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Research Paper

Evaluating the Spatial Effect of the Contribution of Different Types of Land Use in the Occurrence of Crashes

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Abstract

The type of land use in each traffic area zone (TAZ) is the most important factor determining the number of vehicles, geometric and traffic characteristics in that zone. Any factor in the urban environment that causes congestion and attraction of vehicles at certain times increases the probability of a crash in that area. The purpose of this study is to investigate the effect of the share of different types of uses in various traffic areas of Shiraz city on the probability of a crash. A two-step method, including identifying the types of uses influencing the occurrence of crashes and spatial effects between independent variables and crash data in space Kernel density estimate (KDE) methods, has also been used to find the suitable bandwidth for searching observations. In order to investigate the spatial effects of land use types on crash incidence, geographically weighted regressions (GWRs) and geographically weighted Poisson regressions (GWPRs) were used. Based on the validation criteria, the local GWPR model performs better than the global Poisson model and the local GWR model among the mentioned models .Additionally, the presence of residential, commercial, barren, and abandoned uses, as well as the mixing of residential and non-residential uses, significantly impact crashes. Examining the spatial effects of land use types in this study's traffic areas can be very important in carrying out safety measures.

Keywords: Land Use; Crash; KDE; GWPR

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1. Introduction

In recent years, the frequency and severity of injuries caused by urban traffic crashes have been increasing as one of the biggest causes of unnatural deaths in developing countries (Yoon, Kim, & Ji, 2019).

Towards achieving this goal, the United Nations and the World Health Organization are implementing urgent measures (2021-2030 decade of road safety measures) has been put on the agenda in order to improve road safety and reduce injuries caused by traffic crashes (Pal et al., 2018), and many researchers have been researching the environmental factors that influence the occurrence of crashes through micro- and macro-view studies (Zafri & Khan, 2022).

Traffic accidents are one of the leading causes of death on a global scale. Evaluating and understanding land-use features will aid in identifying environmental elements that contributed to the accident (Mathew, Pulugurtha, & Duvvuri, 2022). After increasing traffic volume, land use is one of the most crucial factors in metropolitan network development. Multiple studies have proven that an increase in the density of various urban uses raises the accident rate (Almasi & Behnood, 2022; Aribigbola, 2008; Ikhuoria, 1987; Larson, Liu, & Yezer, 2012; Leibowicz, 2020; Zhong, Jiang, & Nielsen, 2022). Based on the volume of trips absorbed and produced as a result of increased vehicle interaction, land use indirectly causes an increase in accidents (Effati & Saheli, 2022; WEDAGAMA, Roger, & Dissanayake, 2008). In past studies, the spatial relationship between the number of accidents and the density of different types of uses has been investigated, and it has been shown that changing urban patterns have played a significant role in increasing urban safety (Ewing & Dumbaugh, 2009; Wedagama, Bird, & Metcalfe, 2006; Wier, Weintraub, Humphreys, Seto, & Bhatia, 2009). However, the growth in density and mix of uses has led to an increase in the incidence of accidents, particularly among pedestrians (Lee, Zegras, & Ben-Joseph, 2013; Merlin, Cherry, Mohamadi-Hezaveh, & Dumbaugh, 2020) based on past studies of data Accident counts in different positions have spatial heterogeneity, which means that due to the spatial dependence on the surrounding environment, they require spatial modeling to be able to include the spatial correlation between the crash position and the surrounding environment in the model. Therefore, the spatial analysis of crash data in estimating the occurrence of a crash based on local variables is more accurate than traditional models (Almasi, Behnood, & Arvin, 2021). Regression is one of the most well-known statistical models in the study of crash data, and numerous researchers have used it to estimate the frequency of variables crash(K Kim, Punt, & Yamashita, 2010; Peera, Shekhawat, & Prasad, 2019; Sung, Lee, Cheon, & Yoon, 2022; WEDAGAMA et al., 2008).

Nevertheless, it is important to note that without considering the geographical characteristics, investigating the relationship between crash data and environmental influencing variables in the occurrence of a crash will not produce positive results (Liu, Khattak, & Wali, 2017). As such, spatial statistical models such as weight regression models have been the focus of many researchers for the estimation of crash processing based on geographical characteristics of crash data and environmental factors (Al-Hasani, Asaduzzaman, & Soliman, 2021; Gomes, Cunto, & da Silva, 2017; Khaksar, Almasi, & Goharpoor, 2022; Matkan, Mohaymany, Mirbagheri, & Shahri, 2011; Zhang, Lu, and Qu, 2020).

