



Article

Impact of Rainfall on Traffic Speed in Major Cities of China

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Abstract: The construction of healthy transportation is an important ingredient for promoting the healthy development of cities. The establishment of an urban traffic evaluation mechanism can provide an important basis for the construction of healthy transportation. This study focused on the impact of precipitation on traffic speed and developed an urban traffic vulnerability index. This index reflects the degree of traffic affected by precipitation, which is calculated based on the traffic congestion index under different rainfall intensities. The traffic vulnerability indices of 41 major cities in China under rainfall conditions were evaluated. Based on the above traffic vulnerability indexes, the impact of socioeconomic factors on urban traffic vulnerability was analyzed. The three key findings of this study are as follows: there was a positive correlation between the vulnerability index and the gross domestic product (GDP); the urban population (POP) had a significant impact on the urban traffic vulnerability; and urban car ownership had little impact on traffic vulnerability. Based on these findings, possible measures to improve urban traffic vulnerability are proposed. The construction of an index system provides a basis for enhancing the urban traffic assessment mechanism, promoting the development of urban physical examinations and building healthy transportation and healthy cities.



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1. Introduction

Since the reform and opening up, China has experienced over 40 years of rapid development in urbanization. According to the Statistical Communiqué of the People's Republic of China on 2020 National Economic and Social Development [1], the urbanization rate of the population in China exceeded 60% in 2020. The urbanization process helps to alleviate uneven development in urban and rural areas, improve living environments, and enhance the quality of life for people; it is an important aspect of high-quality socioeconomic development [2,3]. In addition, the urbanization process also encounters the emergence of some challenges, e.g., environmental pollution, traffic congestion, shifts in lifestyle and diet, the transmission of infectious diseases, and employment issues [4–6]. These problems caused by rapid urbanization have an impact on human health and health equality of urban areas [5,7–9]. In response to this challenge, in 1994, the World Health Organization (WHO) proposed the concept of healthy cities, which are “continually creating and improving those physical and social environments and expanding those community resources which enable people to mutually support each other in performing all the functions of life and developing to their maximum potential” [10]. During the urbanization process, China constantly seeks high-quality development and takes measures to build healthy cities [11,12]. For example, the Chinese government has issued the Healthy China 2030 Planning Outline [13]. The Ministry of Housing and Urban-Rural Development has launched the Urban Physical Examination and has established the Urban Physical Examination Evaluation Mechanism [14].

Urban traffic health is closely related to urban health. Urban traffic involves land planning and utilization, vehicles, and energy [15,16], and it is related to social governance, ecological environment, and human well-being [17–20]. In recent years, due to rapid development in urbanization and population growth, urban traffic problems have become increasingly apparent [21]. These have increased travel costs, environmental pollution, and substantial economic losses [22]. Therefore, the promotion of the healthy development of urban traffic has a profound impact on building a healthy city and promoting the sustainable development of a city [17,23,24].

To promote the construction of healthy urban transportation, an important aspect is to construct an urban traffic assessment mechanism. The existing urban traffic assessment methods have primarily focused on convenience, efficiency, and accessibility in traffic travel, and they have quantitatively evaluated the health level of urban traffic at a microscopic scale (e.g., roads and regions) [21,25–27]. Nevertheless, an evaluation of the urban traffic response capability under emergency conditions has been limited, especially for unexpected weather events [28]. Therefore, this study focused on the vulnerability of urban traffic and analyzed the impact of rainfall on urban traffic vulnerability [29–31]. This study used cities as the research unit to construct an urban traffic vulnerability evaluation index system to examine the coping abilities of China's major first-tier, new first-tier, and second-tier cities under weather events. This index system provides a basis for enriching the urban physical examination evaluation mechanism, promoting the development of urban physical examination, and building healthy transportation and healthy cities.

