Mechanism analysis of traffic accident prone points based on The Spatial Durbin Model

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Abstract. The significant increase of freight traffic related collision accidents has aroused people's increasing concern about road safety. Using data from California, this paper studies the spatial relationship between freight related traffic accidents and low-income and minority communities. The study found that household income and minority population were significantly correlated with the density of freight related crashes and freight related crashes that led to serious casualties. Compared with areas with high-income groups, areas with low economic status, such as blacks and Asians, are more than 119% more likely to have traffic accidents. Among them, areas with black populations are more than 39% more likely to have traffic accidents than areas with Asian populations. The results show that freight related collisions are affected by spatial inequality.

Keywords: Road safety, freight movement, spatial inequity.

1. Introduction

In recent years, due to the rise of e-commerce and other reasons, freight demand in many countries and regions has increased unprecedentedly. Trucks are often used to transport goods in urban areas. These vehicles even operate 24 hours a day, which will not only cause environmental problems such as pollution and noise, but also lead to road safety problems. Due to the significant increase in traffic accidents and deaths related to freight transport, road safety issues have attracted more and more attention.

Attention to spatial distribution is conducive to the in-depth study of the causes of freight related collisions. The occurrence of traffic freight related collisions is not only related to the behavior of vehicle drivers and other road users, but also affected by road environment, population density, social economy and other factors. This paper studies the spatial relationship between freight related traffic accidents and socially vulnerable communities, and evaluates whether freight related crashes occur disproportionately in socially vulnerable communities. This study builds a conceptual model: the dependent variable measures the spatial distribution of freight related collisions in each block; The independent variable measures the spatial inequality of community composition and economic status related to demographic characteristics. The occurrence of freight related accidents is related to many factors. This study hopes to provide local traffic engineers and planners with an overall picture of road safety spatial inequality related to freight transport, and help them better alleviate spatial inequality.

This paper aims to investigate the spatial relationship between traffic accidents related to freight transport and socially vulnerable communities. In the next section, the interaction between freight traffic safety and spatial inequality will be studied. Then, this research design builds empirical tests, develop statistical models, and quantify the impact of different road safety factors on freight related crashes. Finally, the research results will be discussed in detail.

2. Literature Review

In previous studies, road safety analysis mainly focused on exploring the relationship between traffic accidents and factors such as road characteristics [1], geographical characteristics [2], building environment [3], traffic density [4]. Although studies have shown that these factors are directly related to traffic accidents, they cannot fully explain the risk of traffic accidents at the level of spatial distribution.

More and more studies explore the relationship between traffic safety and different socio-economic backgrounds and demographic factors. These studies usually take the annual average daily traffic volume (AADT) as the independent variable and the number of crashes [5] or injury severity [6] as the dependent variable to analyze the distribution of traffic accidents. Some literatures conduct Accident Research Based on different types of social development backgrounds, such as finding that its variables and urbanization variables in the era of e-commerce have a positive effect on freight accidents [7] [8]. More studies have emphasized the importance of linking traffic accidents with the socio-economic characteristics of communities. For example, someone evaluated the inclusion of social equity in the transportation plans of 18 North American metropolitan areas [9], and took accessibility as an indicator to measure social equity in urban transportation. According to the research results of accident hot spots, the street sections are divided into four categories: non dangerous, low dangerous, medium dangerous and high dangerous, and the social groups prone to traffic accidents are analyzed [10]. In Wyoming, a rural state, 68% of heavy trucks account for a high proportion of crashes on interstate highways, and the incidence of crashes involving trucks in bad weather (such as strong winds or heavy snow) is 19% higher than those without trucks [11]. There is a correlation between socio demographic characteristics and the dependent variables of each bicycle lane [12], and areas with more children have less opportunities to use protected bicycle lanes [13]. In the Minneapolis St. Paul metropolitan area, including seven counties and two core cities of Minneapolis and St. Paul, household income and the percentage of minority population are significantly correlated with the density of freight related crashes and freight related crashes that cause serious casualties [14]. The situation of ethnic minorities in the census area is closely related to the overall traffic accidents in North Central and northeast Texas, while the socio-economic situation is closely related to the fatal traffic accidents in the state [15].