In spatial statistics models, the choice of brave search or bandwidth is considered one of the most important criteria of spatial data analysis, estimated using kernel density. If the size of the kernel density search radius is not chosen correctly, the modeling results do not have acceptable accuracy, which is the reason that high search radii cause a lot of overlap and selection of dense areas, and on the other hand, choosing a small search radius causes a large number of Do not consider observations (Kazmi, Ahmed, Mumtaz, & Anwar, 2022; Le, Liu, & Lin, 2020; Srikanth & Srikanth, 2020). Considering the significance of the density of different types of land use in the production and attraction of travel in a traffic area and the increase in conflict between vehicles and road users in previous studies, the spatial relationship between the number of crashes and types of land use based on traffic areas was determined by the studies conducted. Furthermore, the simultaneous effect of the density of different types of uses and the blending of numerous uses in a traffic region has not been examined. And in the second phase, by selecting an appropriate spatial search radius, the impact of the density of types of uses and the mixture of types of uses in Shiraz's traffic zones will be examined. Examining the spatial effect between kinds of land use in different geographical regions (this study is based on the TAZ level) and the occurrence of crashes might improve the efficacy of attempts to protect urban roads.The problems and limitations of the research include: the lack of quick and accurate cooperation of the police, municipality, etc. in providing complete information about crashes, the time it takes to receive information about land use, the lack of providing basic information about traffic areas (TAZ) & O/D matrix.

2. Literature Review

Ouyang & Bejleri investigated the environmental impact of traffic crashes using a comprehensive method based on geographic information systems. To analyze the crash data, the distance to the destination was taken into account. Based on their study, it was found that the length of the road and the density of the workshop environment significantly increase the frequency of crashes. In contrast, the increase in intersections led to an increase in crashes as a result of the increased number of intersections crashecrashcrashecrashe(Ouyang & Bejleri, 2014). Merlin et al. conducted a study in Florida, USA, that examined the relationship between residential access and the probability of a crash within three years. In their study, people's access to residential areas was assessed based on vehicle mile travel (VMT) in the event of a crash. Results of the study show that commercial areas located at a distance of at least 10 minutes from residential areas have fewer crashes than those located at a greater distance. Within 20 to 30 minutes of residential areas crash(Merlin, Cherry, et al., 2020; Merlin, Guerra, & Dumbaugh, 2020), studies have shown a theoretical relationship between access to certain uses and the occurrence of two-way crashes and a potential effect on the number of crashes so that the reduction of access distance is related to the reduction of vehicle miles traveled for households.

Therefore, the probability of crashes is less (Ewing & Cervero, 2010; Stevens, 2017). Other studies have shown that the access distance to certain uses increases the probability of the presence of different vehicles in that area, followed by an increase in conflicts between vehicles and in. Finally, it leads to crashes (Marshall & Garrick, 2011; Quddus, 2008), so the type of environmental uses has a significant effect on increasing the frequency of crashes (Ewing & Cervero, 2010; Rothman, Buliung, Macarthur, To, & Howard, 2014; Stoker et al., 2015). Due to the development of technology and the increasing availability of spatial information, a growing number of researchers are interested in assessing the factors influencing crashes using crash geographical data (Levine, Kim, & Nitz, 1995). According to studies, the number of crashes fluctuates spatially (has spatial heterogeneity) in response to varying traffic patterns and vehicle volumes. More crashes occur near commercial and business hubs than residential regions (Karl Kim, Pant, & Yamashita, 2010; Levine et al., 1995). In addition, based on the spatial delay models of accident analysis, the relationship between the number of motor vehicle crashes with population density, occupation, and road characteristics has been obtained, which shows that crashes are scattered in space due to different travel activities and during They change significantly day by day (Aguero-Valverde & Jovanis, 2008; Bindra, Ivan, & Jonsson, 2009; Levine et al., 1995) so the use of geographic user information system (GIS) due to the use of spatial correlation can provide Spatial correlation of crash exposure criteria should be included in the prediction of crashes and thus provide acceptable results (Bindra et al., 2009; F. Saccomanno, Chong, & Nassar, 1997; F. F. Saccomanno, Fu, & Roy, 2001).

In addition to the geographic information system, the use of generalized linear regression models and geographically weighted Poisson regression considering the spatial relationship between crash data and environmental exposure factors have attracted the attention of researchers. In some studies, the correlation matrix created between independent variables has shown a high correlation between population density and residential area. Also, generalized linear regression analysis shows that employment density, residential density, and road length positively correlate with road traffic crashes. At the same time, mixed land use negatively correlates with road traffic crashes (Peera et al., 2019). Furthermore, the empirical Bayes model has been used to investigate the relationship between the geometry of road design and crash frequency, in addition to the aforementioned spatial models (Wang, Yang, Lee, Ji, & You, 2016). Other studies have shown that the mixing of moderate uses at the level of traffic areas is the most important cause of crashes, so these areas should be prioritized for safety improvement measures (Karl Kim et al., 2010). Also, the spatial investigation between the occurrence of crashes and environmental factors has shown that commercial areas have a high spatial correlation with injury and fatal crashes.