2. Study Area and Data Preprocessing

2.1. Study Area

The research area covered China's major first-tier cities, new first-tier cities, and second-tier cities, including 4 first-tier cities (Beijing, Shanghai, Guangzhou, and Shenzhen), 13 new first-tier cities (Chengdu, Hangzhou, Chongqing, Wuhan, Xi'an, Suzhou, Tianjin, Nanjing, Zhengzhou, Dongguan, Qingdao, Shenyang, and Ningbo), and 24 second-tier cities (Wuxi, Foshan, Hefei, Fuzhou, Xiamen, Harbin, Jinan, Wenzhou, Nanning, Changchun, Quanzhou, Guiyang, Nanchang, Jinhua, Changzhou, Nantong, Jiaxing, Taiyuan, Xuzhou, Huizhou, Zhongshan, Taizhou, Shaoxing, and Yangzhou), for a total of 41 cities.

The study area spanned the primary densely populated areas in China, encompassing first-tier, new first-tier, and second-tier cities with different levels of development. There were various climate types, including dry areas in the north and wet areas in the south. The cities considered in this study had a wide latitude coverage, including the northernmost city, called Harbin ($45^{\circ}45'N$), and Zhongshan ($22^{\circ}52'N$) in the south (Figure 1).

2.2. Data Preprocessing

2.2.1. Collection and Preprocessing of the Traffic Data

The traffic data used in this study were primarily derived from the Baidu Map Smart Transportation Platform (<https://jiaotong.baidu.com/>, accessed on 23 January 2021). Based on real-time traffic information and a unified algorithm, the platform calculates the traffic congestion index and average speed for major cities in China.

The “traffic congestion index” was used as a measure of urban traffic conditions, which was calculated as the ratio of the actual travel time to the unobstructed travel time. A large traffic congestion index meant high traffic congestion, and vice versa [32,33]. The time coverage of the traffic data was two years (i.e., from 1 January 2018 to 31 December 2019), and the time resolution was one hour. The spatial coverage was the urban-level traffic operation indicators of the 41 major first-tier cities, new first-tier cities, and second-tier cities in China. The data contained several advantages, i.e., long durations, wide spatial coverages, and high temporal resolutions.

In general, traffic conditions exhibit periodic change patterns in time and space and experience change patterns in different periods (e.g., month, week, and day). To eliminate the influence of the periodic changes in traffic conditions of working and non-working

days on the results, the traffic data of working days in the 41 cities during 2018–2019 were selected in order to remove the changes in traffic conditions caused by the morning and evening rush hours of the day. The hourly traffic congestion index was averaged throughout the working day, and finally, the daily average of the traffic congestion of a working day was obtained.



Figure 1. Distribution map of the study area.

2.2.2. Collection and Preprocessing of Rainfall Data

The rainfall data were sourced from NASA's Global Precipitation Measurement (<https://gpm.nasa.gov/data/directory>, accessed on 15 January 2021), which adopts satellite observations to gather precipitation information with high spatial resolution and a wide spatial coverage (global coverage). By using the multi-satellite inversion, grid data with high temporal resolution (half-hour precipitation, daily precipitation, and monthly average precipitation) were acquired. In addition, the Global Precipitation Measurement (GPM) data have a high observation accuracy for low precipitation and solid-state precipitation, a strong ability to capture heavy rainfall, and a high accuracy and high temporal and spatial resolution [34].

In this study, the latitude and longitude coordinates of the 41 first-tier and second-tier cities in China were used to obtain the daily precipitation data of the grid point where each city was located. The time coverage of the data was from 1 January 2018 to 31 December 2019. The time resolution was one day, the spatial resolution was $0.1^\circ \times 0.1^\circ$, and the unit was mm/day.

2.2.3. Collection and Preprocessing of Socioeconomic Data

The socioeconomic data used in this study were derived from the Statistical Communique of the People's Republic of China on the 2019 National Economic and Social Development [35] issued by the statistical bureaus of the above 41 cities. Population (POP), gross domestic product (GDP), and car ownership data from the report were utilized to measure the level of socioeconomic development of the different cities.

