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Severity, Spatial Pattern and Statistical Analysis of Road Traffic Crash Hot Spots in Ethiopia

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Abstract: The reduction of traffic crashes, as well as their socio-economic consequences, has captivated the attention of safety professionals and transportation agencies. The most important activity for an effective road safety practice is to identify hazardous roadway areas based on a spatial pattern analysis of crashes and an evaluation of crash spatial relations with neighboring areas and other relevant factors. For decades, safety researchers have adopted several techniques to analyze historical road traffic crash (RTC) information using the advanced GIS-based hot spot analysis. The objective of this study is to present a GIS technique for identifying crash hot spots based on spatial autocorrelation analysis using a four-year (2014–2017) crash data across Ethiopian regions, as well as zones and towns in the Oromia region. The study considered the corresponding severity values of RTCs for the analysis and ranking of crash hot spot areas. The spatial autocorrelation tool in ArcGIS 10.5 was used to analyze the spatial patterns of RTCs and then the Getis Ord *Gi** statistics tool was used to identify high and low crash severity cluster zones. The results showed that the methods used in this analysis, which incorporated Moran's I spatial autocorrelation of crash incidents, Getis Ord *Gi** and crash severity index, proved to be a fruitful strategy for identifying and ranking crash hot spots. The identified crash hot spot areas are along the entrance to and exit from Addis Ababa, Ethiopia's capital city, so the responsible bodies and traffic management agencies should give top priority attention and conduct a thorough study to reduce the socio-economic effect of RTCs.

Keywords: crash severity; Getis Ord *Gi**; road traffic crash (RTC); spatial autocorrelation

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1. Introduction

Road traffic safety has become a major apprehension for human beings since the emerging of roadway transport and motor vehicles. According to the World Health Organization (WHO), RTC (road traffic crash) is the 8th most common means of death for all age groups. Nowadays, it is the top reason for the death of children and young adults aged 5–29 years [1]. Road traffic safety analysis has been employed to save the loss of lives by understanding the cause of traffic crashes and coming up with safety mitigations. The analysis aims to investigate pieces of information needed by decision makers to apply suitable safety measures to eliminate and minimize the occurrence of traffic crashes [2].

Because of the presence of distance in the road networks, the spatial pattern of crashes must be examined in traffic safety studies. Spatial analysis is the inspection of crash occurrence patterns by considering their relative locations or zones. Traffic crashes meet the main characteristics of spatial heterogeneity and spatial dependence of point data. Spatial dependence belongs to the influence of events at a location by neighboring events, while spatial heterogeneity happens when the spatial relationships among observed incidents and random parameters in the developed model are not established spatially [3].

The emergence of GIS has provided a vital tool for community health study [4–6]. Moellering used a Geographical Information System (GIS) to analyze traffic collisions for the first time in 1976 in his work of "a computer-animated film in the analysis of geographical patterns of traffic crashes" [7]. Since then, the geographical information system has been used extensively in road traffic safety studies over the past five decades [3,8]. Its application varies from simple mapping and visualization roles to further advanced methods such as spatial statistical models and the analysis of large data methods. Nowadays, the precise and exact location of RTCs and their attributes are stored in the GIS database. GIS software allows us to gather spatial data in which we can store, manipulate, analyze and visualize it with ease [9,10]. Even though a comprehensive review and evaluation of analytical approaches have been conducted [11], numerous research works have demonstrated that spatially enriched crash analysis shows potential in establishing a better insight into road safety by revealing areas with safety issues [12,13].

In terms of crash prevention programs, there are minimal indications regarding road safety measures being implemented in low and middle-income countries [14], where the majority of crashes occur. Ethiopia (a low-income country), along with Uganda, Bangladesh and Vietnam, is among the four nations in the world with an exceptionally high health concern, with more than 1000 fatalities per 100,000 motorized vehicles [15]. Therefore, it is important to map crash hot spots by analyzing the severity and spatial pattern of crash incidences in Ethiopia in order to provide information on where to invest a limited budget to improve road safety efficiently.

In Ethiopia, the majority of road safety analysis methodologies employed by transportation authorities and safety specialists are classic descriptive approaches focused on quantifying and summarizing crash data. While crashes are random incidents that occur in space and time [10], they also reflect spatial dependency and spatial autocorrelation, which should be taken into account while analyzing them [16]. Furthermore, at present, in Ethiopia, GIS is not used widely in crash data recording and identifying RTC hot spot locations. To identify RTC hot spots, a GIS-based spatial analysis has been a promising tool and widely used [17,18]. The GIS-based hot spot analysis result is presented accurately on a single map with the related attribute data of each RTC which may advance the understanding of road safety researchers regarding the reasons for each crash occurrence [19].

With the most up-to-date analytical techniques of the GIS's Getis Ord *Gi** statistics, this study aimed to analyze the severity and spatial pattern of crash incidents, as well as map crash hot spots in Ethiopia. While some scholars have studied crash events in Ethiopia [20–23], none have utilized spatially enriched and statistically integrated analyses like Getis Ord *Gi** statistics. Hence, the current study is significant in that it illustrates the benefit of utilizing spatial autocorrelation and statistical techniques to identify crash-intensive prone zones, as well as demonstrating its effectiveness in Ethiopia. Moreover, the study will provide guidance to decision-makers on where to best invest or implement safety measures.

2. Literature Review

There is no universally acknowledged definition of Road Traffic Crash (RTC) hot spot identification [10]. Some safety researchers prioritize sites by crash rate (i.e., crashes per vehicle-kilometers for segments and crashes per entering vehicles for intersections), others use crash frequency (i.e., crashes per year), some use spatial analysis of crashes and others adopt the integration of the above and the rest uses regression modeling (i.e., the predictive approach of Crash Prediction Model, CPM) [24]. RTC hot spot analysis, in general, attempted to identify and prioritize road segments in need of immediate safety improvements to achieve valuable crash reduction through effective safety mitigation. In addition to crash analysis, local expertise and expert judgment are used to identify RTC hot spots. This work (road safety management) comprises the following tasks [25,26]:

1. Targeting or identifying crash hot spots on the road network;
2. Studying safety issues in each hot spot;

3. Identifying contributing factors and design mitigations;
4. Evaluating the safety effects of the possible mitigations;
5. Prioritizing the hot spots to apply cost-effective safety mitigations; and
6. Evaluating the effectiveness of applied treatments.

This review has mainly focused on the first task of identifying crash hot spots on the road network. Since RTC analysis is such an important activity for improving roadway safety, it has been extensively researched in the academic press. Despite the lack of consensus on crash hot spot analysis, researchers and experts have developed various methods for crash event analysis. The simplest and most straightforward method for crash hot spot analysis is detecting where the crash rate per unit exposure exceeds a given normal threshold [27].

Although most of the traditional approaches of crash analysis focus on the time dimension, nowadays, the spatial dimension of traffic crashes has got more attention from researchers [16,28]. This facilitates the application of GIS into crash hot spot analysis. In recent years, several RTC databases recorded the precise locations of crashes through the application of GPS devices; hence, it is no longer necessary to identify the crash hot spot section of a road from aggregated data [2,29]. By having these accurate locations of RTC, road safety analysts can focus on the highly clustered crash locations.

Generally, the most frequently used methods of crash hot spot analysis can be categorized into two. These are:

- Non-Spatial Model Analysis (NSMA): which uses the traditional approaches of statistics such as regression models [30], Empirical Bayes [31], and full Bayesian [32];
- Geo-Statistical Analysis (GSA): by analyzing the spatial units of crashes (i.e., Density Estimation, DE) [33,34] or spatial arrangement of each crash attribute value (i.e., Spatial-Autocorrelation, SA) [35–37].