In contrast, demographic variables have a higher spatial correlation with the rate of pedestrian and bicycle injuries (Wedagama et al., 2006). As stated in the introduction section, choosing the optimal search radius in spatial models significantly impacts the accuracy of spatial models in selecting observations (Almasi & Behnood, 2022). By analyzing past research, we determined that density and type of use are among the most influential environmental factors on the occurrence of crashes; therefore, it is crucial to determine the effect of types of uses on crashes. Also, crash data has spatial heterogeneity, a phenomenon that is known as spatial correlation, which means that in addition to the influence of environmental variables on the occurrence of a crash, the local characteristics of each crash are different from one location to another, so without considering the local characteristics and their spatial relationship with each other, the statistical models of the results. They will not offer anything. Models based on geographic information systems, spatial delay models, geographically weighted regression models, and geographically weighted Poisson regression can be used to model the spatial relationship between crash data in different locations, the most important of which are models based on geographic information systems, spatial delay models.

In the first step of this study, the most important factors influencing the occurrence of crashes at the level of traffic areas are identified. In the next step, geographically weighted and geographically weighted Poisson regression models are employed for counting data to investigate the impact of environmental factors, taking into account spatial heterogeneity, which will be used to estimate the number of crashes within the city of Shiraz.

3. Methodology

The scope of this study is the traffic area zones (TAZ) of Shiraz city, the capital of Fars province, Iran country (Figure 1). The data of this study has been collected from two sources: the first category of locational data of urban crashes in Shiraz city from 2020 to 2022, a total of 34588 reported by the police, was prepared from the deputy transport and traffic department of Shiraz municipality, the second category is information layers of land uses of Shiraz city were collected from Shiraz municipality. Descriptive statistics of the data of this study is shown in Table 1. The city of Shiraz has 325 traffic areas, and the variety of land uses in them has been divided into 37 categories based on studies of the comprehensive transportation plan in this study to investigate the correlation between independent variables and reduce its error in modeling, firstly based on the model Pearson correlation of independent variables was evaluated. In the first step, the variables with a high correlation were included in the modeling and other similar variables. After that, if there was a correlation between the independent variables, some variables were removed in order to reduce the model error caused by the correlation between the independent variables.

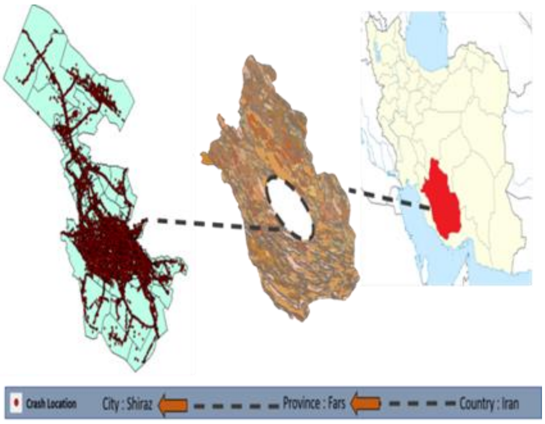

Figure 1. The Study Area

Finally, based on the Pearson model, land uses were classified into 14 categories with the lowest correlation. Based on the area, this study identified the following land uses: the road network, the number of residential units, the number of commercial units, cultural and religious activities, athletic activities, education, healthcare, green space, agriculture, administrative headquarters, industries, and facilities, transportation, barren and dilapidated, mixed residential and non-residential, and other uses include: cemetery, livestock, military, river. Based on aggregation methods and correlation reduction, 37 categories of users were reduced to 14 categories in this study by using Pearson's correlation test in the first step. As a result of the extraction of observations, the effect of independent variables has been evaluated by considering spatial correlations in the estimation of the frequency of crashes in Shiraz based on GWR and GWPR models.