3. Research Approach

The purpose of this study is to investigate the impact of traffic accident susceptibility on spatial inequality. It examines the spatial distribution of traffic accident-sensitive areas. In order to facilitate the evaluation of the model, we define the traffic accident-sensitive area as the area where the LN value of traffic accident density is greater than 1. From a practical point of view, there are many factors affecting the sensitivity of traffic accidents. Therefore, this study adopts two conceptual models (equations) OLS and SDM. The dependent variable measures the spatial distribution of traffic accident susceptibility at each geographic location. The main independent variables measure the traffic flow in different geographic locations, including passenger and freight vehicle flow, and the unequal spatial distribution of road at different grades. Control variables are other factors that theoretically affect the susceptibility of traffic accidents, including racial composition of geographic units and employment characteristics.

Our analysis uses the OLS (Ordinal Least Squares) model to test the spatial relationship between collision density and neighborhood characteristics related to freight transport. Spatial autocorrelation occurs when events in nearby locations are correlated. For the macroscopic study of traffic accidents, this problem is likely to exist. Therefore, we use the SDM (Spatial Dobbin Model) to explain the spatial autocorrelation problem, in which the spatial correlation is modeled. In this study, we use spatial neighborhood to explain spatial correlation.

OLS is mainly used to estimate the parameters of linear regression. Linear regression refers to the analysis of parameters β It is a linear regression model (i. e. the parameters only appear in the form of the power of one). The model idea of OLS is that the value with the minimum square sum of the difference between the actual value and the model estimated value is used as the parameter estimation. In other words, it is to find the best function matching of data by minimizing the sum of squares of errors. The unknown data can be easily obtained by using the least square method, and the square sum of errors between these obtained data and the actual data can be minimized. OLS model is shown in Eq. (1):

$$y_i = \beta_0 + \sum_{j=1}^{n} X_{ij}\beta_i + \varepsilon_i \tag{1}$$

Where y_i denotes the traffic accidents density of the i region (i.e. the ratio of the number of the traffic accidents in a region to the area of that region); X_{ij} denotes the j observation in the i region; β_0 and β_i are the regression coefficient, estimated using ordinary least squares; and ε_i is the disturbance term.

However, the most important prerequisite for the establishment of OLS is that explanatory variables (independent variables) are not related to the disturbance term, that is, explanatory variables are not endogenous. Otherwise, OLS estimators will be biased and inconsistent.

SDM can not only solve the problem of bias in the regression results caused by the spatial correlation of the interference terms of the ordinary least squares regression method, but also solve the problem of ignoring the explanatory variables whose covariance with the explanatory variables in the model is not zero when processing the sample data. In fact, the spatial Durbin model is an OLS model strengthened by adding spatial lag variables. The specific structural model is shown in Eq. (2):

$$y_i = \rho \sum_{\substack{j\in J \\ j\neq i}} W_{ij}\, y_j + \sum_{k\in K} \beta_k\, X_{ik} + \sum_{\substack{j\in J \\ j\neq i}} \sum_{k\in K} W_{ij}\, \beta_k' X_{jk} + \varepsilon_i \tag{2}$$

Where y_i denotes the traffic accidents density of the i region; ρ is the corresponding spatial parameter; X_{ik} is the spatial weight matrix, denotes the observation in the region; W_{ij} denote the spatial correlation of dependent variables or independent variables, which can be set to the same or different matrix; β_k' is the spatial autocorrelation coefficient of the exogenous variable; ε_i is a random perturbation term satisfying normal independent identical distribution.

The spatial weight matrix uses geographical distance weights, i.e.

$$w_{ij} = \frac{1}{d_{ij}} \tag{3}$$

Where d_{ij} is the distance critical value.