As compared to NSMA, Geo-Statistical crash hot spot analysis needs fewer data and is easier to apply due to the simplified mathematical calculations [38] and its integration of crash incidence with spatial factors and, also, the presentation of clear visualization in the result. The adoption of the spatial arrangement of attribute values from each unit is more advantageous than using a spatial unit of crashes due to its consideration of spatial dependence of attribute values and the geographical location of incident points [39]. For a thorough understanding of the Geo-Statistical analysis of crashes, readers are recommended to a review paper [40] dedicated to reviewing the scientific literature on spatial approaches and spatial analysis in road safety.

GSA can be further divided into two groups such as Global Indexes (GI) for instance Global *Moran's I* (Spatial-Autocorrelation), Getis-Ord G statistic and Geary's C; and Local Indexes (LI) these are Local Anselin Moran's I (Cluster and Outlier Analysis), planar Kernel Density Estimation (KDE), Getis Ord *Gi** and kriging. Except for kriging and KDE, the rest incorporates a procedure for testing the statistical significance of clustered incidents. In the global index analysis, the spatial pattern incidence of the entire network is assessed and it analyzes whether data is clustered in a group, dispersed, or randomly distributed, whereas the local indexes are used to study the microscopic pattern of incidents to determine the spatial location and extension of these clusters [41,42].

Several studies have used planar KDE [17,33], which works by creating a continuous surface of total event density within a search bandwidth and network space KDE [34,43], which is generalized to calculate the crash density over a distance unit rather than an area unit for crash hot spot identification. The major limitations of both planar and network space KDE's are the lack of statistical significance test in the analysis [17,34,44] and also, there are no criteria for prioritizing crash hot spots [34]. Research has developed and used KDE+ as an effective tool for crash hot spot identification and site prioritization to overcome the limitation of the network and planar KDE approach [45,46]. The KDE+ analysis works based on the standard KDE approach with the addition of statistical significance testing of clustered points.

Compared to KDE, for both *Moran's I* and Geary's C the statistical significance of clustered crashes is determined using Z-Score [47,48]. Indeed, *Moran's I* and Geary's C follow the global statistics approach which is the measure of the whole study network. The local statistics approach (such as Getis-Ord *Gi** statistics [37] and local *Moran's I* [35]) is superior to the global statistics system for studying spatial variance and spatial dependency. The Getis-Ord *Gi** statistic, in particular, has been validated to identify statistically significant values of crash hot spots or cold spots and has proven to be useful [10,49].

3. Methods and Materials

3.1. Study Area and Data Collection

This research was carried out in Ethiopia to identify and prioritize Road Traffic Crash (RTC) hotspot regions, with a particular emphasis on the Oromia region (see Figure 1). RTC data of Ethiopia was obtained from the Ethiopian federal police commission, traffic police division. The commission records crash data for all regions and federal territories. Crash data of four consecutive years (from 2014 to 2017) were used for crash severity analysis and hot spot identification. All collision types acquired from the police commission (i.e., single-vehicle collision, multiple vehicle collision, collision with pedestrians, collision with animals and so on) were utilized for analysis. The Ethiopian Geospatial Information Agency (EGIA) provided a map of Ethiopia divided into regions and federal territories, as well as a map of the Oromia region, divided into zones and towns. In these maps, roadway networks and other important features were included as a shapefile.

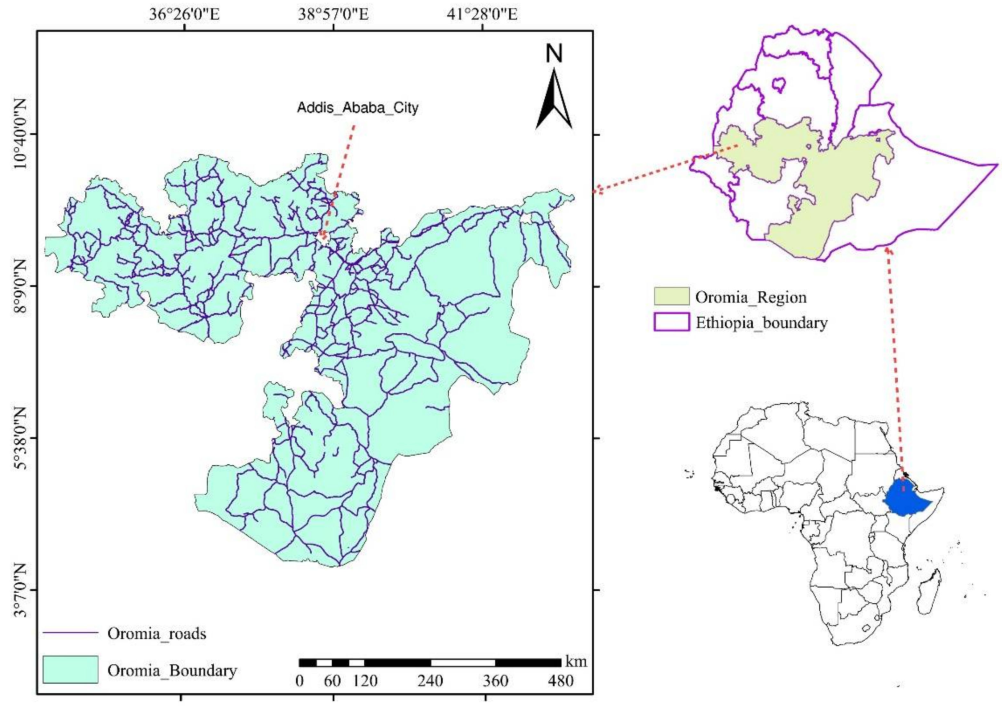


Figure 1. Map of the study area in Ethiopia.

3.2. Methods

For RTC hot spot identification, this study used the spatial statistics toolbox of ArcGIS 10.5. Supporting tools such as Google Earth and Google Maps were also utilized. For RTC hot spot identification, the procedure used in this study can be divided into the following steps: (i) projecting the map, (ii) computing the severity value of each crash, (iii) analyzing the spatial pattern of RTCs to measure the fluctuating threshold distance of RTC clustering by using *Moran's I* index of incremental spatial autocorrelation tool and (iv) identifying and prioritizing highly clustered RTCs or hot spot zones. The detailed steps and the theoretical basis are discussed as follows.

Instead of using a geographical coordinate system, the map used to identify crash hot spots was a projected coordinate system. The map dataset obtained from Ethiopian Geospatial Information Agency (EGIA) was in a geographic coordinate system. Since distance is among parameters to be considered in crash hot spot analysis [50], the analyzed maps were projected using the UTM (Universal Transverse Mercator) coordinate system in World Geodetic System WGS84.

3.2.1. Crash Severity

In addition to crash rates, crash hot spot zones are classified based on their severity index. The crash severity index determines the weight of a single crash. So, to accurately identify high or low clustered zones, it is important to incorporate crash severity index in hot spot analysis. The concept of crash severity index is accrediting the higher values to severer crashes based on the expenditures. Many past studies associated crash severity weights in crash hot spot analysis, for instance, Geurts et al. [51] used severity index developed by the Belgian government by giving values of 5, 3 and 1 for fatal, serious injury and slight injury, respectively. Because Ethiopia lacks a traffic crash costing platform for particular crash severity levels, the crash severity index developed by the Roads and Traffic Authority of New South Wales [52] was utilized in this study. In this system, each crash incident is provided a value of 3.0 for fatal, 1.8 for serious injury, 1.3 for slight injury and 1.0 for property damage only crashes. The crash severity index of each zone can be computed by Equation (1) [52].

$$SI = 3.0 \cdot X_1 + 1.8 \cdot X_2 + 1.3 \cdot X_3 + 1.0 \cdot X_4 \tag{1}$$

where X_1 is fatal crashes, X_2 is serious injury crashes, X_3 is slight injury crashes, X_4 is Property-damage-only crashes.