Table 1. Descriptive characteristics of study variables

Variables	Min	Max	Sum	Mean	Sd.	Var.
Number of crash	7.00	686.00	34588.00	106.42	84.34	7113.62
Road network	0.00	73.34	7960.66	24.49	11.00	120.97
Residential	0.00	70.18	9223.37	30.21	18.87	356.16
Cultural & Tourism	0.00	30.66	435.59	1.34	3.59	12.88
Healthcare	0.00	84.45	313.72	0.97	5.33	28.42
Sporty	0.00	35.18	134.19	0.41	2.20	4.84
Official	0.00	87.83	556.76	1.71	5.88	34.60
Green space	0.00	86.59	2413.15	7.43	13.75	188.94
Commercial	0.00	30.44	670.48	2.06	3.97	15.75
Facilities	0.00	94.26	1093.31	3.36	7.69	59.09

Variables	Min	Max	Sum	Mean	Sd.	Var.
Barren and abandoned	0.00	94.31	3956.12	12.17	16.92	286.14
Educational	0.00	73.30	786.77	2.42	6.10	37.16
Mixed	0.00	14.16	667.19	2.05	2.52	6.34
Mixed non-residential	0.00	36.37	190.30	0.59	2.52	6.35
Other Land Use	0.00	100.00	3504.81	10.78	25.45	647.94

3.1. Kernel Density Estimate (KDE)

This method investigates an urban network's spatial correlation of point events, such as crashes. The KDE network method is used to estimate the network position density.

An unbiased kernel function should be used to avoid false conclusions. Therefore, the formulation of the "equal split discontinuous estimate function" method has been studied in this study. Using this approach, the network kernel performance is defined for two cases: (1) kernel center q with one node and (2) kernel center q with two nodes simultaneously. In the first case, the following function is defined. In this relation, k(x) is a basic kernel function, y is the center of the kernel, d is the distance between the path y and x, h is the bandwidth, and the degree of the node is removed.

3.2. Geographical Weighing Regression (GWR)

Fields that use spatial data and the like are increasing. In classic statistical regressions, such as ordinary least squares (OLS) regression, we assume that the relationship we want to model between a dependent variable and a number of independent variables is the same throughout the studied range, which is incorrect in many cases. Geographically weighted regression does this by preparing separate regression equations for each complication considering the dependent and independent variables that fall within the band or range of the complication. In the GWR model, unlike the OLS model, the coefficients or parameters of the model at the level of the study area are not constant and depend on the spatial coordinates (spatial and geographical weight), and the value and sign of each of them have spatial variability.

$$k_q(p) = \begin{cases} 0 & , \quad d_s(q,p) \geq h \\ \dfrac{k\big(d_s(q,p)\big)}{(n_{i1}-1)(n_{i2}-1)\dots(n_{ik}-1)} & , \; d_s(q,v_{ik}-1) \leq \; d_s(q,p) < d_s(q,v_{ik}) \end{cases} \tag{1}$$

$$y_i = \beta_0(u_i,v_i) + \sum_{k=1}^{k} \beta_k(u_i,v_i)\, x_{ik} + \varepsilon_i \tag{2}$$

3.3. Geographical Weighing Poisson Regression (GWPR)

GWR forms a weight matrix for each i. These weights are different according to the position of each i. Thus, closer positions gain more weight. The heterogeneous distribution of the relationship between two variables, which can be positive or negative and strong or weak according to the location, can be reflected in space using the GWR technique. In a GWPR, the number of crashes is predicted by a set of explanatory variables whose parameters are allowed to vary in space. This model can be rewritten as relation 3.

$$\begin{aligned} \ln(\lambda_i) &= \beta_0(u_i,v_i) + \beta_1(u_i,v_i)\ln(E_{vi}) + \sum_{k=1}^{k} \beta_k(u_i,v_i)\, x_{ij} \ln(\lambda_i) \\ &= \beta_0(u_i,v_i) + \beta_1(u_i,v_i)\ln(E_{vi}) + \sum_{k=1}^{k} \beta_k(u_i,v_i)\, x_{ij} \end{aligned} \tag{3}$$

3.4. Validation of Models

To evaluate and compare the performance of GWR models, three statistics have been used to measure the accuracy of the estimation. First, AIC will be used as the goodness of fit, and the lowest value of this AIC measure indicates the model's goodness of fit (Bozdogan, 1987). The AIC measure is as follows defined:

$$AIC = D + 2Kz \tag{4}$$

$$AIC_C = -2L(\beta, \alpha) + 2K + \frac{2K(K+1)}{n-K-1} \tag{5}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \overline{y_i})^2} \tag{6}$$

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - p_{i)}{}^2} \tag{7}$$

$$MAPE = \frac{\sum_{i=1}^{n}\left|\frac{y_i - p_i}{y_i}\right|}{n} \times 100 \tag{8}$$

$$MAD = \frac{\sum_{i=1}^{n}|y_i - p_i|}{n} \tag{9}$$

where D represents the variance of the model and k is the number of parameters. In GWPR, due to the non-parametric framework of the model, the number of parameters is meaningless; Therefore, a sufficient number of parameters should be considered.