The SDM also includes many broad models:

When $\beta_k' = 0$, it includes the spatial lag of the dependent variable and excludes the explanatory variable of the spatial lag, thus becoming a spatial autoregressive model (SAR), that is:

$$y_i = \rho \sum_{\substack{j\in J \\ j\neq i}} W_{ij}\, y_j + \sum_{k\in K} \beta_k\, X_{ik} + \varepsilon_i \tag{4}$$

When $\rho = 0$, that is, assuming that the observed values between dependent variables are not related, but the dependent variables are related to the characteristics of adjacent regions (in the form of spatial lag explanatory variables), the model becomes a spatial lag model of explanatory variables:

$$y_i = \sum_{k\in K} \beta_k\, X_{ik} + \sum_{\substack{j\in J \\ j\neq i}} \sum_{k\in K} W_{ij}\, \beta_k' X_{jk} + \varepsilon_i \tag{5}$$

When $\rho = 0$ and $\beta_k' = 0$, the model becomes a standard least square regression model of the following form:

$$y_i = \sum_{k \in K} \beta_k X_{ik} + \varepsilon_i \quad (6)$$

The dependent variable is the density of traffic accidents. The independent variable measures the spatial inequality of community composition and economic status related to demographic characteristics. Control variables are other factors that theoretically affect the susceptibility of traffic accidents, including racial composition of geographic units and employment.

Factors related to the social environment include the proportion of ethnic minorities and the median household income. Please note that we define the minority population as a non white population because this population group is socially and politically disadvantaged relative to the white population. Metrics that are positively related to the road environment include "NON", "IS", "NIS", "SC", "ON", "AIC", "PA MAP-21". We rank the above seven indicators from low to high according to the road grade, in which "NON" is the lowest road grade and "PA MAP-21" is the highest road grade. Indicators related to the population composition of the community include: "Hispanic" means the largest minority group in the United States; "white" also known as the Europa race, Caucasian race, located in the second most populous ethnic group; "black" is long to the social vulnerable group due to the existence of racial discrimination; "Asian" living in California are the fourth largest population in the United States. Indicators related to regional economic and income levels include: "OP1" used to describe the industry with the largest number of employees in a region; "OP2" used to describe the second largest employment sector in the region; "OP3" used to describe the region's third largest employment sector.

4. Results

4.1. Study area and statistical analysis

Fig. 1 shows the spatial distribution of freight-related crashes in California area. California is a state along the Pacific coast in the west of the United States, with a population of 39.3 million and a total area of 423970 square kilometers. It is obvious that in addition to the communities in large cities, some freight related accident hotspots are distributed in other areas. Therefore, the spatial distribution pattern of freight accidents has little relationship with the urban structure of the region. Some communities with large traffic volume close to major cities do not necessarily have high risks, and freight related collisions are affected by spatial inequality. In this study, the spatial unit of analysis is the census area, which is the smallest spatial unit available for census data. Data on traffic accidents, ethnic composition, employment characteristics, traffic flow and other variables were collected. Variables related to the driving environment, such as geographical location, road type and quantity, are collected from the open street map.