3.2.2. Getis Ord *Gi**

For RTC hot spot identification, spatial analysis using local spatial autocorrelation is preferable. Local *Moran's I* is among the well-known local spatial autocorrelation approach used commonly in motor vehicle crash hot spot analysis [53]. However, the family of Moran indices does not differentiate between hot or cold spots. Getis Ord *Gi** is, therefore, more appropriate since it distinguishes clusters with high and low feature attribute values among local events. In this study, Getis Ord *Gi** statistics method was used to identify RTC hot spots.

*Gi** statistics aims to investigate the presence of a spatial pattern for an arbitrary variable *X*, where a selected event (with a value of x_i) is autonomously connected to the field. As a result, if x_i is analogous to adjacent regions, it can be seen that variable *X* has spatial autocorrelation over area *i*. A simple form of *Gi** statistics is defined as Equation (2), which is derived by dividing the study zone into *n* indefinite extent of regions, each with accurate Cartesian coordinates and a central point *i* (*i* = 1, 2, 3, . . . *n*) [37].

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

where *Gi** is a statistic that describes the spatial dependency of feature *i*, x_j is the value of variable *X* at feature location *j*. w_{ij} is the spatial weight between feature *i* and *j*.

The conceptualized-spatial relationship around distance *d* (for instance Cartesian distance) is used to calculate w_{ij}. The result of *Gi** statistics may vary based on the choice of *d*. The value of *d* is a user-defined threshold. The most straightforward way to think about w_{ij} is in binary form, with 1 indicating inclusion and 0 indicating exclusion of the association between *i* and *j* events. However, in practice, w_{ij} can have non-binary values and the total weights (W_i) are expressed in Equation (3).

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

Readers are referred to a paper on Getis Ord *Gi** statistics [54] to learn more about the statistical elements such as *Gi** expectation, *Gi** variance and sample mean and variance for the variable *X*. Finally, as shown in Equation (4), *Gi** statistics are typically standardized using the sample mean and variance for a normal asymptotical condition.

$$Z(G_i^*) = \frac{\sum_{j=1}^{n} w_{ij}x_j - \overline{x}\sum_{j=1}^{n} w_{ij}^2}{s\sqrt{\frac{n\sum_{j=1}^{n} w_{ij}^2 - \left(\sum_{j=1}^{n} w_{ij}\right)^2}{n-1}}} \quad (4)$$

This standardized *Gi** statistics is a Z-score, which is associated with the statistical significance of each target region. The null hypothesis for the Getis Ord *Gi** hot spot analysis tool is that crashes are caused by Complete Spatial Randomness (CSR) or are randomly distributed. The null hypothesis would be rejected or accepted based on the Z-score and *p*-values obtained from the Getis Ord *Gi** analysis tool. The *p*-value for the spatial pattern analysis is the probability that the observed crash incidents occurred in some arbitrary manner. When the returned *p*-value from the hot spot analysis tool is very small, it is very unlikely that the observed crash incident is to be distributed randomly; thus, the null hypothesis can be rejected. The tails of the standard normal distribution curve have very small *p*-values and very high absolute values of Z-scores. When the value of the Z-score is closer to zero it implies that there is a random distribution of spatial events in the region. The maximum absolute values of *Gi** statistics, on the other hand, represent clusters of low-valued events for negative or high-valued events for positive.

ArcGIS' Getis Ord *Gi** hot spot analysis tool uses the *Gi** statistics index to identify a significant hot/cold spot based on neighboring attribute values. Regions with statistically significant positive Z-scores (hot spots) are surrounded by neighbors with high feature values, whereas regions with statistically significant negative Z-scores (cold spots) are surrounded by neighbors with low feature values. If the local aggregate of the target area and its neighboring values differ significantly from the likely local value to be random distribution, a statistically significant Z-score is produced.

The final statistical significance for hot spot identification has been adjusted by taking multiple testing and spatial dependency into account and has taken the form of Equation (5). This final equation is incorporated in ArcGIS' Getis Ord *Gi** hot spot analysis tool to identify and prioritize crash hot spots. Thus, the final form of statistical significance for hot spot identification (in Equation (5)) was used in this study by running ArcGIS' Getis Ord *Gi** hot spot analysis tool.

$$G_i^* = \frac{\sum_{j=1}^{n} w_{ij}x_j - \left(\frac{\sum_{j=1}^{n} x_j}{n}\right) * \sum_{j=1}^{n} w_{ij}}{\sqrt{\frac{\sum_{j=1}^{n} x_j^2 - \sum_{j=1}^{n} x_j}{n}} * \sqrt{\frac{n\sum_{j=1}^{n} w_{ij}^2 - \left(\sum_{j=1}^{n} w_{ij}\right)^2}{n-1}}} \quad (5)$$

3.2.3. Spatial Autocorrelation

In the spatial planar analysis, the distance methods used are Manhattan or Euclidean. In the analysis of spatial autocorrelation, the choice of conceptualization of the spatial association among crash events could be based on knowledge of the interactions among the features to be analyzed. There are several ways to conceptualize the spatial association between events, including fixed distance, inverse distance, inverse squared distance, K-nearest neighbors, the zone of indifference, the space-time window method and contiguity edges and corners. The result of the crash hot spot from global spatial autocorrelation and Getis Ord *Gi** can be improved by applying Anselin Local *Moran's I* to the aggregated traffic crashes [55]. The selection of appropriate spatial relationships among features for the use of local spatial autocorrelation analysis may help to reflect the distributional and spatial situation of definite target features [56]. The fixed distance approach was used in this study to conceptualize the spatial association among events.

In this study, the incremental spatial autocorrelation tool of ArcGIS 10.5 was used to estimate the fluctuating value of spatial autocorrelation as a distance threshold. In this tool, Global *Moran's I* index approach is employed to quantify the distance bandwidth (i.e., a distance in which maximum crash events are clustered [57]) across the entire area. The equations of *Moran's I* index (I), the expected value (*E[I]*), variance (*V[I]*) and Z-score (Z_Score) are presented in Equation (6) to Equation (9) respectively:

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{i=1}^{n} w_{i,j}} * \frac{\sum_{i=1}^{n}\sum_{i=1}^{n} w_{i,j}\left(x_i - \overline{X}\right)\left(x_j - \overline{X}\right)}{\sum_{i=1}^{n}\left(x_i - \overline{X}\right)^2} \tag{6}$$

$$E[I] = \frac{-1}{(n-1)} \tag{7}$$

$$V[I] = E\left[I^2\right] - E[I]^2 \tag{8}$$

$$Z\_Score = \frac{I - E[I]}{\sqrt{V[I]}} \tag{9}$$

where x_i is an attribute value of target feature at location i, x_j is an attribute value of neighboring feature at location j, w_{ij} is the spatial weight between features at location i and j.

A statistically significant Z-score (peaked) shows a critical distance threshold at which spatial autocorrelations are highly clustered. The first peak was used as the distance threshold in this study because it tends to best describe the spatial variation analysis and is recommended for use when there are multiple peaks [58].

4. Results and Discussions

This section presents statistical trends of crash fatalities as well as the findings of crash hot spot analyses for Ethiopian regions and federal territories, as well as Oromia zones and special towns, followed by discussions.