3. Research Methods

3.1. Establishment of the Traffic Vulnerability Evaluation Index

To evaluate the response of the different cities to different rainfall intensities, an urban traffic vulnerability evaluation index in response to rainfall conditions was developed. In this study, we used the daily precipitation and the daily average vehicle speed (traffic congestion index) to establish the traffic vulnerability evaluation index. There are some implications for the evaluation at the daily scale. After precipitation ends, its impact on traffic will still last for a while (dredging of road surface water and evacuation of traffic congestion), and multiple precipitation events can occur in one day. The daily average impact can be assessed by using the daily precipitation and the traffic congestion index. The basic idea of the evaluation index is described below (Figure 2). After performing the rainfall classification, the average value of the traffic congestion index under each precipitation category was calculated. The average value of the traffic congestion index and the rainfall category after the classification statistics were analyzed using regression analysis. The obtained regression coefficient was considered the traffic vulnerability index of the urban traffic affected by rainfall.

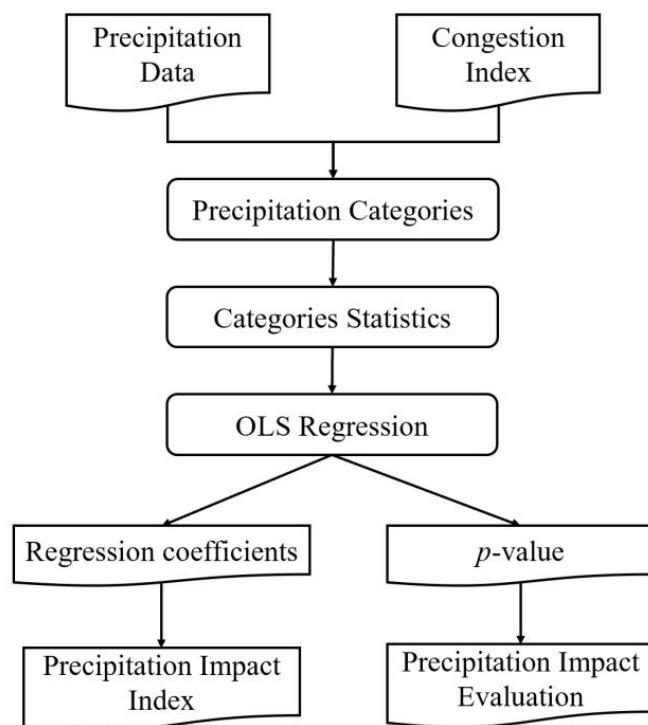


Figure 2. Flow chart of the construction of the traffic vulnerability evaluation index.

3.2. Rainfall Classification and Statistical Analysis

Rainfall refers to the depth of rain falling on a horizontal surface of an area during a specific period. For example, daily rainfall refers to the total amount of rain falling on the horizontal surface of an area in a day in mm/day [36,37].

Within the variation range of the rainfall intensity of each city, the variation range of the rainfall intensity was divided evenly according to the classification interval. Then, the average value of the urban traffic congestion index during each rainfall interval was calculated. In this way, the urban traffic congestion index values of the different cities under different rainfall intervals were obtained.

$$N = (max - min) / interval \quad (1)$$

where N represents the grading number of a city, \max represents the maximum daily rainfall of a city from 2018–2019, \min represents the minimum daily rainfall of a city from 2018–2019, and $interval$ represents the minimum interval of the grading statistics. To refine and investigate the congestion index of the different rainfall intensities, this study used 1 mm as the minimum interval for classification.

The results of the above classification statistics enabled a comparison (between cities) of the operation of urban traffic in the different cities under the same rainfall intensity. The urban traffic conditions of the same city under the different rainfall intensities were longitudinally compared.

3.3. Ordinary Least Squares (OLS) Regression Analysis

A regression analysis was utilized to analyze the correlation between variables. The ordinary least squares (OLS) method is a linear regression method used to estimate the least squares of unknown parameters in a model. According to the principle of least squares, the OLS determines the parameters of a set of linear functions of explanatory variables so as to achieve the minimum sum of squares of the residuals between the observed dependent variable and the predicted values.