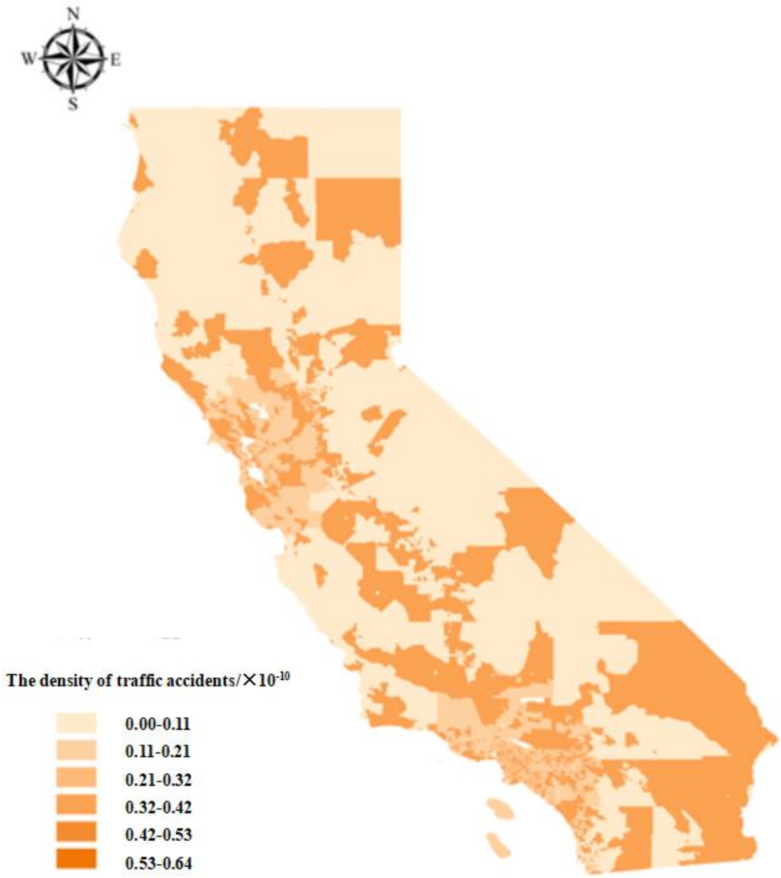

Figure 1. Spatial distribution of freight-related crashes in the California area

For different geographical locations, different geographical numbers are used to distinguish. Table I shows descriptive statistical data. Count the number of traffic accidents in different geographical locations, and divide the number of traffic accidents in a geographical location by the area of the region to obtain the density of traffic accidents in the region. Traffic accident density uses the total number of traffic accidents in a geographical unit over a period of time divided by the area of the geographical location. In order to make the experimental results significant, the results after division are removed from the LN value. According to the availability of variables in traffic accident data, we selected the geographical location where the LN value of traffic accident density is greater than 1 as the traffic accident sensitive area.

Incorporate passenger car traffic density and truck traffic density into the model as a measure of passenger car traffic and truck traffic. The measure is calculated based on the volume of passenger and truck traffic in each geographic location and the area of the different geographic locations. Besides, according to different geographical locations, the types and quantities of roads of various grades in the area are counted. Finally, seven main road grades are obtained from high to low as "NON", "IS", "NIS", "SC", "ON", "AIC" , "PA MAP-21". Different levels of roads differ in terms of traffic functions, speed limits, and road widths. We calculated the densities of roads in different classes for each geographic location by dividing the number of crashes by the area of roads in each class. Because the number of roads of each level in different geographical locations is different and the sample data of each group is relatively close, in order to obtain significant results, the LN value of each group of data is taken into the model for calculation. According to the standard deviation in the table, the degree of discrete distribution of the average value of each level of road can be obtained. Among them, the road standard deviation of the "NON" level is 0.83, with the largest degree of dispersion; "AIC: The road standard deviation of the level is 0.10, and the degree of dispersion is the smallest. According to the ranking of road grades from high to low, it is more appropriate to select the middle-grade road grade indicator "SC" as the reference group, and focus on testing the other six groups in traffic flow. Whether the spatial distribution of accident-sensitive occurrences differs from the reference group.

Ethnic composition and employment characteristics were included as control variables in the model. For the racial composition, we divided the residents of California into two categories according to the local social background, namely the white and the minority population. For ethnic minorities, according to statistics, three ethnic groups with a large number of people are selected for research, namely Hispanic, yellows, and blacks. Among them, the Hispanic population is the largest and the black population is the smallest. At the same time, for the employment characteristics of people in this region, this study counts three industries with a large number of people as a research reference.

Table 1. Descriptive Statistics of Variables

Variable	Trends and degrees of dispersion in data sets		
	Description	Mean	Std. Dev.
Traffic accident occurrence density(collision/square)	Describe the specific circumstances of traffic accidents in different geographical locations(collision/square)	3.21×10^{-8}	1.39×10^{-7}
AADT	Bus traffic flow	10.09	4.90
AADTT	Truck traffic flow	7.64	3.96
NON	Not on the road of the national highway system	0.34	0.83
IS	A road connecting two states	0.15	0.41
NIS	A network of strategic highway corridors that are not within the boundaries of interstates	0.08	0.37
SC	Roads connecting to the strategic highway corridor network	0.01	0.15
ON	Other roads in the national highway system	0.16	0.49
AIC	Prescribed state-to-state highways	0.02	0.10
PA MAP-21	Roads that carry a lot of traffic under MAP-21	0.84	0.73
Hispanic	Largest minority group in the United States	7.06	1.12
White	Also known as the Europa race, Caucasian race, located in the second most populous ethnic group	7.02	1.33
Black	Due to the existence of racial discrimination, they belong to the social vulnerable groups	4.38	1.93
Asian	Asians living in California are the fourth largest population in the United States	5.51	1.77
OP1	Used to describe the industry with the largest number of employees in a region	2.24	2.23
OP2	Used to describe the second largest employment sector in the region	4.00	1.85
OP3	Used to describe the region's third largest employment sector	1.76	1.86