4.1. Death Rate and Trend of Road Safety in Ethiopia

The analysis to figure out the trends of fatalities that occurred due to road traffic crashes (RTCs) in Ethiopia was done based on eight consecutive years (2010–2017). The crash history from Ethiopian Traffic Police Commission has shown that in 2010, 2541 fatalities occurred as a result of traffic collisions (see Figure 2). There was a slight increase in fatalities until 2013, then a significant increase in 2014, when the number of people killed in crashes shockingly reached 4883. Even if a slight decrease was seen in 2015, it increased again and finally, 5118 deaths were recorded in 2017. According to the data from the Ethiopian Roads Authority (ERA) [59], from 2009 to 2017, 77,980 kilometers of road networks were newly constructed total highways (asphalt and gravel), with an annual growth rate of 13.08%. Despite the Ethiopian government's efforts to improve access and mobility for road users, the significant growth of motor vehicles was a contributing factor to the increase in traffic fatalities. The motor vehicle registration record of the Ethiopian Federal Transport Authority disclosed that in 2009 the number of vehicles in Ethiopia was about 276,794 in which had exceeded 831,000 motor vehicles in 2017 with an annual average growth rate of 15.28% [60]. The Ethiopian Police Commission-Department of Traffic Police reported that the day-to-day increase of RTC fatalities caused by alcohol use has become their main concern. As previously stated, the reasons for the increase of fatalities may be attributed to a significant growth rate of motor vehicles relative to road networks (the road network's growth rate is 13.08%, while motor vehicles' growth rate is 15.28%) and alcohol consumptions of drivers. The detail of these trends is presented in Figure 2.

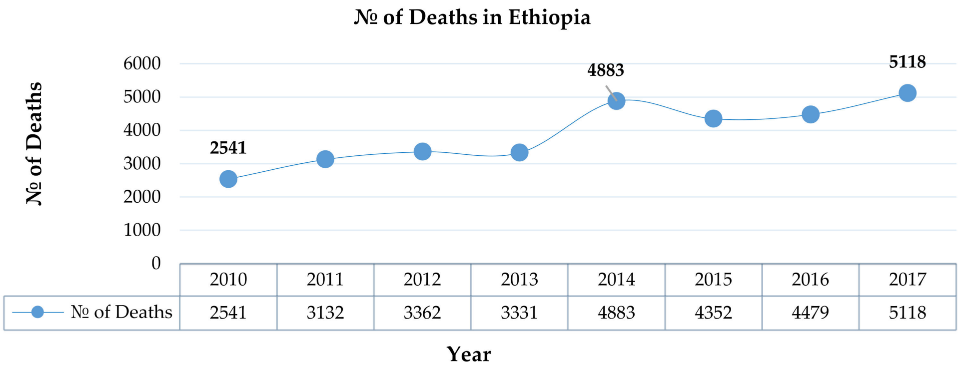


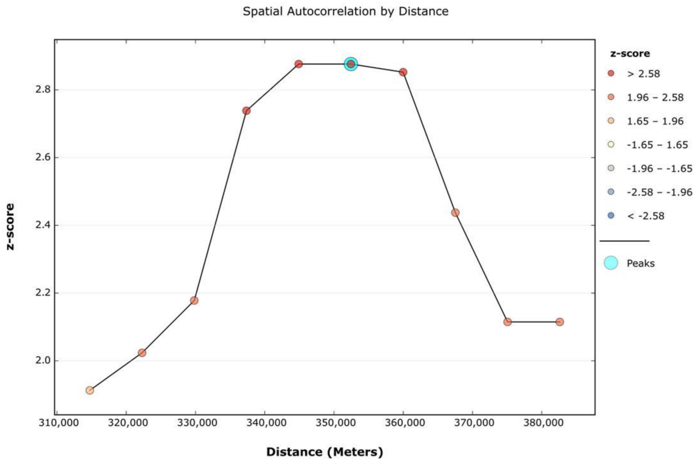
Figure 2. Number of deaths recorded in Ethiopia from 2010–2017.

4.2. Crash Hot Spot Analysis of Ethiopian Regions and Towns

Crash hot spot analysis was done at a regional level as a polygon feature dataset by applying the computed crash severity values of each region in the attribute table. The incremental spatial autocorrelation toolbox of ArcGIS was used to choose the distance bandwidth and the results are shown in Figure 3. The maximum and first peak distance obtained from incremental spatial autocorrelation analysis was 352.441 kilometers, indicating that RTC incidents are highly clustered at a distance band of 352.441 kilometers with a statistical significance of 0.01 (the p-value obtained is 0.402% < 1%; thus, the confidence level is 99%). The bigger threshold distance values can be explained by the fact that the polygons in the analysis (i.e., the regions and administrative cities) have larger area coverages. For example, Oromia, Ethiopia's largest region, has an area of around 355,423 km^2. In distance computations for polygon features, feature centroids are considered. The weighted mean center of all feature components is used to compute the centroid for various portions of the polygon feature. The weighted mean center for point features is 1, length for line features and area for polygon features [61]. Thus, in the case of this analysis, features such as polygons with wider regions were expected to have a larger threshold distance. Furthermore, the default *Beginning Distance* was applied in this study while executing the incremental spatial autocorrelation. The minimum distance for which each feature in the dataset has at least one neighbor is set as the default value for *Beginning Distance.* As a result, the beginning distance for incremental spatial autocorrelation analysis increases since larger regions (polygons) demands longer distances to reach at least one neighbor from their centroids. In fact, the higher beginning distance used to determine the first peak has a direct influence on the value of the threshold distance. This value was used as the threshold distance in Getis Ord *Gi** crash hot spot identification. Accordingly, crash hot spot identification and ranking of Ethiopian regions and federal territories were performed by considering the spatial patterns and spatial dependence of crashes. The result obtained from Getis Ord *Gi** crash hot spot analysis is presented in Figure 4 and Table 1.

Table 1. Crash Hot Spot Result of Getis Ord *Gi**.

OBJ_ID	Crash Severity	Shape_L. (m)	Shape_A. (m^2)	GiZScore	GiPValue	NNeighbors	Region_Names
1	109,518	106,098	525,638,401	2.87230	0.00407	3	Addis Ababa
8	30,661	6,403,850	355,423,484,208	2.55848	0.01051	3	Oromia
9	11,192	2,806,015	117,263,152,867	0.85676	0.39158	3	SNNP
2	19,831	2,689,742	153,443,579,103	0.49482	0.62073	5	Amhara
11	8201	1,580,725	56,451,528,629	−0.07804	0.93780	3	Tigrai
4	1477	1,630,480	48,889,173,519	−0.54855	0.58331	3	B_Gumuz
6	845	908,665	25,649,364,273	−0.86238	0.38848	3	Gambella
3	1693	1,920,341	95,242,894,663	−0.94792	0.34317	5	Afar
10	2179	3,677,531	278,073,581,426	−1.40998	0.15855	3	Somali R.
5	2780	215,410	1,507,085,646	−1.77287	0.07625	4	Dire-Dawa
7	8201	93,895	394,011,903	−1.77287	0.07625	4	Harari



(**a**)

Global Moran's I Summary by Distance

Distance	Moran's Index	Expected Index	Variance	z-score	p-value
314,741.00	0.461465	-0.100000	0.086164	1.912753	0.055780
322,281.05	0.476175	-0.100000	0.081075	2.023533	0.043018
329,821.10	0.490757	-0.100000	0.073574	2.177947	0.029410
337,361.15	0.594947	-0.100000	0.064400	2.738484	0.006172
344,901.20	0.592407	-0.100000	0.057952	2.876256	0.004024
352,441.26	0.592407	-0.100000	0.057952	2.876256	0.004024
359,981.31	0.550215	-0.100000	0.051965	2.852342	0.004340
367,521.36	0.436121	-0.100000	0.048377	2.437502	0.014789
375,061.41	0.350231	-0.100000	0.045328	2.114726	0.034453
382,601.46	0.350231	-0.100000	0.045328	2.114726	0.034453

First Peak (Distance, Value): 352,441.26, 2.876256

Max Peak (Distance, Value): 352,441.26, 2.876256

Distance measured in Meters

(**b**)

Figure 3. (**a**) Result of spatial autocorrelation; (**b**) Attribute table result of spatial autocorrelation.