Suppose a set of data, X , is given as follows:

$$X = \{(x_1, y_1), (x_2, y_2) \dots (x_n, y_n)\} \quad (2)$$

A straight line Equation (3) is obtained by the OLS to fit the points in the data, X , and satisfy the minimum residual sum of squares (RSS) Equation (4). The purpose is to minimize the difference between the true value and the predicted value. It is noted that x_i is the independent variable, y_i is the dependent variable, and k and $\hat{\beta}$ are the parameters that need to be determined using the least square method (also known as the regression coefficients), where k is the slope coefficient and $\hat{\beta}$ is the intercept coefficient.

$$y = xk + \hat{\beta} \quad (3)$$

$$RSS = \sum_{i=0}^n (y_i - x_i \hat{\beta})^2 \quad (4)$$

Hypothesis testing was performed on the results of the regression analysis. A value of $p < 0.05$ was considered statistically significant.

In this vulnerability evaluation index, the slope of the regression coefficient represents the degree of influence of the rainfall intensity on the urban traffic congestion index, i.e., the traffic vulnerability index.

4. Research Results

4.1. Results of the Traffic Vulnerability Evaluation

First, the daily rainfall intensities (1 mm) of working days in the 41 first-tier, new first-tier cities, and second-tier cities in China from 1 January 2018 to 31 December 2019 were classified. The daily averages of the traffic congestion index were counted, and a scatter plot was constructed (Figure 3). The order of the subfigures was arranged according to the tier of the city development (first-tier, new first-tier, and second-tier cities), and each tier was arranged from the north to the south according to the latitude of the city.

For each city, an OLS regression analysis was performed on the result of a hierarchical statistical scatter plot to obtain the k value of the traffic vulnerability index and the p -value of the significance test. Then, the OLS fitting line graph was constructed. The main parameters of OLS regression (slope k , intercept $\hat{\beta}$, p -value, and t -value) are summarized in Table A1 in Appendix A, using only the parameters of k and p -value. We also conducted residual normality test QQ plots to evaluate the fit (Figure A1 in Appendix B).