4.2. Results

OLS results in Table II show that NON, IS, NIS, and ON have a significant negative effect on the increase in the density of traffic accidents. Areas that are not densely populated by motorways, interstates, road corridor networks, connecting routes of road corridor networks and other low-level roads tend not to experience high accident densities, probably due to the low density of traffic activity and vehicle activity on these roads. In addition, the increase in trunk roads has a significant negative effect on the increase in crash density, with areas with more new trunk roads being less likely to have crashes. The addition of trunk roads somewhat reduces the density of traffic in the city and reduces the density of traffic activity on the trunk roads, resulting in a lower number of traffic accidents. The increase in the total number of people in the area has a significant positive effect on the increase in the density of traffic accidents. The total number of people reflects urban density, and an increase in urban density leads to more conflicts between vehicles, cyclists and pedestrians, resulting in more crashes.

When specifically analyzing the effect of total number of people on the occurrence of crashes, areas with high income group such as Caucasian are less likely to have crashes. In contrast, areas where people of color with lower economic status, such as Blacks and Asians, are concentrated are regularly involved in traffic accidents. Finally, the increase in total regional employment has a significant positive effect on the increase in the density of traffic accidents. When analyzing this effect specifically, the risk of accidents is significantly higher in regions with a high density of employment in transport, while differences in employment in services and logistics have a statistically insignificant effect on the occurrence of accidents.

Table 2. Results of OLS Model

Variable	Coefficient	Std. Error
AADT	-7.65×10^{-10}	1.62×10^{-9}
AADTT	2.88×10^{-9}	2.30×10^{-9}
NON	-2.60×10^{-9}*	1.35×10^{-9}
IS	-1.38×10^{-8}***	3.66×10^{-9}
NIS	-1.28×10^{-8}***	2.92×10^{-9}
SC	-8.28×10^{-9}**	3.59×10^{-9}
ON	-1.29×10^{-8}***	2.18×10^{-9}
AIC	-8.75×10^{-9}	1.17×10^{-8}
PA MAP-21	-1.15×10^{-8}***	2.65×10^{-9}
total	1.31×10^{-8}*	7.78×10^{-9}
Hispanic	-1.51×10^{-8}***	5.85×10^{-9}
White	-2.14×10^{-8}***	3.63×10^{-9}
Black	5.39×10^{-9}***	7.98×10^{-10}
Asian	2.88×10^{-9}***	9.29×10^{-10}
OP	1.13×10^{-8}***	2.35×10^{-9}
OP1	1.19×10^{-9}	8.45×10^{-10}
OP2	2.33×10^{-9}***	7.50×10^{-10}
OP3	-6.92×10^{-10}	1.98×10^{-9}
cons	5.41×10^{-8}**	2.10×10^{-8}

Standard errors in parentheses
$^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

4.3. Disccusion

Table III shows the results of applying spatial Dobbin model (SDM) to analyze the influencing factors of traffic accidents in California. Compared with the OLS model, the SDM results show that although the coefficients of a considerable number of variables show different statistical significance, only a few parameters(AADT, Hispanic) show sign changes. This indicates that when we control spatial autocorrelation, the importance of predicting the collision rate of a certain variable with respect to trucks may change. According to the explanatory variables we obtained, the results of the spatial Dobbin model can present a more accurate relationship.

