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Research Paper

Development an Analytical Model of Accidents using Geographically Weighted Modeling

(Case Study: City of Zanjan)

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Abstract

Traffic accidents represent one of the major global challenges affecting public safety, have become a serious threat to public health, resulting in substantial human and financial losses for various countries each year. This study examines the spatial distribution of traffic accidents in the city of Zanjan. In this research, the spatial distribution pattern of accidents was examined using the Moran's I spatial autocorrelation method and spatial statistical analyses in a GIS environment. For this purpose, ten effective parameters were analyzed, including the type of road artery, speed limit, one-way roads, road width, population density, density of land uses, traffic intersection density, density of transportation axes, density of commercial and service land uses, and trip attraction intensity as influential factors in the occurrence of accidents. The results showed that these factors have a direct and significant relationship with road accidents in the city of Zanjan. The most significant impacts, in order, were from the parameters of one-way roads, road width, population density, density of land uses, intersection density, and trip attraction intensity. Additionally, the spatial pattern of accidents was generally clustered, and hazardous points were clearly identifiable. Based on these findings, recommendations for improving traffic safety in Zanjan have been provided, including geometric modifications of intersections, management of commercial and service land uses, adjustment of speed limits on busy streets, enhancement of traffic management, and implementation of immediate safety measures at accident-prone locations. This study can guide decision-making and planning to reduce accidents and improve urban safety in Zanjan.

Keywords: Accident Modeling, Geographically Weighted Modeling, Geographic Information Systems

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1. Introduction

Among the numerous challenges associated with urban transportation systems, traffic accidents constitute one of the most critical and far-reaching issues affecting public safety in both developed and developing societies. Owing to their inherently spatial and multi-causal nature, traffic accidents are influenced by a complex combination of environmental, infrastructural, socio-demographic, and behavioral factors. This complexity has restricted the effectiveness of conventional statistical methods, particularly those based on the assumption that relationships between dependent and explanatory variables remain constant across space.

To overcome this limitation, Geographically Weighted Regression (GWR) has been introduced as an advanced and powerful approach for the analysis of spatial data. In contrast to classical regression models, which estimate a single global relationship between variables over the entire study area, GWR enables the investigation of spatial variations in these relationships at the local level. By explicitly accounting for spatial heterogeneity, GWR provides a more accurate and context-sensitive understanding of how explanatory variables influence traffic accident occurrence across different geographic locations. Accordingly, this method is particularly suitable for urban traffic accident studies, where contributing factors such as population density, transportation infrastructure, road geometry, land-use patterns, and driver behavior may vary substantially from one area to another.

In this study, several GIS-based approaches to traffic accident modeling are examined, including Kernel Density Estimation (KDE), kriging-based modeling, spatial autocorrelation analysis, and Geographically Weighted Regression (GWR). A common strength of these methods is their ability to generate deeper, more precise, and spatially explicit insights into the distribution and clustering patterns of traffic accidents, compared with purely descriptive GIS analyses. Within this framework, the application of GWR provides researchers, urban planners, and policymakers with a valuable analytical basis for identifying local variations in accident-related factors. Such knowledge can support the design and implementation of more targeted, effective, and evidence-based interventions and policies that are better aligned with the specific conditions of different urban areas.

2. Geographically Weighted Regression (GWR)

Geographically Weighted Regression (GWR) is an advanced spatial statistical technique developed to model the relationships between dependent and independent variables while explicitly accounting for spatial heterogeneity. This approach is particularly useful in studies where the strength, direction, or significance of relationships between variables is expected to vary across geographic space.

In conventional regression models, such as Ordinary Least Squares (OLS), the relationship between the dependent variable and explanatory variables is generally assumed to be spatially stationary; that is, a single set of regression coefficients is estimated and applied uniformly across all spatial units within the study area. However, in many real-world spatial phenomena—particularly those related to traffic accidents—such relationships are rarely constant across space. Instead, the effects of explanatory factors may differ considerably from one location to another due to variations in land use, road network characteristics, population density, traffic conditions, and local environmental or behavioral factors.

GWR addresses this limitation by incorporating spatial weighting into the regression framework and estimating a separate local regression model for each observation, location, or spatial unit. As a result, the model parameters are allowed to vary geographically, enabling the identification and interpretation of local patterns that may be obscured in global regression models. The spatial weighting process is commonly based on geographic distance, whereby observations located closer to a given location are assigned greater weights and therefore exert stronger influence on the estimation of the local model, while more distant observations contribute less. Through this mechanism, GWR provides a more flexible and spatially sensitive analytical framework for examining non-stationary relationships in spatial data.

2.1. Spatial Autocorrelation using Moran's I

A prominent component of spatial statistics is the Moran's I statistic, which is widely used to assess spatial autocorrelation. In a general statistical context, autocorrelation refers to the degree of association among residuals or observed values, particularly when these values are systematically interrelated rather than independently distributed. Spatial autocorrelation extends this concept to geographic data by evaluating whether the spatial distribution of a phenomenon, such as traffic accidents and their associated explanatory factors, exhibits clustered, dispersed, or random patterns across space.

In traffic safety studies, spatial autocorrelation is of particular importance because accident occurrences are often not distributed independently across an urban network. Instead, they may be influenced by local road characteristics, traffic conditions, land-use patterns, demographic composition, and environmental factors. Moran's I provides a quantitative measure of such spatial dependency, and its statistical significance is commonly evaluated using a standardized z-score and corresponding p-value. The Moran's I statistic is generally expressed as follows:

$$I = \frac{N}{S_0}\frac{\sum_{i=1}^{n}\sum_{j=1}^{n} \mathbf{w}_{i,j} z_i z_j}{\sum_{j=1}^{n} {z_i}^2} \qquad (1)$$

If we assume the presence of a number of geographic features with specific attributes, then z_i represents the difference between the attribute value of feature i and its mean $(x_i - \bar{x})$. The term w_{ij}denotes the spatial weight between features i and j. N refers to the total number of geographic features included in the utilized layer, while S_0 represents the sum of all spatial weights.