Furthermore, along with the two criteria mentioned in this study, BIC, R^2, adjusted R^2, RMSE, MAD, MSE, and MAPE were also considered. Previous studies have demonstrated that lower values of AIC and AICC, as well as R^2 and R^2 adjusted for each, indicate a better model. BIC evaluates models based on matter and error values similar to AIC, and the closer the matter and error values are to 1, the better the model.

4. Analysis of the Results

Based on Table 1, in this study, the estimation of the number of crashes in 325 traffic areas of Shiraz city has been evaluated using land use variables. From 2020 to 2022, 34588 crashes were reported in the city, with an average of 106 crashees in each traffic area zone(minimum 7 and maximum 686). The road network accounts for an average of 24 percent of the traffic in each traffic area zone (minimum 0 and maximum 73 percent), and in some areas of urban centers, the share of road use is significantly higher than other uses. Residential units occupy an average of 30% of the area of traffic areas, which in some residential areas with high density has occupied up to 70% of the area of traffic areas (minimum 0 and maximum 70%).

The total of cultural, religious, and tourism uses on average occupies 1.3% of the area of traffic areas, the maximum of which is up to 30% of the area of traffic areas in the traditional areas of Shiraz (minimum 0 and maximum 30 Percentage). The percentage of the area used for healthcare is on average about 1%, sports use is about 0.5%, office uses on average is 1.7%, barren and abandoned land use is on average 12%, mixed residential and non-residential uses are on average 4%. It has an area of traffic areas. Almost 90% of the correlation between the independent variables is within the acceptable range (less than 0.4). In this study, 4 search radius have been carried out using the Kernel density estimate method, and among them (Harirforoush & Bellalite, 2019; Le, Liu, & Lin, 2022), the 300-meter radius has been chosen which has the best coverage of the observation values (Figure 2).

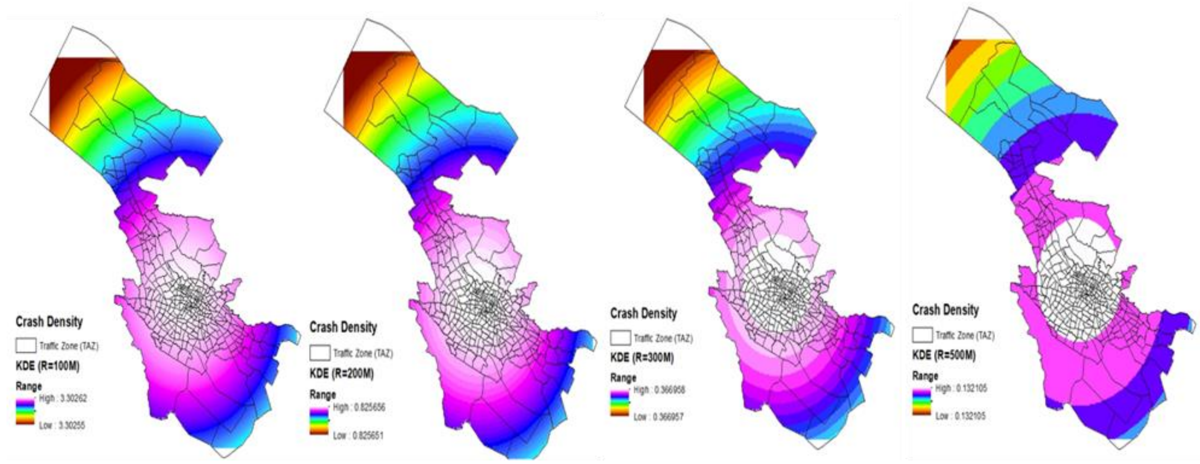

Figure 2. Kernel density estimate with different search radius

And as a result, the results of the model are reported with higher accuracy (Harirforoush & Bellalite, 2019.According to the exponential relationship of the Poisson regression model, an increase of one unit of barren land use area in the local model causes 0.95 units to increase the probability of a crash, which is 0.83 in the global model. The results are consistent with the study (Fuentes et al., 2022; Wedagama et al., 2006).

