are essential for mitigating the risk factors contributing to high crash severities across these diverse districts in Punjab. This comprehensive strategy should focus on the peculiarities of each district, ensuring that solutions are as varied and specific as the problems they aim to solve.

5.2 Intra-city hotspot prioritization

The ranking of hotspot locations within a city or district, categorised by all crash incidents and pedestrian-specific crashes, is presented in *Table 4*. The initial section of the table that encompasses all types of crashes reveals that high Crash Severity Index (CSI) scores are commonly linked with unsignalised intersections. These intersections lack crucial traffic control measures, creating significant risk zones where road users' paths converge, increasing the probability of collisions. These areas often experience a mix of high vehicular traffic and complex driving behaviours, such as poor lane discipline and failure to yield, which escalate the risk of accidents. Additionally, the table highlights that pedestrian-specific crashes predominantly occur in areas bustling with pedestrian traffic where jaywalking is rampant. This underscores a glaring shortfall in pedestrian infrastructure, including crosswalks, pedestrian signals and safety barriers, which are vital for secure pedestrian navigation across busy roadways. These locations are also prone to poor visibility issues, inadequate street lighting, or deficient road signage, further heightening the risk of incidents involving both pedestrians and drivers. Other critical zones requiring focus include high-traffic commercial areas, vicinities around educational institutions and universities, public transportation hubs, residential sectors with limited recreational spaces and densely populated marketplaces or event spots.

To mitigate these risks, targeted measures are necessary, such as installing traffic control devices at unsignalised junctions, enhancing pedestrian infrastructure and initiating public education campaigns to curb jaywalking and promote safer crossing habits. By addressing these behaviours and infrastructural deficiencies, such interventions are expected to considerably reduce both vehicular and pedestrian-related crashes, thereby improving overall traffic safety. Prioritising these hotspots is crucial for urban planners and traffic safety officials to efficiently allocate resources and tackle the most perilous conditions in urban settings.

Table 4 – Intra-city crash hotspot prioritization

Type of crash	Rank	Crashes			Crash Severity Index (CSI)	Crash hotspot	
		Total fatal	Total serious	Total minor		Latitude	Longitude
All crashes	1	10	33	4	153	31.25	75.70
	2	15	23	7	151	30.66	76.29
	3	9	18	9	108	30.94	75.83
	4	9	18	1	100	31.49	75.89
	5	6	19	9	96	30.27	76.04
	6	7	19	3	95	31.38	75.38
	7	8	16	4	92	31.82	75.66
	8	5	21	4	92	30.97	75.81
	9	6	17	4	85	30.89	75.89
	10	3	21	3	81	30.90	75.88
Pedestrian crashes	1	2	2	3	19	30.13	75.82
	2	2	2	3	19	30.25	75.84
	3	0	6	0	18	30.18	74.32
	4	3	1	0	18	30.58	74.83
	5	3	1	0	18	30.64	76.82
	6	2	2	0	16	31.57	75.04
	7	2	1	3	16	30.16	75.89
	8	2	1	2	15	30.26	75.99
	9	2	0	4	14	30.26	75.94
	10	1	3	0	14	30.74	76.69

6. CONCLUSION

The principal aim of hotspot analysis is to accomplish two main objectives of effective road safety management, which are as follows:

1) Identifying dangerous road stretches or crash hotspots.
2) Ranking crash hotspots to strategically deploy crash countermeasures.

This study intended to demonstrate a GIS technique for locating and quantifying statistically significant spatial distribution based on crash severity and frequency in Punjab. Analysis of the spatial pattern of crash locations helps identify spatial autocorrelation among crashes. Using Getis Ord *Gi** in conjugation with integrating individual crash locations allowed for identifying crash hotspots based on crash severity. One benefit of using spatial autocorrelation is that it enables statistical investigation of the spatial pattern of crashes. *Gi** statistics is superior to Moran's I index for detecting crash hotspots since it can distinguish between high and low crash clusters. The crash frequency is often considered the critical parameter for blackspot/hotspot prioritization. This study proves that crash severity is a more significant factor for hotspot analysis as it considers the costs associated with and damage inflicted by accidents.