Moran's I is therefore a useful statistical tool for measuring the spatial dependence of accident locations. It enables researchers to determine whether accident patterns are spatially clustered, dispersed, or randomly distributed, while also providing insight into the degree of spatial concentration. According to Erdogan (2009), Moran's I generates a single measure of spatial correlation and facilitates the examination of clustering patterns in geographic data. The underlying measure of similarity between two locations is defined based on the deviation of their observed values from the overall mean (Erdogan 2009).

Pirdavani et al. (2014) developed accident prediction models using Geographically Weighted Regression (GWR), incorporating Moran's I for both selected explanatory variables and dependent variables. Their findings emphasized the importance of accounting for spatial autocorrelation when developing accident prediction models, as ignoring spatial dependency may lead to biased estimates and reduced model reliability (Pirdavani, Bellemans et al. 2014).

Levine et al. (1995) conducted one of the earliest GIS-based spatial analyses of motor vehicle accidents in Honolulu using accident data from 1990. By applying geocoding techniques, they were able to accurately identify the locations of approximately 98% of the recorded accidents and developed software tools to describe their spatial concentration. Their analysis also incorporated a temporal dimension by examining the spatial patterns of different accident types across hours of the day, weekdays, and weekends. The results indicated that accidents were more frequent near employment centers than in residential areas.

Overall, the study demonstrated that motor vehicle accidents in Honolulu followed distinct spatial patterns associated with demographic and environmental characteristics (Levine, Kim et al. 1995).

A temporal analysis was also carried out, examining spatial patterns of different accident types across hours of the day, weekdays, and weekends. The study found that accidents were more frequent near employment centers compared to residential areas, ultimately demonstrating that motor vehicle accidents in Honolulu exhibit distinct spatial patterns associated with demographic and environmental factors.

Brunsdon, Fotheringham, and Charlton (1998), in one of the pioneering studies on Geographically Weighted Regression, introduced and developed GWR as a method for analyzing spatial non-stationarity in relationships among variables within geographic data. Their study demonstrated that the relationships between dependent and independent variables may vary across space, a feature that conventional global regression models are unable to capture. Using housing data from the Bristol area in the United Kingdom, they showed that GWR replaces a single global set of regression coefficients with location-specific coefficients estimated for each spatial unit. These local coefficients are calculated using distance-based weighting functions, such as Gaussian kernels, thereby allowing the model to reveal how relationships among variables change across geographic space (Brunsdon, Fotheringham et al. 1998).

LaScala, Gerber, and Gruenewald (2000) examined demographic and environmental factors associated with pedestrian accidents in San Francisco. Their study aimed to identify variables influencing pedestrian injury rates by integrating 1990 pedestrian accident data with demographic indicators, including population density, unemployment rate, age-group composition, and educational attainment, as well as environmental variables such as traffic flow, road system characteristics, and alcohol outlet density. GIS was used to examine accident locations, and regression models adjusted for spatial autocorrelation were applied. The results showed that pedestrian injury rates were significantly influenced by a combination of demographic and environmental factors, highlighting the importance of such analyses for urban planning and traffic safety policymaking (LaScala, Gerber et al. 2000).

Erdogan (2009) applied GWR to analyze traffic accidents and road fatalities in Turkey using data from 81 provinces over the period 2001–2006. Two fatality ratios were considered: fatalities per population and fatalities per registered vehicle. The spatial analyses revealed non-random accident distributions, with significant clustering patterns particularly evident in provinces located along the Istanbul–Ankara–Antalya corridors. The results indicated that GWR outperformed traditional regression models by capturing local variations in spatial distributions and accident rates. The adjusted (R^2) values obtained from the GWR models ranged from 0.89 to 0.99, compared with 0.88 to 0.95 for classical regression models (Erdogan 2009).

Prasannakumar et al. (2011) assessed road accident hotspots in a city in southern India, where poorly developed road networks frequently contribute to traffic congestion and accidents. GIS-based tools were used to analyze accident location patterns and identify spatial and temporal influences. Moran's I indicated an overall clustered distribution of accidents; however, spatial-temporal classification revealed random distributions for specific accident categories, including injury crashes, fatal crashes, and property-damage-only crashes. The study also showed that monsoon seasons and school reopening periods contributed to accident clustering. These findings emphasized the importance of micro-level studies that integrate demographic, vehicular, and road-specific data to improve traffic management and reduce accident occurrence (Prasannakumar, Vijith et al. 2011). Li et al. (2011) were among the first researchers to apply GWR to the analysis of urban intersection accidents. They used the model to predict accident occurrence at intersections by considering factors such as traffic volume and street geometry. Their findings demonstrated that GWR outperformed traditional linear regression models and was able to effectively capture spatial variations in the effects of accident-related factors (Li, Lee et al. 2011).

Xie and Yan (2013) integrated Network Kernel Density Estimation (NKDE) with local spatial statistics, such as Local Indicators of Spatial Association (LISA), to improve the identification of traffic accident hotspots. Their approach was designed to enhance the detection of accident clusters in urban road networks by estimating accident densities along street networks rather than dispersing crash data over a two-dimensional planar surface. Using real crash data from Austin, Texas, their case study demonstrated that this network-based approach provides more accurate results than traditional hotspot detection methods (Xie and Yan 2013).