The increase of one unit of residential use area in the local model is 0.91, and in the global model, 0.97 has been effective in increasing the number of crashes; these results are in accordance with the study (Ouyang & Bejleri, 2014) as well as the mixing of residential and Non-residential has been effective in increasing the frequency of crashes by 1.12 units in the local model and 1.17 units in the global model, which the study (Musa & Moses, 2014) confirms the effect of mixed use on increasing the frequency of crashes .In Table 2, the validation results of the models are reported, in which lower values of AIC and AICC, values close to 1 parameter, R^2, and lower values of RMSE-MSE-MAPE-MAD indicate that the model is better (Liu et al., 2017). Based on that, local models have higher accuracy than global models. Almasi and Behnoud's study results have also shown that local models have more acceptable accuracy in predicting the frequency of crashes (Almasi et al., 2021; Khaksar et al., 2022) and among the local models, the GWPR model has a higher accuracy than the GWR. Therefore, the continuation of the modeling has been done based on the optimal GWPR model.

Figure 3 shows the estimation of the values of independent variables in each of the areas in the local model, based on which the variable effect of the residential use area in the north of Shiraz city on the occurrence of crashes is greater than in other traffic areas. This is consistent with the study (Fuentes et al., 2022; Ouyang & Bejleri, 2014; Wedagama et al., 2006).

Also, the impact of industries, equipment, and transportation on crashes has been obtained in Also, the impact of the use of green and recreational spaces in city centers is more than in other areas in the occurrence of crashes.The southern part and south of the center of Shiraz city more than in other areas (to see the impact of other uses in different traffic areas, refer to Figure 3). Figure 4 shows the prediction results of GWPR and GWR models along with the values of the residuals and R^2 for all traffic areas, based on which it can be found that in the traffic areas, the value of R^2 is closer to 1, and the residual values are closer to zero. The model has predicted the frequency of crashes with higher accuracy (Kramer, 2005).