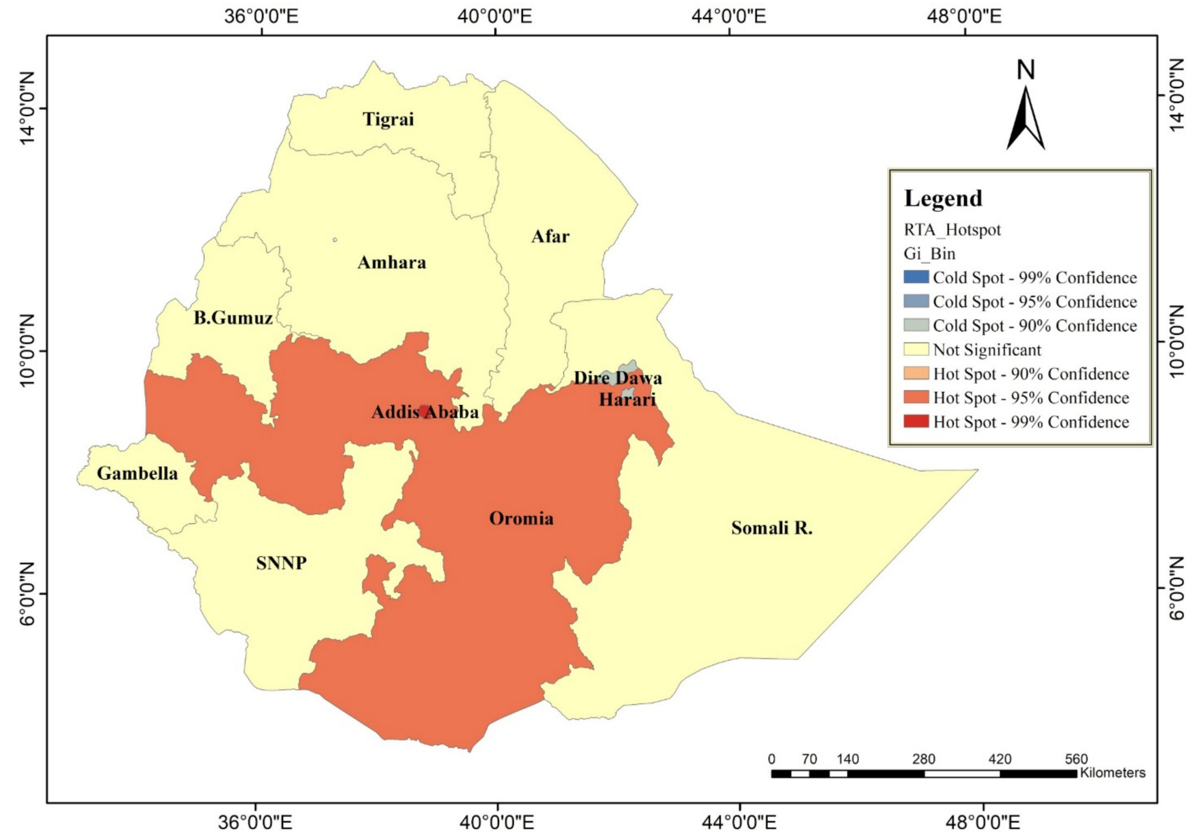


Figure 4. RTC Hot spot map of Ethiopia regions and federal territories.

With confidence intervals of 99% and 95%, Addis Ababa and the Oromia region were identified as crash hotspots. Furthermore, with a 90% confidence interval, two federal territories, 'Dire-Dawa' and 'Harari,' were revealed as low clusters of crash severity areas or cold spots. Crash hot spot zones are primarily characterized as highly densified areas that are associated with the presence of numerous activities that result in a large number of pedestrians, traffic volumes, populations and intersections. Addis Ababa, the capital city of Ethiopia was revealed as the first crash hot spot. The city is the home of AU (African Union), the Economic Commission for Africa (ECA) and over one hundred (100) embassies of several countries. The financial and administrative capital city of Ethiopia, Addis Ababa, is facing persistent growth and change. The city is transforming from its current administrative center to the central business district and an industrial center. Due to this change and rapid growth, there is an excessive transportation demand for the mobility of goods and people and, also, there is a higher attraction of people to the city in which a population of 3.6 million in 2013 is forecasted to be nearly 10 million in 2037 [62]. Whereas the city's efficient share of roadway infrastructures in land use requires 20% to 25%, the current share is 7%, indicating that the city's road transport system is inadequate [63].

The city's modernization, combined with an increase in motor vehicle ownership, increases the number of vehicles in the city; for example, of all registered motor vehicles in Ethiopia, 77% are found in Addis Ababa, with a yearly growth rate of 5.8% [64]. Walking (pedestrians) is a substantial portion of Addis Ababa's transportation modes, accounting for even more than 60% of daily journeys [65]. This high proportion of pedestrian road users in the city, combined with limited sidewalk facilities (such as crowded sidewalks, unpaved or inaccessible sidewalks), increases the number of pedestrian-related crashes. This is demonstrated by the fact that about 89% of the city's recorded crash causalities were pedestrian-related [66].

Addis Ababa City, the first-ranked crash hot spot zone, has a radial-shaped road network with five major roadways radiating in and out of the city's central business and administrative district. All traffic flows entering and leaving the city via these five roadways pass through the Oromia region, which was prioritized as the second crash hot spot area. High traffic volumes entering and leaving Addis Ababa have an impact on the Oromia region, which shares a common periphery on all sides with Addis Ababa (Finfinnee). Oromia was prioritized as the second hot spot due to higher traffic volumes, spatial dependence with Addis Ababa, larger size (inland coverage, roadway length and population number) and unsustainable traffic management in the region.

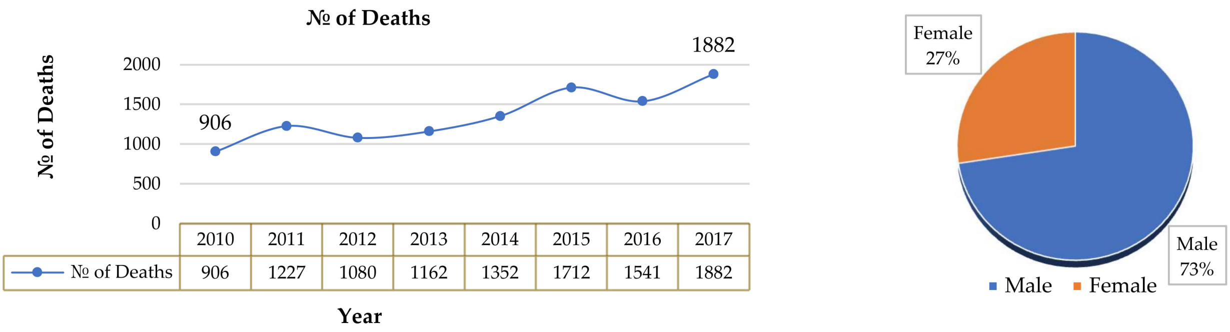
4.3. Crash Analysis of Oromia Region

4.3.1. Number of Deaths Due to RTCs in the Oromia Region

According to the Oromia traffic police bureau's eight-year (2010–2017) crash database record, fatalities that occurred due to RTCs had shown an increasing trend. Despite population growth, the number of crash fatalities increased by more than double from 906 in 2010 to 1882 in 2017 (see Figure 5a). The Ethiopian Federal Transport Authority has stated that there has been significant motor vehicle growth in the Oromia region, which has a strong correlation with the increased fatalities [60]. According to the Oromia Traffic Police Bureau crash data, denying priority for pedestrians pass, unsafe vehicle passing, driver's alcohol and drug consumptions, over-speeding, driver workload, insufficient vehicle following time and vehicle problems are the recognized significant factors for the increasing number of deaths in Oromia [67]. This increase in fatalities in the region demonstrates the impact of road traffic crashes on the socio-economic well-being of the country as a whole and the Oromia region in particular. To minimize road traffic crashes and their consequences, the Oromia transport bureau, traffic management, traffic police, road authority and concerned governmental and non-governmental organizations should all work together to address this serious problem. Figure 5a depicts the number of RTC fatalities in the Oromia region over eight consecutive years.