Castro et al. (2013) investigated factors influencing injury severity in highway traffic accidents in Texas, USA. They proposed a Spatial Generalized Ordered Response Model to analyze crash injury severity, with the dependent variable defined as injury severity level, ranging from no injury to fatality. Their model incorporated spatial effects and data heterogeneity, both of which are often overlooked in classical modeling approaches. The results indicated that variables such as crash type, weather conditions, vehicle type, driver characteristics, and road conditions significantly influenced injury severity. In addition, spatial correlation among accidents was observed, and accounting for this correlation improved model accuracy (Castro, Paleti et al. 2013).

Liu et al. (2017) examined whether Safety Performance Functions (SPFs), which are commonly used to predict accident frequency, vary significantly across different locations. Their primary objective was to develop models that incorporate spatial heterogeneity and provide more accurate predictions of crash frequency. Using freeway accident and traffic data from Virginia for the year 2013, they developed a Geographically Weighted Negative Binomial Regression (GWNBR) model to generate Local Safety Performance Functions (L-SPFs). These functions captured spatial relationships between crash-related variables and accident frequency. The results showed that parameters such as Annual Average Daily Traffic (AADT) and segment length varied significantly across locations. The GWNBR model outperformed the traditional negative binomial model, reinforcing the importance of considering spatial heterogeneity in crash prediction modeling (Liu, Khattak et al. 2017).

Gomes et al. (2017) evaluated improvements in traffic crash modeling through the application of spatial regression techniques. Their main objective was to compare the performance of traditional Generalized Linear Models (GLMs) with negative binomial distribution against spatial models, including Geographically Weighted Poisson Regression (GWPR) and Geographically Weighted Negative Binomial Regression (GWNBR), for predicting injury crashes across traffic analysis zones in Fortaleza, Brazil. The dataset included 126 zones and incorporated road network characteristics, socio-economic variables, land-use attributes, and exposure measures. The spatial models, particularly GWPR and GWNBR, demonstrated superior performance in terms of model fit. Among them, GWNBR was especially effective in identifying spatial heterogeneity in crash frequencies and was considered suitable for regional traffic safety analysis due to its ability to model spatial dependence and heterogeneity (Gomes, Cunto et al. 2017).

Hezaveh et al. (2019) estimated the comprehensive costs of traffic crashes in

Tennessee using a Geographically Weighted Poisson Regression (GWPR) model. Unlike conventional methods that allocate crash costs to the crash location, their study adopted a residence-based approach, assigning costs to the residential locations of the individuals involved in crashes. The GWPR model outperformed the standard Poisson regression model. The findings indicated that factors such as elderly population, household income, and population density had negative effects on crash costs, whereas vehicle miles traveled and vehicle ownership per capita had positive effects (Hezaveh, Arvin et al. 2019).

Hu et al. (2020) conducted a spatial analysis of 791 pedestrian crashes in urban Changsha, China, covering the period from 2014 to 2016. By integrating GIS, Baidu Maps, and Google Street View, the study aimed to examine the spatial patterns of pedestrian crashes and identify environmental contributors to pedestrian injury severity. GIS was used to visualize crash distributions and analyze their relationships with population characteristics, road network attributes, land use, and public service facilities. A combination of binary logistic regression and tree-based models was employed to evaluate the effects of environmental and roadway features. The results showed that pedestrian crash severity was significantly influenced by darkness, lighting conditions, road separation facilities, pedestrian age, and pedestrian behavior. The study demonstrated that combining spatial analysis with statistical modeling can help identify key determinants of pedestrian safety (Hu, Wu et al. 2020).

Khaksar et al. (2022) investigated the spatial distribution and prediction of road crashes along the main suburban road network of Hamadan Province, Iran, using spatially explicit modeling approaches. Crash data recorded from 2017 to 2019 were analyzed through kernel density estimation, Geographically Weighted Regression (GWR), and Geographically Weighted Poisson Regression (GWPR) to account for the inherent spatial dependence and heterogeneity of traffic crashes. The study emphasized that conventional crash prediction and hotspot identification methods may inadequately represent spatial variations in crash occurrence, whereas geographically weighted models can capture local variations in the relationships between crash frequency and contributing factors. Comparison of the applied models demonstrated that GWPR provided superior performance in predicting crash-prone locations and more effectively represented the spatial distribution of crash frequency (Khaksar, Almasi et al. 2022).

Shamanian Esfahani et al. (2022) investigated the influence of urban fringe areas on rural road crashes in Iran by developing linear and logistic regression models to determine the boundary of influence areas (BIA) near city entrances. The results showed that access-point density and the length of adjacent land uses were the most significant factors affecting the extent of these high-risk zones. The study also demonstrated that using a fixed 30-km buffer for all city entrances may not adequately represent crash-affected areas, emphasizing the need for location-specific modeling in traffic safety analysis (Shamanian Esfahani, Afandizadeh et al. 2022).

Tavakoli Kashani et al. (2023) analyzed the spatial and temporal patterns of urban traffic accidents in Qazvin over a three-year period. Their main objective was to identify crash hotspots based on driver age and time of occurrence. Spatial analysis was conducted using Kernel Density Estimation in ArcGIS, while temporal patterns were examined using spider charts in Excel. The results indicated that Islamic Republic Highway had the highest concentration of crashes and required improved management of vehicle types. The time interval between 12:00 and 2:00 p.m. was identified as the riskiest period, and younger drivers, particularly those under 26 years old and those aged 26–34, were most frequently involved in severe crashes. The study emphasized the need for increased education, enforcement, and monitoring of these age groups (Tavakoli Kashani, Javan et al. 2023).