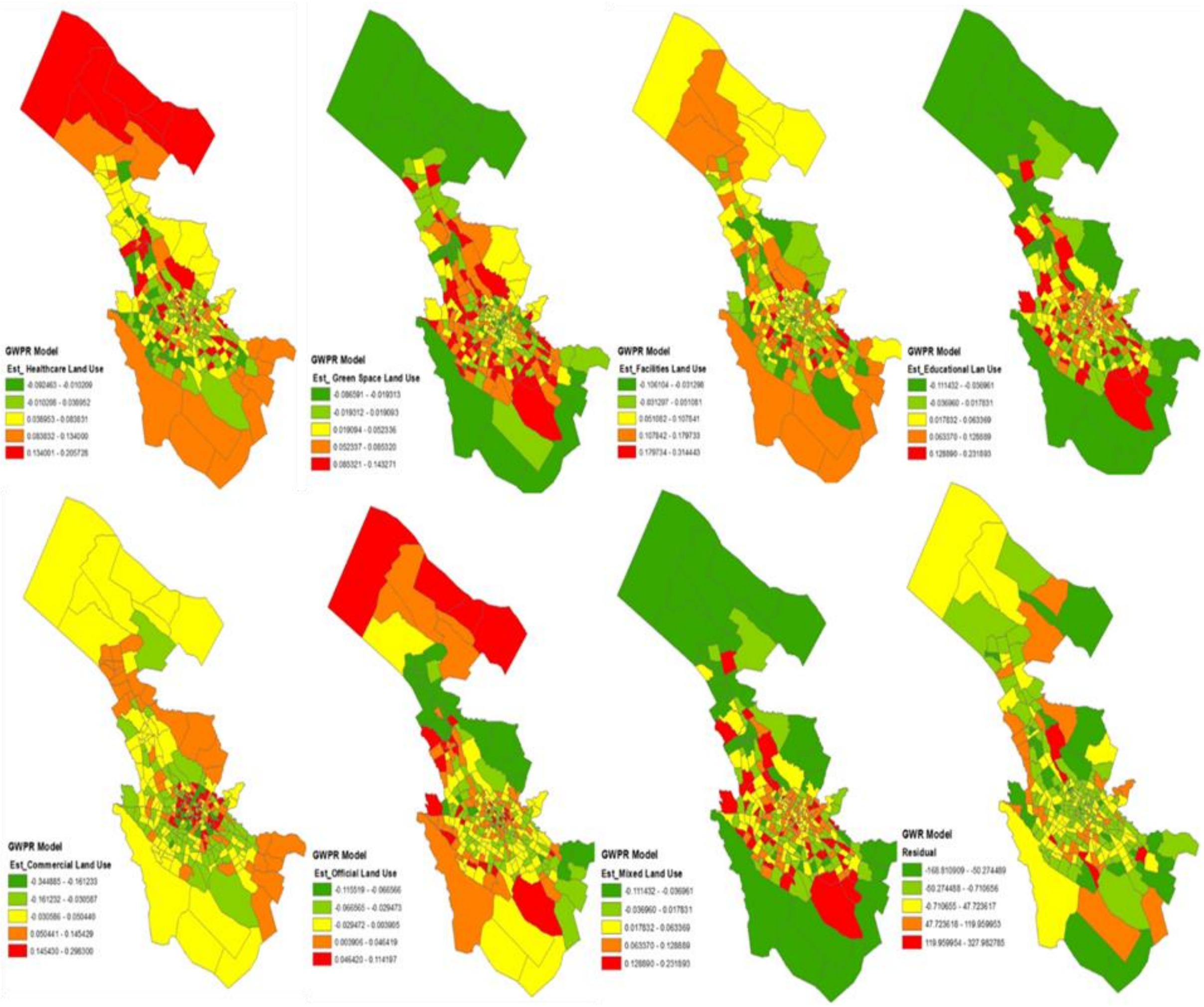

Figure 3. Estimation of independent variables in the GWPR method

Table 2. Validation of models

Variables	Local models		Global models
	GWR	**GWPR**	**Poison**
AIC	4235.154	3898.41	9432.214
AIC_C	3585.21	3426.214	9434.0254
∑	57.45	-	-
R^2	0.58	0.65	0.55
Adj R^2	0.53	0.59	0.51
BIC	-	4405.32	9482.614
RMSE	109.38	38.52	141.214
MSE	11964.85	1484.514	11975.214
MAPE	104.31	33.25	109.361
MAD	68.014	26.06	75.86