Male fatalities were 2.7 times higher than females (Figure 5). According to the population census commission's 2007 survey, the percentage of males and females in Oromia was roughly equal; moreover, males accounted for 73% of the region's road traffic crash victims. This can be explained by the fact that, in comparison to females, males have greater exposure to road transportation as drivers and passengers for a variety of reasons. For example, males are over-represented in professional driving careers (i.e., jobs in remote areas, operators, taxi, nighttime driving and so on) and females are under-represented in self/paid employment or outdoor activities in Ethiopia [68], which could reduce female vulnerability to RTCs. Furthermore, males are more likely than females to engage in risky driving behaviors such as careless overtaking, the use of alcohol, impatience, exceeding posted speed limits and having a lower risk perception [69,70]. As compared to females,

males' higher use of two-wheeled motor vehicles and bicycles for transport can also affect their susceptibility to traffic crashes [71].



(a) (b)

Figure 5. (**a**) Total lives lost due to RTCs; (**b**) Percentage deaths (Female versus Male).

4.3.2. Crash Severity

Table 2 shows that there were 17,259 traffic crashes in the Oromia region during the last four years, from 2014 to 2017.

Table 2. A four-year number of traffic crashes reported in their respective severity type.

Year	Fatal	Serious Injury	Slight Injury	PDO	Total
2014	1310	901	1100	1722	5033
2015	1356	623	515	1446	3940
2016	1188	568	518	1626	3900
2017	1319	729	532	1806	4386
Percentage (%)	29.97	16.35	15.44	38.24	100

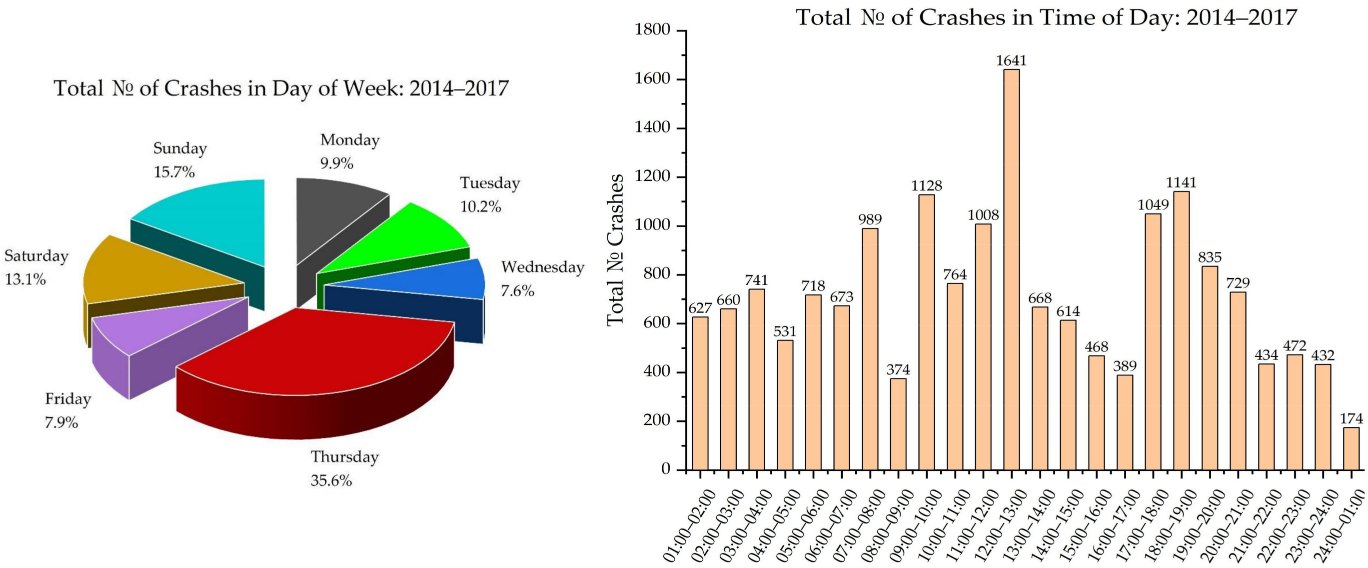
PDO: Property damage only.

4.3.3. Crashes in the Day of Week and Time of Day

RTCs occur more frequently on Thursday and then on Sunday in a week and from 12:00 to 13:00, 18:00 to 19:00 and 09:00 to 10:00 in a day. We recommend that the Oromia region's traffic management, transportation authority and traffic police bureau intervene and monitor traffic flows during peak crash days and times when a higher number of crashes are likely to occur. The details are demonstrated in Figure 6. Thursday is more likely associated with a market day in the Oromia region, when a large number of people may travel from place to place and Sunday is an off-day, but most of the society and road users may prefer to consume alcohol, resulting in more traffic crashes. Crash rates were higher from 12:00 to 13:00 and 09:00 to 10:00 during the day and these are the times when higher traffic flows are observed (peak hours), so the risk of RTC could be increased. Another critical time revealed was 18:00 to 19:00. This was most often associated with overnight collisions when there would be insufficient visibility for vision.

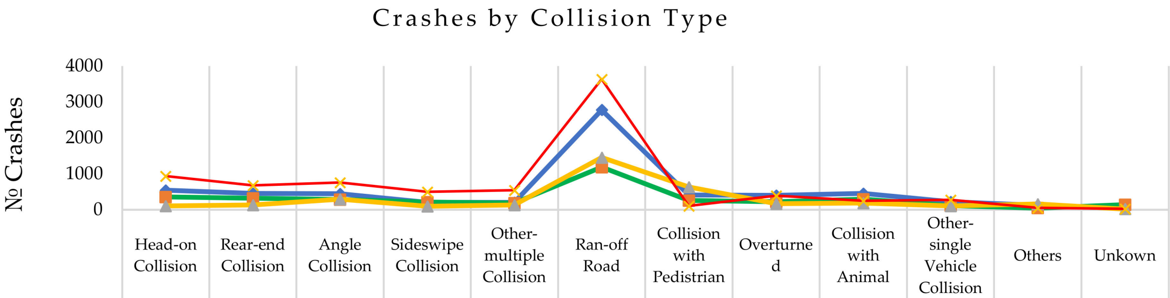
4.3.4. Crashes by Collision Type

In Oromia, crashes were more likely to occur with a collision type of 'Ran-Off-Road (ROR)' see Figure 7. A run-off-road (ROR) collision happens when a moving car overturns on impassable ground or goes out of the roadway and strikes an object. From the critical reasons for ROR collisions, over 95% were driver-related factors [72]. Among the significant driver-related factors that contribute to ROR collisions were the internal problem (i.e., heart attack or other health deficiency), too fast for over-compensation, speeding on curves and sleeping or 'fatigued driving', respectively, in a descending manner [72]. However, a thorough investigation into the factors that contribute to the frequency of higher ROR collisions in the Oromia region is needed.