Bavar et al. (2023) evaluated the spatial effects of built-environment factors on urban crash frequency at the Traffic Analysis Zone (TAZ) level in Shiraz, Iran. Using geographically weighted regression and Bayesian spatial models, the study found that models incorporating spatial dependence through distance and contiguity provided more accurate crash estimates. Land-use diversity and public transport accessibility were associated with higher crash frequencies, highlighting the importance of accounting for spatial relationships and environmental characteristics in urban road safety analysis (Bavar, Naderan et al. 2023).

Hassanpour and Afandizadeh (2023) addressed the limitations of traditional approaches in traffic accident analysis, particularly their inability to adequately consider the probability density of contributing factors. Their study proposed a probabilistic density framework based on a multivariate Gaussian model to evaluate factors affecting injury severity in traffic accidents on the Borujerd–Khorramabad four-lane rural highway during 2015–2017. The study highlighted the importance of considering interdependencies among variables when modeling traffic safety on rural highway (Hassanpour and Afandizadeh 2023).

Da Silva and Buffone (2024) evaluated the effectiveness of the Geographically Weighted Beta Regression (GWBR) model in analyzing injury crashes, including fatal and non-fatal injury crashes, in Fortaleza, Brazil, using data from 2009 to 2011. They compared GWBR with traditional models such as Ordinary Least Squares (OLS) and Geographically Weighted Regression (GWR) to assess its advantages in modeling ratio data characterized by asymmetric distributions and spatial dependence. The results demonstrated that GWBR outperformed the alternative models and provided a more accurate framework for analyzing spatially dependent and skewed crash data (da Silva and Buffone 2024).

Almasi et al. (2024) analyzed crash frequency on suburban roads in Hamedan Province, Iran, using spatial regression and localized safety performance functions. The results showed that heavy-vehicle traffic, segment length, speed, lighting, shoulder width, and road slope significantly influenced crash occurrence. Localized models outperformed global approaches, emphasizing the importance of spatial heterogeneity in identifying high-risk road segments (Almasi, Bakhshi Lomer et al. 2024).

Wang et al. (2024) applied the Geographically Weighted Random Forest (GW-RF) model to examine local relationships between crash frequency and contributing factors across the United States. Their study focused on modeling spatial heterogeneity in crash frequency arising from different determinants. The findings indicated that road network characteristics, particularly intersection density, played a critical role in explaining crash frequency. Socio-economic variables had moderate effects, while land-use variables showed relatively limited influence (Wang, Gao et al. 2024).

Alisan and Ozguven (2024) analyzed the relationship between built environment characteristics and severe traffic crashes resulting in serious injury or death in Florida. Their study aimed to assess spatial heterogeneity by comparing a range of spatial regression models. Global models, including Ordinary Least Squares (OLS), Spatial Error Model (SEM), and Spatial Lag Model (SLM), were compared with local models such as Geographically Weighted Regression (GWR), Multiscale Geographically Weighted Regression (MGWR), and MGWR with a Spatially Lagged Dependent Variable (MGWRL). The local models outperformed the global models, demonstrating the presence of spatial non-stationarity in the relationships between explanatory variables and crash outcomes. The GWR results indicated that census blocks closer to urban areas, characterized by higher educational attainment and lower vehicle ownership, tended to have lower crash rates (Alisan and Ozguven 2024).

Bavar et al. (2024) examined the spatial effects of built-environment, land-use, and transportation factors on urban crash frequency in Shiraz, Iran. Using geographically weighted and Bayesian spatial count models, the study found that accounting for spatial dependence significantly improved crash prediction. Land-use diversity and public transportation accessibility were among the factors associated with higher crash frequencies. The findings highlight the importance of incorporating spatial heterogeneity and built-environment characteristics into urban road-safety analysis (Bavar, Naderan et al. 2024).

Clemente et al. (2024) analyzed road crash risk in Milan by integrating road infrastructure attributes, network theory, and advanced statistical modeling. The primary objective of their study was to improve understanding of how road infrastructure characteristics influence crash risk. They combined Conditional Autoregressive (CAR) models with a two-step Geographically Weighted Poisson Regression approach to simultaneously assess global and local effects of crash risk factors. Their modeling framework was able to capture both general trends and local variations in crash risk, and several street-level attributes were identified as significant contributors to crash occurrence (Clemente, Della Corte et al. 2024).

Tian Li et al. (2025) examined the spatial heterogeneity of built environment factors affecting traffic safety in Jinan, China. They noted that many previous studies assumed spatially uniform effects of built environment variables, an assumption that may produce inconsistent or contradictory findings. To address this limitation, they developed a Geographically Weighted Atrial Convolutional Neural Network Regression (GACNNWR) model to capture spatial heterogeneity with greater precision. Their findings showed that intersection density and bus stop density had stronger effects on traffic crashes than population density, land-use mix, and destination accessibility. The GACNNWR model provided more precise local insights than traditional GWR and was shown to support the development of context-sensitive built environment designs and localized traffic safety strategies (Li, Liu et al. 2025).

Based on the reviewed literature, spatial statistical methods have become increasingly important in traffic accident analysis because they allow researchers to identify spatial dependence, local variation, and non-stationary relationships that are often overlooked by conventional global models. Methods such as Moran’s I, KDE, NKDE, GWR, GWPR, GWNBR, MGWR, GWBR, and geographically weighted machine-learning approaches provide valuable tools for understanding the spatial structure of traffic accidents and the factors influencing their occurrence and severity.

Accordingly, the primary objective of the present study is to analyze the urban road network of Zanjan by incorporating intra-urban crash indicators and traffic-related urban elements. These elements include distance to main roads, one-way street status, street width, legal speed limits, arterial road classifications, and intersection density. By examining these variables within a spatial analytical framework, the study aims to provide a more detailed understanding of the spatial patterns of urban traffic accidents and to support the development of targeted, evidence-based traffic safety interventions.