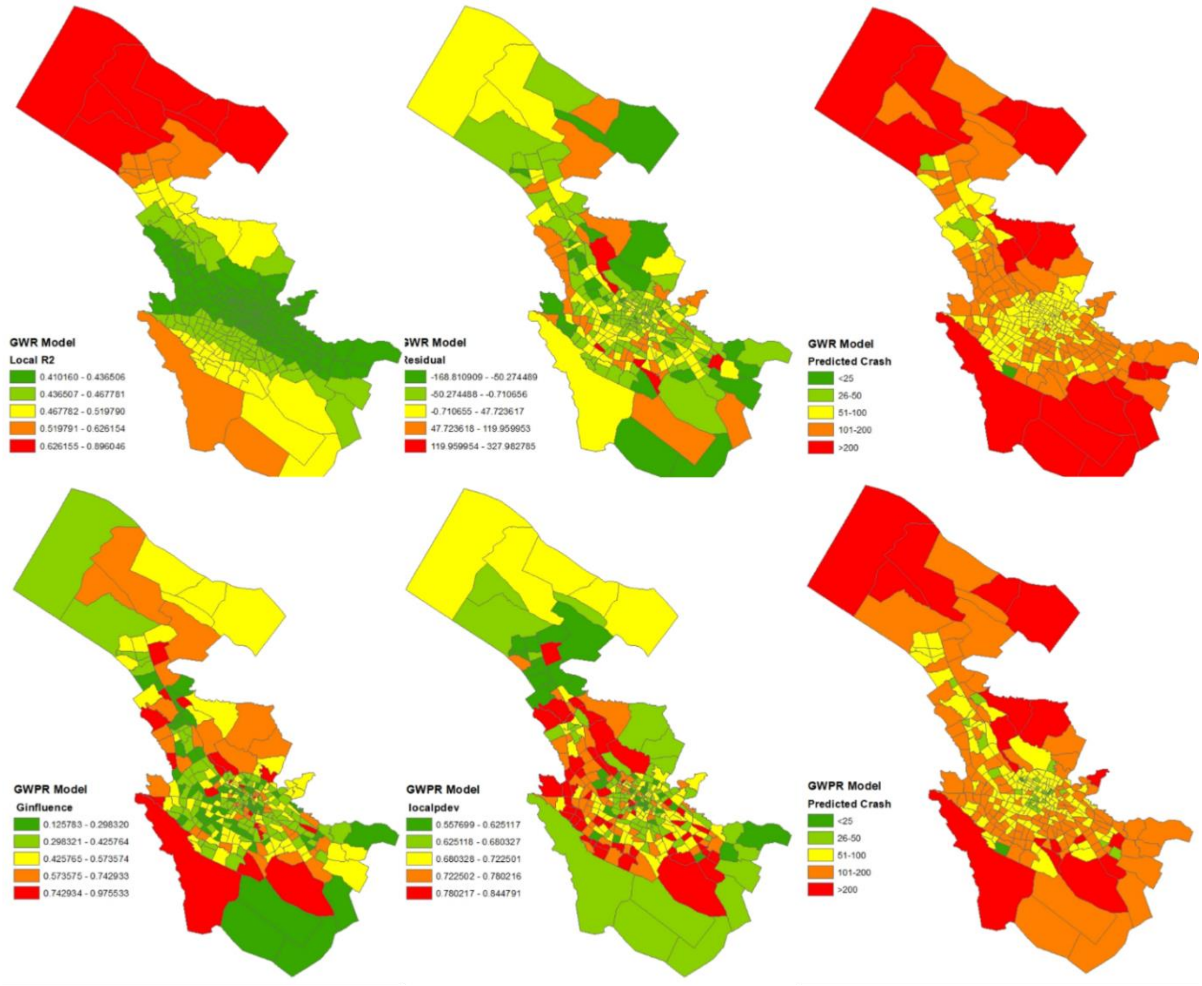

Figure 4. Comparison of GWR and GWPR modeling results

5. Conclusion

In this study, a systematic approach has been used to investigate the effect of land use area on the occurrence of crashes in the traffic areas of Shiraz city. In this study, in the first step, among 37 types of urban land use, 13 land use types have been selected. The selected uses have been selected by combining the area of similar uses in order to reduce the correlation between independent variables. In the second step, the appropriate search radius of the observations has been selected using the kernel density method, and in the following, two local and global modeling approaches have been adopted. The study results have shown that the local models are a better fit than the global model in estimating the frequency of crashes. Also, among the two GWPR and GWR models, the first model has provided better results. This study identified residential, commercial, barren land, and mixed residential use variables as the most important influencing variables in the increase of crashes (Karl Kim & Yamashita, 2002; Musa & Moses, 2014). Therefore, the correct control and management of these uses have a more significant impact on It reduces crashes compared to other uses. In this study, the effect of the significant difference in the area of different types of uses at the level of traffic areas on the occurrence of crashes is quite noticeable. In some traffic areas, up to 80% of the area is of one type of use, and the high standard deviation shows the dispersion of uses in the city. For example, the high standard deviation of healthcare use (Table 1) shows that this user has the least mixing with other uses at the district level. On the other hand, the accumulation of this type of use in certain traffic areas is seen more than in other uses. Sports uses, like healthcare, have a smaller area than other uses in traffic areas; its low variance (4.5%) shows that the mixing of this type of use is more than other uses (Kruskal & Wallis). ,1952) and is scattered in different proportions in the city. In office and headquarters use, due to the very high density (up to 87% of the area of the traffic area) in a number of traffic areas, as well as less variance compared to residential and commercial uses, it shows that the dispersion of this use at the level of traffic areas is more as a result of mixing They have more with other users. Also, considering the high area percentage (94%) of the use of facilities and industries in some areas and the high variance, it shows that the dispersion of these uses in Shiraz is less. There is less mixing with other uses; in other words, there is a large area of this Users are concentrated in limited traffic areas, which shows that the high share of one user in a traffic area has less effect than mixing types of users in increasing the frequency of crashes. In such a way that traffic areas with one type of land use depending on the type of land use, on average, have a greater effect than traffic areas with mixed land use in increasing the frequency of crashes, as shown in Figure 3 (Duan, Ya, Zhang, & Jia, 2013; Umair, Rana, & Lodhi, 2022) ,the standard deviation values from the critical value show that all independent variables have spatial correlation, so as expected, the local model has provided more acceptable results than the global model. (Almasi & Behnood, 2022; Liu et al., 2017). As mentioned in the methodology section, lower values of AIC, AICC, and BIC and error values indicate a better fit of the model, and R2 and R2 values closer to 1, the more optimal the model. . And considering the low variance, also the difference of 14% of the area between the minimum and maximum value shows that this type of mixing is widely spread in the city of Shiraz. In general, the spatial effect between independent and dependent variables is stronger in traffic areas with a great variety of uses compared to other traffic areas. Also, the values of the residuals in Figure 3 shows that the estimated frequency of crashes in the central areas of Shiraz city to the values observed is closer, and in other areas, the difference between the observed and predicted values is greater, which shows that the overdispersion of the data is greater in these areas (Atumo, Li, & Jiang, 2022). Considering the prioritizing of safety measures, the results of this study can be incorporated into long-term operating strategies to reduce the occurrence of crashes. The authors of this study suggest that the negative binomial distribution method, which considers the over-dispersion of crash data, should be investigated in future studies to predict the frequency of crashes. In this study, a systematic approach has been used to investigate the effect of land use area on the occurrence of crashes in the traffic areas of Shiraz city.Therefore, in order to reduce crashes based on the division of TAZ and Land uses, it leads to the prioritization of crash-prone areas and more accurate and continuous monitoring by the municipality, therefore, in the short term, traffic safety of crash-prone areas will significantly reduce the number of crashes and It leads to the increase of traffic safety in every region and city.

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