*Gi** statistics were applied after studying the spatial dependency of crashes to pinpoint clusters with high and low crash severity, i.e. hotspots and coldspots. According to the region-wise hotspot evaluation, Sangrur, Hoshiarpur and Fatehgarh Sahib are the top three hotspots (high clusters) in Punjab, while Gurdaspur, Pathankot and Rupnagar are major coldspots (low clusters). The intra-city hotspot study resulted in the prioritization of individual crash locations (for all crashes and pedestrian crashes) based on the Crash Severity Index (CSI).

The study's findings suggest that crash hotspot detection techniques, such as using Getis Ord *Gi** and integrating crash locations, can be used to evaluate geographical patterns of accidents and identify high-severity (hotspots) and low-severity (coldspots) clusters. The study demonstrated the significant advantage of using Getis Ord *Gi** to analyse crash data in Punjab for selecting suitable sites to deploy crash countermeasures. Hence, the inclusion of Getis Ord *Gi** in accident hotspot analysis should be prioritised for future road safety research in India.

To further advance the robustness and applicability of the proposed framework, future studies will explore the incorporation of alternative weighting systems, such as those suggested by the World Road Association – PIARC and other possible ratios, to evaluate their effectiveness in enhancing the precision of our proposed framework for various regional contexts. Further strengthening of the proposed methodology in terms of high performance, even in the case of a small sample size (very few crashes), may be taken up as a future study.

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कलीप्रसन्न मुदुली, देओरीशभ साहू, इंद्रजीत घोष

सड़क यातायात दुर्घटना हॉटस्पॉट्स की पहचान और प्राथमिकता निर्धारण के लिए एक वैज्ञानिक रूपरेखा

सारांश

यह अध्ययन Getis Ord Gi* स्थानिक सहसंबंध उपकरण का उपयोग करके सड़क यातायात दुर्घटना हॉटस्पॉट्स की पहचान और प्राथमिकता निर्धारण के लिए एक नवीन और अनुकूलनीय रूपरेखा प्रस्तुत करता है। यह रूपरेखा दुर्घटना की गंभीरता और आवृत्ति के आधार पर क्षेत्रों को हॉटस्पॉट या कोल्डस्पॉट के रूप में वर्गीकृत करती है। इसमें एक अद्वितीय वेटिंग सिस्टम विकसित किया गया है, जो दुर्घटना गंभीरता सूचकांक (CSI) की गणना के लिए दुर्घटनाओं की गंभीरता को मृत्युओं और घायलों के संदर्भ में ध्यान में रखता है। पहचाने गए हॉटस्पॉट्स को CSI के माध्यम से प्राथमिकता दी जाती है, जिससे नीति निर्माताओं को दुर्घटना निवारण उपायों के लिए संसाधन आवंटित करने का एक संरचित दृष्टिकोण मिलता है। इस अध्ययन का मुख्य योगदान एक लचीली रूपरेखा का विकास है, जो विभिन्न शहरों, राज्यों या देशों में सड़क सुरक्षा सुधार के लिए लागू की जा सकती है। इस रूपरेखा की प्रभावशीलता पंजाब, भारत के एक केस स्टडी के माध्यम से प्रदर्शित की गई है, जिसमें संगरूर, होशियारपुर, और पुलिस आयुक्तालय लुधियाना शीर्ष तीन हॉटस्पॉट्स के रूप में उभरते हैं। अध्ययन पंजाब में दुर्घटना आँकड़ों का विस्तृत विश्लेषण भी प्रस्तुत करता है, जो पैदल यात्री दुर्घटनाओं की गंभीरता पर जोर देता है। यह दृष्टिकोण हॉटस्पॉट पहचान और प्राथमिकता निर्धारण की मौजूदा संरचनात्मक रणनीतियों की कमी को दूर करता है, जो सड़क सुरक्षा प्रबंधन में एक महत्वपूर्ण प्रगति को चिह्नित करता है।

प्रमुख शब्द

सड़क यातायात दुर्घटनाएँ; हॉटस्पॉट पहचान; दुर्घटना गंभीरता; स्थानिक विश्लेषण; सड़क सुरक्षा प्रबंधन; संसाधन आवंटन।