3. Methodology and Findings

3.1. Study Area

Zanjan, the capital city of Zanjan Province, is located in northwestern Iran and occupies a strategically important geographic position. Owing to its location within the regional transportation and settlement network, the city plays an important role in connecting several neighboring provinces. Zanjan is bordered by Ardabil Province to the north, East Azerbaijan Province to the west, Hamedan Province to the south, and Qazvin Province to the east.

The urban area of Zanjan covers approximately 6,161 hectares. According to the most recent national Population and Housing Census conducted in 2016, the city had a population of 433,475 residents, ranking it as the twentieth most populous city in Iran. From an administrative perspective, Zanjan is divided into four municipal districts, 35 urban zones, and 110 neighborhoods.

The city's urban transportation network constitutes a substantial component of its physical structure. The total length of urban streets in Zanjan is approximately 11,065,095 meters, and 17.93% of the city's land use is allocated to street and transportation infrastructure. These characteristics highlight the significance of the urban road network in shaping mobility patterns, spatial accessibility, and traffic-related conditions within the city.

Figure 1. Location of the study area

4. Discussion

4.1. Urban Accident Index

This index represents the spatial density of urban traffic accidents and was derived from crash data obtained from the Zanjan County Traffic Police Department. In a given urban area, a higher frequency of recorded accidents indicates locations with greater crash risk and may therefore be interpreted as hazardous or accident-prone zones. The spatial distribution and density patterns of accidents provide insight into the dispersion and concentration of crash events across the urban area of Zanjan. Figure 2 illustrates the spatial concentration of urban traffic accidents within the city.

Several notable patterns can be identified from the accident density map:

- First, traffic accidents are distributed across different parts of Zanjan, indicating that crash occurrence is not limited to a single location or district. Nevertheless, certain areas exhibit substantially higher accident densities and can be regarded as major concentration zones.
- Second, the central area of Zanjan shows the highest concentration of traffic accidents. A considerable proportion of recorded crashes is clustered within the urban core, while the main arterial routes and urban corridors leading into this central area also display elevated accident densities. This pattern may be associated with higher traffic volumes, greater pedestrian activity, land-use intensity, and the convergence of major transportation flows in the city center.
- Third, increased accident intensity is observed at the main entrances and exits of Zanjan. In particular, the eastern and western segments of Khayyam Highway appear as critical accident hotspots within the urban network. This concentration is likely related to heavy traffic demand, higher vehicle speeds, and the role of these corridors in connecting intra-urban and intercity movements.

In the accident density map, red-shaded areas indicate zones with the highest levels of urban traffic accident concentration, whereas green- and yellow-shaded areas represent locations with relatively lower accident densities. Overall, the observed spatial pattern highlights the need for targeted traffic safety interventions in the central core, major access corridors, and principal city gateways of Zanjan.

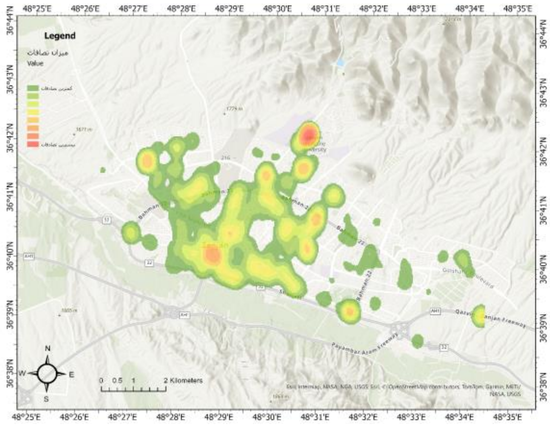

Figure 2. Density of urban accidents

4.2. Distance to Major Roads

The map illustrates the distance to major roads in Zanjan. The areas with the densest major roads are shown in darker green. These roads carry the highest traffic volume in the city. Red, yellow, and orange regions represent areas with fewer main roads.

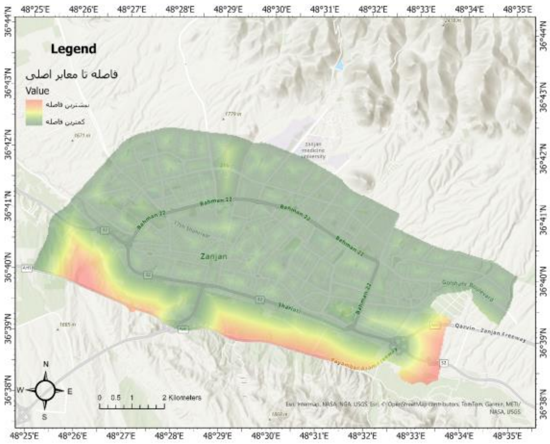

Figure 3. Distance to the city's Major Roads

4.3. One-Way Streets

One-way streets constitute an important component of the urban transportation network and may contribute to the formation of accident-prone areas. The spatial distribution of one-way streets in Zanjan is presented on the map, where these streets are displayed in blue and were extracted from OpenStreetMap data. Although one-way streets are distributed across different parts of the city, their concentration is noticeably higher in the central urban area. This pattern may reflect the compact street structure, higher traffic demand, and traffic management strategies commonly implemented in dense urban cores.