(**a**) (**b**)

Figure 6. (**a**) Crashes occurred in a day of the week: from 2014–2017; (**b**) Crashes occurred in the time of the day: from 2014–2017.

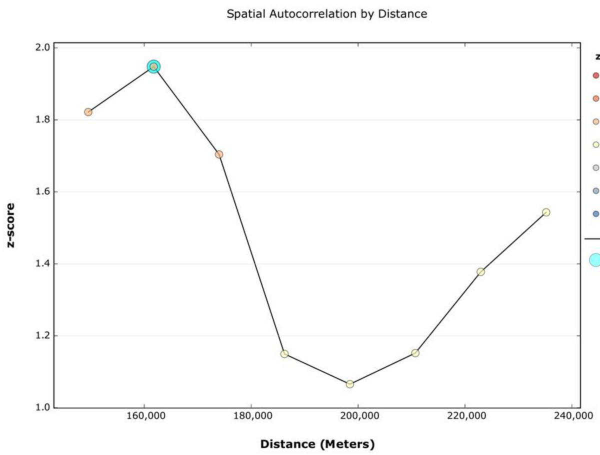


	Head-on Collision	Rear-end Collision	Angle Collision	Sideswipe Collision	Other-multiple Collision	Ran-off Road	Collision with Pedestrian	Overturned	Collision with Animal	Other-single Vehicle Collision	Others	Unkown
Fatal	537	444	438	197	201	2782	399	398	446	218	120	31
Serious Injury	351	311	282	204	182	1183	252	215	288	104	43	139
Slight Injury	100	129	284	88	129	1453	627	163	176	100	149	18
PDO	933	670	751	493	536	3636	100	388	246	273	42	22

Figure 7. Crashes analyzed by collision types: 2014–2017.

4.3.5. Crash Hot Spot Analysis

The threshold distance for identifying crash hot spots was determined using the results of *Moran's I* spatial autocorrelation analysis, which is shown in Figure 8. The threshold distance used in Getis Ord *Gi** crash hot spot analysis is the distance at which crashes are highly clustered. As a result, the incremental spatial autocorrelation analysis of the Oromia region yielded a threshold distance of 161.764 kilometers with a statistical significance level of 0.10 (such that the p-value obtained is 5.14% < 10% thus, the confidence level is 90%). Even though the current analysis's first peak has been cut by more than half due to the reduced analysis coverage from regions to zones within a single region (Oromia), the threshold distance remains higher. As explained earlier (in Section 4.2), larger zones (e.g., Borena with 45,463 km^2 area coverage and Bale with 44,912 km^2 area coverage) necessitate longer distances to reach at least one neighbor from their centroids, resulting in a higher default *Beginning Distance* and threshold distance. Figure 9 and Table 3 show the results of Getis Ord *Gi** statistics for identifying crash hot spots in the Oromia region. Getis Ord *Gi** statistics' crash hot spot analysis identified six hot spot areas, which are listed in the attribute table's result (see Table 3). The rankings were based on each zona's computed Z-score.



(**a**)

Global Moran's I Summary by Distance

Distance	Moran's Index	Expected Index	Variance	z-score	p-value
149,528.00	0.320943	-0.050000	0.041457	1.821830	0.068481
161,764.94	0.306443	-0.050000	0.033481	1.948015	0.051413
174,001.88	0.233465	-0.050000	0.027674	1.703960	0.088389
186,238.83	0.118881	-0.050000	0.021579	1.149655	0.250286
198,475.77	0.094768	-0.050000	0.018456	1.065639	0.286587
210,712.71	0.105634	-0.050000	0.018247	1.152132	0.249267
222,949.65	0.123204	-0.050000	0.015807	1.377624	0.168319
235,186.59	0.133002	-0.050000	0.014064	1.543153	0.122794

First Peak (Distance, Value): 161,764.94, 1.948015

Max Peak (Distance, Value): 161,764.94, 1.948015

Distance measured in Meters

(**b**)

Figure 8. The spatial autocorrelation of Oromia in (**a**) Graph and (**b**) Attribute table.

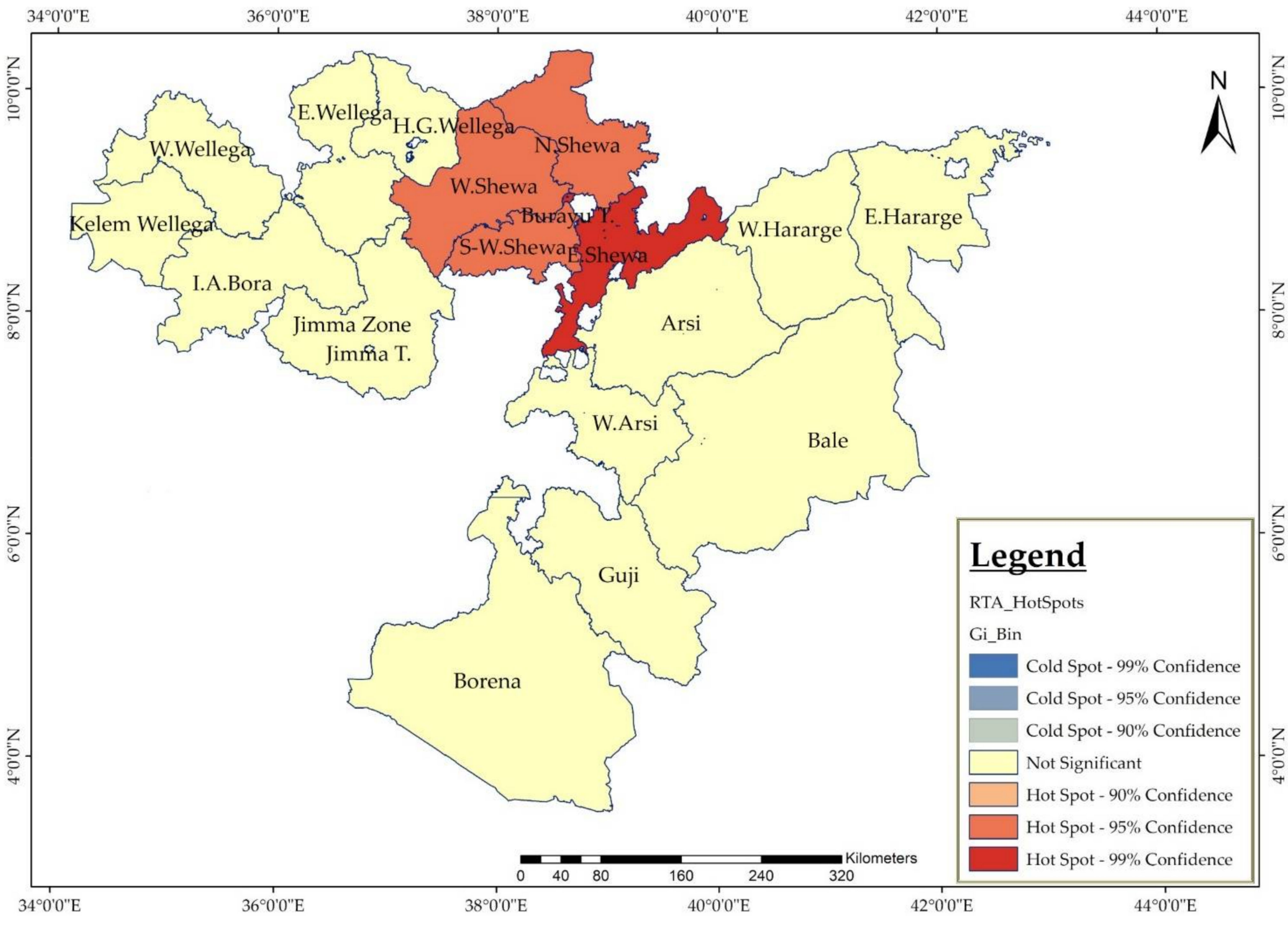


Figure 9. Crash hot spot map of Getis Ord *Gi** statistics of Oromia region.