Table 3. Results of SDM Model

Item	Variable	Coefficient	Std. Error
Main	AADT	-7.65×10^{-10}	0.62×10^{-9}
	AADTT	3.568×10^{-9}***	1.30×10^{-9}
	NON	-2.64×10^{-9}*	1.75×10^{-9}
	IS	-2.38×10^{-8}***	2.66×10^{-9}
	NIS	1.28×10^{-8}***	2.92×10^{-9}
	SC	-6.28×10^{-9}**	3.59×10^{-9}
	ON	-1.29×10^{-8}***	2.18×10^{-9}
	AIC	-8.75×10^{-9}	1.17×10^{-8}
	PA MAP-21	1.15×10^{-8}***	2.65×10^{-9}
	total	1.31×10^{-8}*	7.78×10^{-9}
	Hispanic	-1.51×10^{-8}***	5.85×10^{-9}
	White	-2.14×10^{-8}***	3.63×10^{-9}
	Black	5.39×10^{-9}***	7.98×10^{-10}
	Asian	2.88×10^{-9}***	9.29×10^{-10}
	C000	1.13×10^{-8}***	2.35×10^{-9}
	CNS05	1.19×10^{-9}	8.45×10^{-10}
	CNS07	2.33×10^{-9}***	7.50×10^{-10}
	CNS08	-6.92×10^{-10}	1.98×10^{-9}
	cons	5.41×10^{-8}**	2.10×10^{-8}
Spatial	AADT	3.72×10^{-9}	9.62×10^{-9}
	AADTT	0.568×10^{-9}***	3.30×10^{-9}
	NON	-2.64×10^{-9}*	4.62×10^{-9}
	IS	-2.38×10^{-8}***	2.06×10^{-9}
	NIS	1.99×10^{-8}***	2.02×10^{-9}
	SC	-6.28×10^{-9}**	3.00×10^{-9}
	ON	-1.29×10^{-9}	2.66×10^{-9}
	AIC	-8.66×10^{-9}	1.99×10^{-8}
	PA MAP-21	4.15×10^{-8}	2.65×10^{-9}
	total	8.31×10^{-8}*	7.78×10^{-9}
	Hispanic	4.51×10^{-8}***	5.85×10^{-9}
	White	-2.14×10^{-8}***	3.88×10^{-9}
	Black	5.39×10^{-9}***	7.88×10^{-10}
	Asian	3.88×10^{-9}***	9.29×10^{-10}
	OP	1.63×10^{-8}***	2.35×10^{-9}
	OP1	4.19×10^{-9}	9.45×10^{-10}
	OP2	8.33×10^{-9}	9.50×10^{-10}
	OP3	-6.92×10^{-10}	7.98×10^{-9}
	cons	0.65×10^{-8}**	8.10×10^{-8}

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5. Conclusion

The study examined whether freight related accident risks are proportionally distributed among low-income and minority communities in California. Low income and ethnic minority communities tend to have higher freight related collision risk, as measured by "traffic incident occurrence density". Passenger traffic flow, freight traffic flow, number of roads of different grades and types and employment characteristics are also related to more freight collisions. The control variables refer to other factors that affect the occurrence of traffic accidents. The control variables in this paper are the ethnic composition and employment characteristics of geographical units. After controlling for these variables, household income and the percentage of minority population were still significantly correlated with freight related collisions. Studies have shown that freight related traffic accidents are more likely to occur in low-income and minority communities. There may be other factors in these neighborhoods, such as lack of freight infrastructure. Local communities can take measures to mitigate road safety threats. For example, the installation of speed limit signs for trucks or the holding of road safety community seminars related to freight can mitigate the impact of frequent movement of freight vehicles. For the entire transport network, regional traffic managers need to conduct more research and Analysis on road safety related to freight transport, so as to enhance the understanding of the behavior of freight vehicle drivers and further prevent freight transport related accidents in local communities, especially low-income or ethnic minority communities.

This study emphasizes the key role of freight transport in road safety outcomes and reveals the inequities in the distribution of road safety outcomes in freight transport. The results of this study may be applicable to other geographical environments, but specific research on the problem is required. There are several possible extensions to this study. First, a detailed analysis of different types of freight related collisions and factors will help to better understand the freight collision results and factors at the community level. Secondly, the variables used in the study are mainly limited to the resident demographic data extracted from the US census, and the infrastructure and land use variables extracted from the public data set. Finally, the addition of extraction variables related to transport networks will help us better understand the relationship between freight related collisions and surrounding features.

References

[1] Krishna N.S. Behara, Alexander Paz, Owen Arndt and Douglas Baker, "A random parameters with heterogeneity in means and Lindley approach to analyze crash data with excessive zeros: A case study of head-on heavy vehicle crashes in Queensland," Accident Analysis & Prevention, Volume 160, 2021, 106308, ISSN 0001 - 4575.