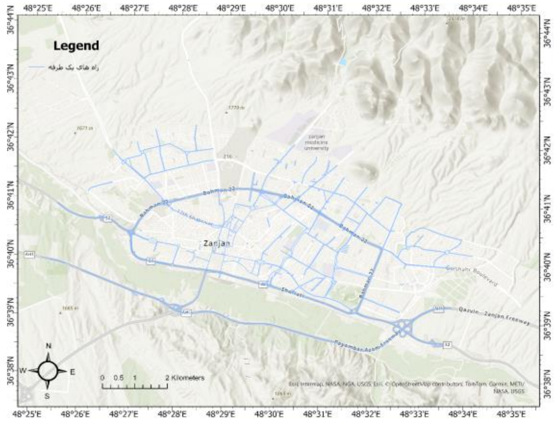

Figure 4. One-way transportation in Zanjan city

4.4. Speed Limits on Roads

Road speed limits represent another influential factor affecting both the frequency and severity of traffic accidents. The corresponding map illustrates the spatial variation of speed limits across Zanjan's road network. In this map, darker colors indicate roads with higher speed limits, whereas lighter yellow and white shades represent roads with lower speed limits. Variations in speed limits across the urban network may influence driving behavior, crash likelihood, and injury severity, particularly along major corridors and access routes with higher traffic volumes.

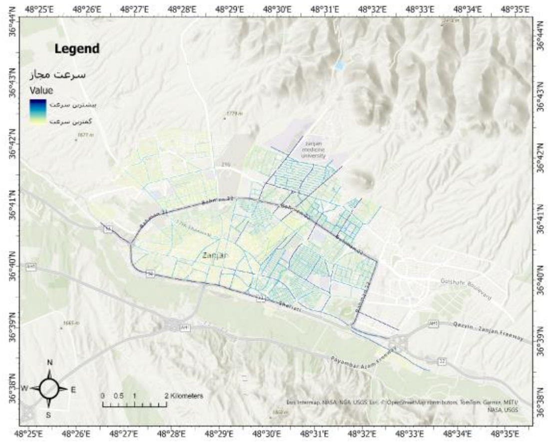

Figure 5. Speed limit of Zanjan's urban road network

4.5. Road Width

Road width is a key geometric characteristic that can affect traffic flow, vehicle interactions, and the frequency and severity of accidents. The road width map shows the spatial distribution of street widths across Zanjan. Narrower streets are generally represented by lighter colors, while wider roads are shown using darker shades. The central part of the city, characterized by an older and more compact urban fabric, contains a higher concentration of narrow streets. Such conditions may increase traffic conflicts, reduce maneuvering space, and contribute to higher accident risk, especially in areas with dense pedestrian and vehicular activity.

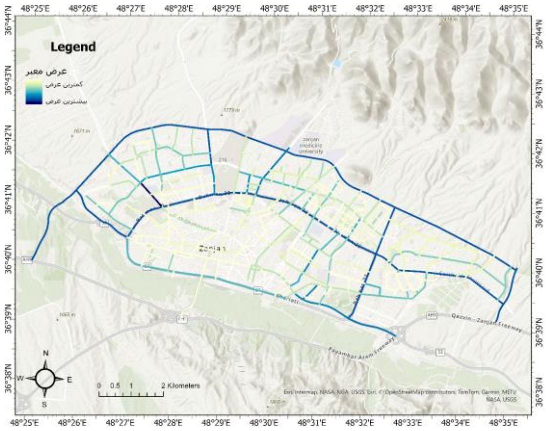

Figure 6. Width of city roads

4.6. Types of Roads

The classification of transportation arteries is an essential factor in understanding the spatial pattern, frequency and severity of urban traffic accidents. Different road types serve different mobility and accessibility functions and are therefore associated with varying traffic volumes, speeds, and conflict levels. In the map, major roads are shown in orange, while secondary roads are displayed in red. The distinction between these road classes provides an important basis for evaluating how the structure and hierarchy of the urban road network influence accident occurrence across the city.

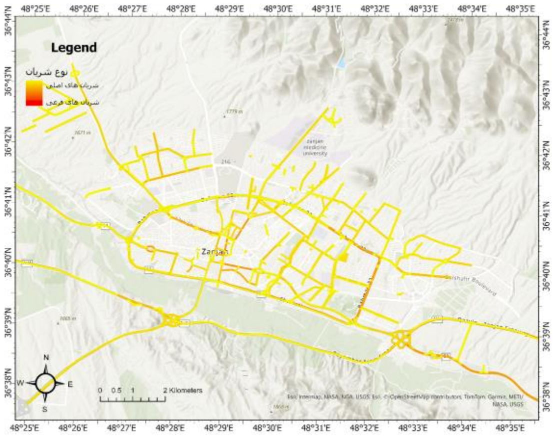

Figure 7. Types of urban arteries

4.7. Intersection Density

Intersections are among the most critical locations for urban traffic accidents because they involve multiple traffic movements, crossing conflicts, turning maneuvers, and interactions between vehicles and pedestrians. The intersection density map identifies areas with high intersection density in red, while areas with lower intersection density are represented by yellow and green shades. The eastern part of the city, particularly the older urban area, exhibits the highest concentration of intersections. This spatial pattern corresponds with areas experiencing higher accident rates and suggests that intersection density is an important factor in explaining the spatial distribution of crashes within Zanjan’s urban network.