Table 3. The Attribute of Crash Hot Spot Result of Getis Ord *Gi**.

OBJ_ID	Crash Severity	Shape L. (m)	Shape_A. (m^2)	GiZScore	GiPValue	NNeighbors	Zone_Names
7	1520	1,269,948	9,892,678,054	2.90573	0.00366	8	E.Shewa
20	429	60,226	85,906,978	2.80042	0.00510	7	Burayu T.
6	1501	913,429	11,530,834,348	2.13166	0.03303	7	N.Shewa
5	1488	1,577,743	14,806,415,071	2.01316	0.04410	7	W.Shewa
15	712	25,993	29,858,260	2.01316	0.04410	7	Adama T.
13	1154	681,347	6,508,288,032	2.00548	0.04491	8	S-W.Shewa
19	149	756,608	8,097,272,756	1.59692	0.11028	5	H.G.Wellega
17	885	1,080,199	11,776,723,820	1.31245	0.18937	4	W.Arsi
10	1155	1,390,038	18,239,926,953	0.80006	0.42367	2	E.Hararge
9	724	768,631	16,523,003,204	0.73969	0.45949	4	W.Hararge
8	798	909,816	20,696,957,154	0.41390	0.67895	7	Arsi
4	634	1,009,026	18,075,624,315	−0.19253	0.84733	5	Jimma_Zone
2	597	980,901	13,830,420,375	−0.19309	0.84689	6	E.Wellega
14	649	985,714	18,577,054,735	−0.43489	0.66364	3	Guji
16	303	38,118	50,520,944	−0.72780	0.46674	3	Jimma_City
12	246	3,121,707	45,463,584,611	−0.82827	0.40752	2	Borena
18	352	642,890	9,851,170,119	−0.83608	0.40311	3	Kelem_Wellega
1	507	892,523	12,744,967,754	−0.86970	0.38446	4	W.Wellega
3	632	999,481	16,516,931,736	−1.24901	0.21166	6	I.A.Bora
11	218	1,434,621	44,912,392,310	−1.49546	0.13479	3	Bale

According to the findings, the East 'Shewa' (E. Shewa) zone and 'Burayu' town (Burayu T.) have the highest values of crash severity clusters and are ranked as priority crash hot spot areas across the Oromia region with a confidence interval of 99%. According to Section 3.1 of this document, Addis Ababa is encircled by five major roadways. These are locally named as; (1) 'Ambo-Ber', (2) 'Tarma-ber' (3), 'Jimma-Ber', (4) 'Gojjam-Ber' and, (5) 'Kality-Ber' or 'Bishoftu-Ber'. The AADT for freight vehicles entering and leaving Addis Ababa is estimated to be 10,725 and 12,890, respectively [73]. More than 70% of these entering and exiting freight vehicle shares have gone through Gate-5 (Kality/Bishoftu-Ber) [73], which is located in the East Shewa zone, Oromia's first-ranked crash hot spot. 'Bishoftu-Ber' is also the key entry point for import and export freight vehicles between Addis Ababa and the port of Djibouti. As a result, the East 'Shewa' zone was expected to experience higher traffic volumes and freight vehicles, which are directly related to the increased crash frequencies. When compared to others, issues related to the second crash hot spot zone, 'Burayu town,' were primarily associated with poor roadway facilities (such as narrow lane width, deteriorated pavement, lack of pedestrian walkway and so on).

5. Limitation of the Study

The availability of crash data recorded with precise incident locations in coordinates (using Global Coordinate System, GPS) or mileposts that could be linked to roadway geometric characteristics drives a well-organized RTC analysis as well as results for specific roadway segments and intersections. The Ethiopian ministry of transport, regional transport authorities and federal police commission-traffic police departments are in charge of collecting and reporting the essential crash data to safety researchers in need of it. However, crash locations that occur along a road alignment (milepost) are not recorded in Ethiopia. This study was unable to investigate the spatial dependence of crashes with roadway parameters (such as road length, degree of curvature, AADT, gradient, stopping sight distance and others) as a contributing factor to crash occurrences due to a lack of crash locations in the given data. Moreover, the crash severity index of each severity level is derived from the respective crash costs in which these costs vary from region to region. However, due to the lack of an agreed-upon or defined crash costing platform for specific crash severity levels in Ethiopia, the severity index developed by the Roads and Traffic Authority of New South Wales [52] was used in this study.

6. Conclusions

The primary goal of crash hot spot analysis is to answer a critical question in road safety practice: where are the hazardous street areas located? This inquiry is addressed scientifically by studying the spatial pattern of crashes. The advantage of using advanced GIS-based hot spot analysis is not limited to the simple presentation of hot spot roadway areas; it also provides the ability to investigate the spatial dependency of crash incidents and spatial connections with other factors. For the past five decades, a GIS application in the field of traffic safety has aided in the advanced realization of crash characteristics, which is then used as a piece of information to improve traffic safety.

This study aimed to present a GIS application to identify and quantify statistically significant spatial patterns based on crash numbers and severity. Based on the severity of the crashes, crash hot spots were identified using the integration of spatial autocorrelation of crashes and Getis Ord *Gi**. The use of spatial autocorrelation has the advantage of allowing statistical analysis of crash spatial patterns. The ability of *Gi** statistics to differentiate high crash clusters from low crash clusters makes it a better approach for identifying crash hot spots than *Moran's I* index. In this study, rather than the total number of collisions, crash counts and severity values were used.

Following the analysis of spatial autocorrelation of crashes, *Gi** statistics were used to identify high and low crash severity clusters. The first analysis result of crash hot spot identification for all Ethiopian regions and federal territories identified Addis Ababa and Oromia region as high crash severity clusters with confidence intervals of 99 percent and 95 percent, respectively. Second, six statistically significant crash hot spots in Oromia were detected through the integration of spatial autocorrelation and *Gi** statistics. With a confidence level of 99%, the quantitative results of Z-Scores prioritized East 'Shewa' zone and 'Burayu' town as the most crash hot spots. All of the six identified crash hot spot zones and towns are near the entrance to Addis Ababa, Ethiopia's capital city. Addis Ababa is linked to other towns, zones and regions by five major roads and all of these connecting roads pass through the identified crash hot spots in Oromia. It can be concluded that the identified crash hot spot locations are along the entrance and exit of Addis Ababa city; therefore, the concerned bodies and traffic management agencies should give these areas top priority and conduct a thorough study in order to reduce the socio-economic impact of traffic collisions.

The results of the study acknowledged that the applied method of crash hot spot identification (such as the integration of spatial autocorrelation of crashes and Getis Ord *Gi**) has the ability to analyze spatial patterns of crashes and identify highly clustered crash severity with a statistical significance. The study demonstrated that using GIS in Ethiopia has a significant benefit when it comes to prioritizing a promising site for safety improvements. Thus, the application of GIS in crash hot spot analysis must have to be considered and need to be used as a tool for road safety study in Ethiopia in the future. The recommendations for future road safety improvements include the development of a national crash hot spot (blackspot) identification manual, the frequent spatial and temporal mapping of crash patterns and the provision of training for safety engineers on the methodologies for identifying crash hot spots, as well as on the advancements of GIS technology to be implemented in the field of road safety. Furthermore, the Ethiopian Ministry of Transport (MoT) must support the crash recording and data-sharing platform with advanced technologies such as developing a computerized crash database system and centralized mobile applications that enable GPS, which improves the identification and analysis of the crash spatial pattern to apply effective safety measures.

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