[2] Mohamed Abdel-Aty, Jaeyoung Lee, Chowdhury Siddiqui and Keechoo Choi, "Geographical unit-based analysis in the context of transportation safety planning," Transportation Research Part A: Policy and Practice, Volume 49, 2013, Pages 62 - 75, ISSN 0965 - 8564.

[3] Peng Chen and Jiangping Zhou, "Effects of the built environment on automobile-involved pedestrian crash frequency and risk," Journal of Transport & Health, Volume 3, Issue 4, 2016, Pages 448 - 456, ISSN 2214 - 1405.

[4] Yiyi Wang and Kara M. Kockelman, "A Poisson-lognormal conditional-autoregressive model for multivariate spatial analysis of pedestrian crash counts across neighborhoods," Accident Analysis & Prevention, Volume 60, 2013, Pages 71 - 84, ISSN 0001 - 4575.

[5] Chunjiao Dong, Shashi S. Nambisan, Stephen H. Richards and Zhuanglin Ma, "Assessment of the effects of highway geometric design features on the frequency of truck involved crashes using bivariate regression," Transportation Research Part A: Policy and Practice, Volume 75, 2015, Pages 30 - 41, ISSN 0965 - 8564.

[6] Narayanamoorthy, Sriram & Paleti, Rajesh & Bhat and Chandra, "On Accommodating Spatial Dependence in Bicycle and Pedestrian Injury Counts by Severity Level," Transportation Research Part B: Methodological. 55. 10.1016/j.trb.2013.07.004.

[7] Linglin Ni, Xiaokun (Cara) Wang, Dapeng Zhang, "Impacts of information technology and urbanization on less-than-truckload freight flows in China: An analysis considering spatial effects," Transportation Research Part A: Policy and Practice, Volume 92, 2016, Pages 12 - 25, ISSN 0965 - 8564.

[8] Chao Yang, Mingyang Chen and Quan Yuan, "The geography of freight-related accidents in the era of E-commerce: Evidence from the Los Angeles metropolitan area," Journal of Transport Geography, Volume 92, 2021, 102989, ISSN 0966 - 6923.

[9] Kevin Manaugh, Madhav G. Badami and Ahmed M. El-Geneidy, "Integrating social equity into urban transportation planning: A critical evaluation of equity objectives and measures in transportation plans in North America," Transport Policy, Volume 37, 2015, Pages 167-176, ISSN 0967 - 070X.

[10] József Benedek, Silviu Marian Ciobanu and Titus Cristian Man, “Hotspots and social background of urban traffic crashes: A case study in Cluj-Napoca (Romania),” Accident Analysis & Prevention, Volume 87, 2016, Pages 117 - 126, ISSN 0001 - 4575.

[11] Mohamed M. Ahmed, Rebecca Franke, Khaled Ksaibati and Debbie S. Shinstine, “Effects of truck traffic on crash injury severity on rural highways in Wyoming using Bayesian binary logit models,” Accident Analysis & Prevention, Volume 117, 2018, Pages 106 - 113, ISSN 0001 - 4575.

[12] Lindsay M. Braun, Daniel A. Rodriguez and Penny Gordon-Larsen, “Social (in)equity in access to cycling infrastructure: Cross-sectional associations between bike lanes and area-level sociodemographic characteristics in 22 large U.S. cities,” Journal of Transport Geography, Volume 80, 2019, 102544, ISSN 0966 - 6923.

[13] Caislin L. Firth, Kate Hosford and Meghan Winters, “Who were these bike lanes built for? Social-spatial inequities in Vancouver's bikeways, 2001–2016,” Journal of Transport Geography, Volume 94, 2021, 103122, ISSN 0966 - 6923.

[14] Quan Yuan and Jueyu Wang, “Goods movement, road safety, and spatial inequity: Evaluating freight-related crashes in low-income or minority neighborhoods,” Journal of Transport Geography, Volume 96, 2021, 103186, ISSN 0966 - 6923.

[15] Xiao Li, Siyu Yu, Xiao Huang, Bahar Dadashova, Wencong Cui and Zhe Zhang, “Do underserved and socially vulnerable communities observe more crashes? A spatial examination of social vulnerability and crash risks in Texas,” Accident Analysis & Prevention, Volume 173, 2022, 106721, ISSN 0001 - 4575.