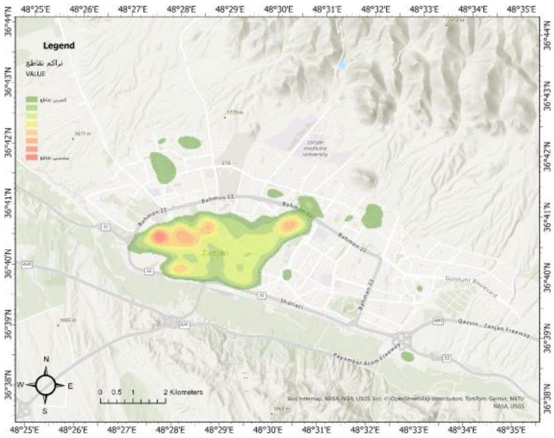

Figure 8. Density of intracity intersections

4.8. Modeling

The modeling procedure in this study was conducted in two main stages. In the first stage, the spatial autocorrelation of the variables was examined in order to determine whether the data exhibit location-dependent variation across the study area. For this purpose, Moran's I statistic was employed to evaluate the degree and significance of spatial autocorrelation among the selected indicators. Table 1 reports the Moran's I results used to test the hypothesis of spatial autocorrelation for the study indices.

As shown in Table 1, the Moran's I values for several variables are greater than zero, indicating the presence of positive spatial autocorrelation in the corresponding data. This suggests that similar values of these variables tend to be spatially clustered rather than randomly distributed across the urban area. Among the examined indicators, trip attraction intensity and intersection density show the highest Moran's I values, equal to 0.58 and 0.50, respectively, indicating relatively strong spatial clustering. In contrast, the variable representing the type of transportation arteries has the lowest Moran's I value, equal to 0.01, suggesting a comparatively weak level of spatial autocorrelation.

Furthermore, the low p-values reported for many of the indices, together with relatively high z-scores in most cases, provide statistical evidence for rejecting the null hypothesis of spatial randomness. These results indicate that the spatial distribution of several variables follows a clustered pattern. More specifically, the distribution patterns of four key variables—one-way streets, road width, intersection density, and trip attraction intensity—exhibit spatial clustering. By contrast, the variables related to artery type, speed limit, and density of transportation axes display a random spatial distribution pattern.

In the second stage of the modeling process, the spatial relationship between the selected indicators and the occurrence of urban traffic accidents was analyzed. As established in the preceding stage, several variables exhibit spatial autocorrelation, indicating that their relationships with accident occurrence may not be spatially uniform. Therefore, regression models capable of accounting for spatial dependence and local variation are required to accurately model these relationships. Accordingly, this study employed the Geographically Weighted Regression (GWR) model to investigate the spatially varying relationships between the explanatory variables and urban accident occurrence. The results obtained from the GWR model are presented in Table 2.

Table 1. Moran's I statistic for testing the hypothesis of spatial autocorrelation of indicators

Parameters	p-value	z-score	Pattern	Expected I	Moran's I
Types of Roads	0.210155	1.0001213	Random	-0.00812	0.01291
Speed Limits on Roads	0.000009	4.895482	Random	-0.00812	0.07127
One-Way Streets	0.005863	3.111302	Clustered	-0.00812	0.49450
Road Width	0	21.525875	Clustered	-0.00812	0.31931
Intersection Density	0	15.12548	Clustered	-0.00812	0.50294

Table 2. Results from the geographical weighted regression model

Parameters	Adjusted R^2	R^2	AICc	Sigma	Residual Squares
Types of Roads	0.4394	0.3751	3580.2	3193.4	722368133
Speed Limits on Roads	0.6591	0.5203	3542.5	2907.8	594863451
One-Way Streets	0.7098	0.5566	3533.4	2835	559769926
Road Width	0.6591	0.5324	3541.2	2893.8	586667060
Intersection Density	0.5239	0.4356	3565.9	3087	671449139

Several diagnostic and performance parameters of the Geographically Weighted Regression (GWR) model are presented in Table 2. Among these parameters, the coefficient of determination R^2 and the adjusted coefficient of determination R^2 are particularly important, as they provide measures of model goodness of fit and explanatory performance. In general, values closer to one indicate that the explanatory variables are more capable of accounting for variations in the dependent variable. As reported in Table 2, all R^2 and adjusted R^2 values are considerably greater than zero, indicating a meaningful association between the selected explanatory variables and the spatial occurrence of urban traffic accidents. The results further show that the density of transportation axes and trip attraction intensity have the highest R^2 values among the examined variables, suggesting that these indicators have greater explanatory power in relation to urban accident occurrence. In other words, areas that attract higher volumes of trips and areas characterized by dense transportation networks appear to be more strongly associated with urban traffic accidents. These findings suggest that crash occurrence may be influenced not only by travel demand intensity but also by inadequacies in street network design, particularly where dense road structures and a high concentration of intersections increase the likelihood of traffic conflicts.

Another important parameter used in the evaluation of the Geographically Weighted Regression model is the corrected Akaike Information Criterion (AICc). The AICc is a relative measure of model quality that evaluates the trade-off between model fit and model complexity. It indicates the extent to which information is lost when a statistical model is used to represent the observed data. Lower AICc values generally indicate that the estimated model provides a better approximation of the observed or real-world values, while avoiding unnecessary complexity. It should be noted that AICc does not have a fixed universal threshold; rather, it is interpreted comparatively across alternative models or explanatory variables. As shown in Table 2, the density of transportation axes and trip attraction intensity exhibit relatively low AICc values compared with the other independent variables. This indicates that the GWR models associated with these variables provide comparatively higher estimation accuracy and better overall model performance. Accordingly, these two indicators can be considered among the most influential spatial factors in explaining the distribution of urban traffic accidents within the study area.

5. Conclusion

This study investigated the spatial distribution of urban traffic accidents in Zanjan using spatial statistical techniques and GIS-based analytical methods. The main objective was to identify accident-prone areas and examine the relationship between urban traffic accidents and selected spatial, geometric, and transportation-related variables, including road type, speed limit, one-way streets, road width, intersection density, transportation network density, land-use characteristics, and trip attraction intensity. The findings confirmed that traffic accidents in Zanjan are not randomly distributed across the urban area; rather, they exhibit a clear spatial clustering pattern, particularly in the central core, major urban corridors, and city entrance and exit routes.

The results of Moran’s I spatial autocorrelation analysis indicated that several explanatory variables display significant spatial clustering. In particular, variables such as one-way streets, road width, intersection density, and trip attraction intensity showed clustered spatial patterns, suggesting that these factors are unevenly distributed across the city and may contribute to the formation of accident-prone zones. By contrast, variables such as road type, speed limit, and density of transportation axes showed relatively weaker or more random spatial patterns. These findings highlight the importance of considering spatial dependency in urban accident analysis, as conventional non-spatial approaches may fail to capture localized variations in accident-related factors.

The application of the Geographically Weighted Regression (GWR) model provided further evidence of spatial heterogeneity in the relationship between traffic accidents and the selected explanatory variables. The GWR results showed that the influence of accident-related factors varies across different parts of Zanjan, confirming that a single global model cannot adequately explain the spatial complexity of urban traffic accidents. Among the examined factors, road width, one-way street configuration, intersection density, transportation network density, and trip attraction intensity were found to have substantial explanatory importance. This indicates that both the physical structure of the road network and the spatial distribution of travel demand play important roles in shaping accident patterns.

The spatial analysis also revealed that urban arteries functioning as the main entry and exit corridors of the city generally experience higher accident concentrations. These corridors accommodate considerable traffic volumes and often involve higher operating speeds, merging and diverging movements, and transitions between intra-urban and intercity traffic flows. In Zanjan, routes such as Khayyam, Sabooti, Northwestern, and Southeastern corridors can be regarded as critical routes due to their functional role in the urban transportation network and their association with higher accident density.

Road width was also identified as an important factor influencing accident occurrence and severity. Streets with widths ranging from 40 to 58 meters, including highways and expressways, were associated with higher accident severity, mainly due to higher operating speeds and greater traffic exposure. Corridors such as 22 Bahman Highway, Shahid Avini Boulevard, peripheral urban routes, and access roads such as the Southwestern Freeway are examples of routes where accident risk is intensified by high-speed traffic conditions. In contrast, secondary streets with widths between 12 and 16 meters were more frequently associated with side-impact collisions, sudden turning movements, and conflicts caused by access to adjacent land uses. Narrow streets with widths of less than 12 meters showed greater involvement of pedestrians and motorcyclists, primarily due to limited roadway space, congestion, and close interaction between vulnerable road users and motor vehicles.

The overlay of accident density maps with transportation network density and intersection density maps demonstrated that many recurrent accident locations are situated in areas with dense road networks and high traffic activity. This confirms that traffic exposure, network complexity, and the concentration of movement flows are key contributors to crash occurrence. High-density accident points were also observed in peripheral areas of Zanjan, particularly along entry and exit routes, where higher vehicle speeds and sudden lane-changing behavior may increase both accident frequency and severity.

Overall, the findings of this study demonstrate that spatial statistical modeling, particularly the combined use of Moran's I and GWR, provides a valuable framework for identifying accident-prone areas and understanding the spatially varying effects of urban traffic factors. The results can support local authorities, traffic engineers, and urban planners in designing targeted and evidence-based safety interventions. Instead of applying uniform traffic safety policies across the entire city, the findings emphasize the need for location-specific measures that respond to the particular characteristics of each accident-prone area. Therefore, the proposed analytical framework can contribute to more effective urban traffic safety management, improved allocation of resources, and the development of safer and more sustainable urban transportation systems in Zanjan.

6. Recommendations

Based on the spatial clustering of traffic accidents in Zanjan and the results of the GWR analysis, traffic safety measures should be implemented in a targeted and location-specific manner rather than through uniform citywide interventions. Priority should be given to accident-prone areas, particularly the central urban core, major intersections, high-traffic corridors, and city entrance and exit routes.

First, high-risk intersections should be redesigned through geometric improvements, better signal timing, clearer lane markings, improved sight distance, and the reduction of conflict points. Since intersection density was identified as an important factor associated with accident concentration, safety audits should be conducted at major crash hotspots before implementing corrective measures.

Second, pedestrian and motorcyclist safety should be improved in narrow and congested streets, especially in areas with widths below 12 meters. Measures such as standard sidewalks, marked pedestrian crossings, improved lighting, physical barriers, and traffic-calming facilities can reduce conflicts between vehicles and vulnerable road users.

Third, speed management should be strengthened on major arterial roads, highways, and city entrance and exit corridors. Installing speed cameras, warning signs, pavement markings, rumble strips, and transition speed zones can help reduce crash frequency and severity, particularly along high-risk routes such as Khayyam Highway, 22 Bahman Highway, Shahid Avini Boulevard, and peripheral access roads.

Fourth, traffic circulation and network organization should be improved in areas where high transportation network density overlaps with accident hotspots. One-way street systems, access management, parking control, and improved lane guidance can reduce sudden maneuvers, side conflicts, and traffic interference, especially in the central area, around Revolution Square, Saadi Street, and the market district.

Fifth, land-use and trip attraction management should be integrated into traffic safety planning. Areas with intensive commercial, service, and administrative activities should be supported by organized parking, designated loading and unloading spaces, improved public transport access, and pedestrian circulation management to reduce traffic conflicts.

Finally, a continuous GIS-based accident monitoring system should be established by the municipality and traffic police. This system can support regular hotspot identification, evaluation of implemented safety measures, and prioritization of future interventions. Future studies are also recommended to incorporate temporal patterns, traffic volume, accident severity, driver behavior, vehicle type, and weather conditions to provide a more comprehensive understanding of urban traffic safety in Zanjan

7. References

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