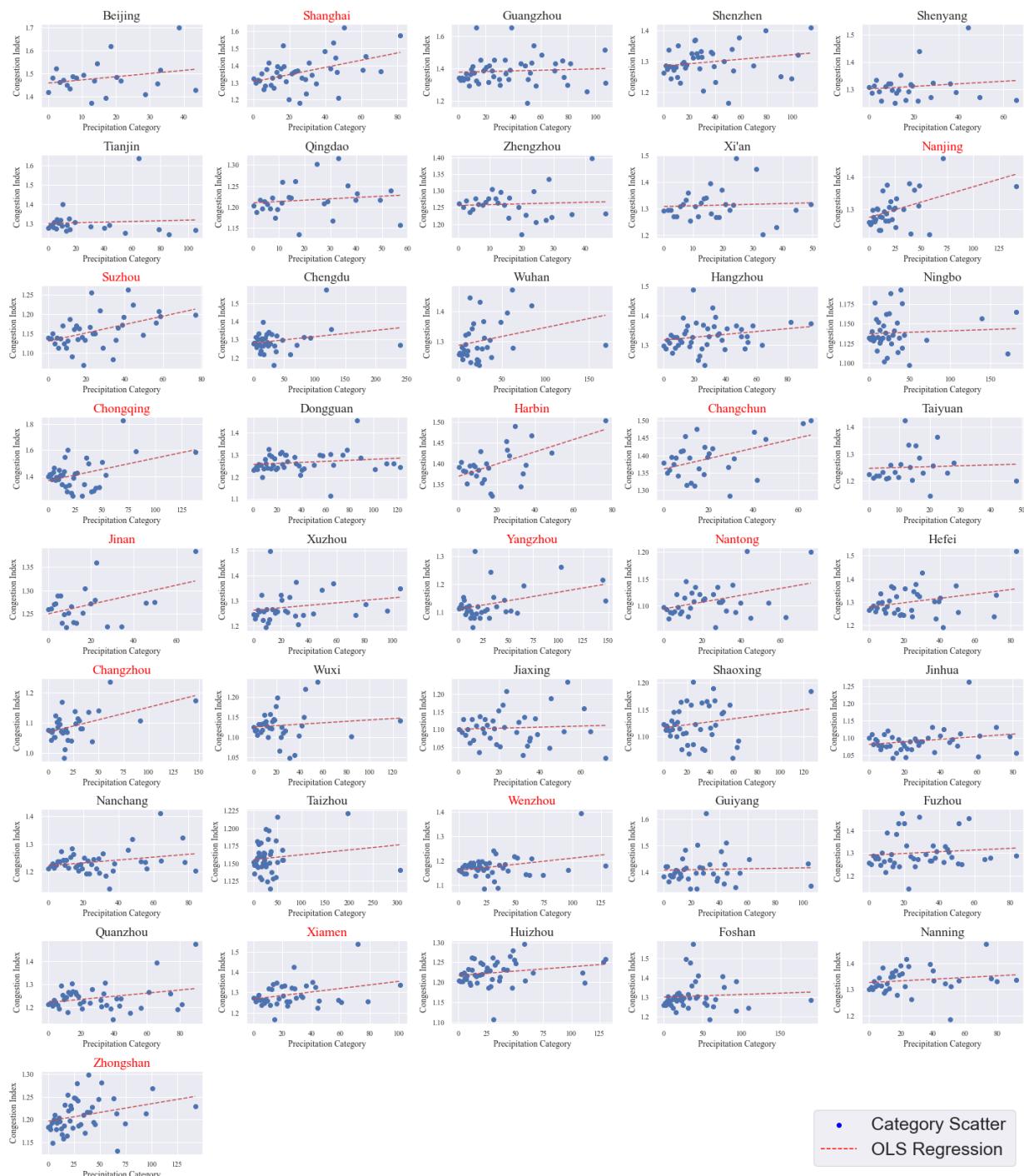


Figure 3. Statistical scatter plots and the ordinary least squares (OLS) regression analysis plots of the rainfall intensities and traffic congestion indexes of the 41 cities.

For the subfigures of the cities marked in red in Figure 3, there was a correlation between the traffic congestion index and the rainfall intensity. The urban traffic was affected by precipitation; thus, the traffic vulnerability was relatively high. For the subfigures of the cities marked in black, there was no correlation between the congestion index and the rainfall intensity. Hence, the urban traffic was not affected by rainfall, and thus the traffic vulnerability was low.

The k values of the traffic vulnerability index and the p -values of the significance tests for the 41 first-tier, new first-tier cities, and second-tier cities in China were then calculated (Table 1).

Table 1. The traffic vulnerability indices (k) of the 41 cities.

City Name	Traffic Vulnerability Index k	p	City Name	Traffic Vulnerability Index k	p
Beijing	0.0014	0.2780	Xuzhou	0.0005	0.2115
Shanghai	0.0021	0.0027	Yangzhou	0.0006	0.0204
Guangzhou	0.0002	0.6306	Nantong	0.0006	0.0251
Shenzhen	0.0004	0.1661	Hefei	0.0009	0.0590
Shenyang	0.0005	0.5116	Changzhou	0.0008	0.0035
Tianjin	0.0002	0.7588	Wuxi	0.0002	0.5085
Qingdao	0.0003	0.4993	Jiaxing	0.0002	0.7128
Zhengzhou	0.0002	0.7375	Shaoxing	0.0003	0.2204
Xi'an	0.0003	0.7609	Jinhua	0.0004	0.1341
Nanjing	0.0009	0.0033	Nanchang	0.0005	0.0774
Suzhou	0.0011	0.0026	Taizhou	0.0001	0.3086
Chengdu	0.0004	0.1228	Wenzhou	0.0005	0.0341
Wuhan	0.0006	0.1078	Guiyang	0.0001	0.8110
Hangzhou	0.0005	0.1339	Fuzhou	0.0004	0.4845
Ningbo	0.0000	0.6817	Quanzhou	0.0007	0.0667
Chongqing	0.0017	0.0142	Xiamen	0.0009	0.0429
Dongguan	0.0002	0.2623	Huizhou	0.0002	0.1346
Harbin	0.0015	0.0017	Foshan	0.0001	0.6547
Changchun	0.0015	0.0120	Nanning	0.0003	0.3509
Taiyuan	0.0003	0.7989	Zhongshan	0.0004	0.0341
Jinan	0.0010	0.0347			

The traffic vulnerability indices in the cities passing the significance test are marked in bold.

The abovementioned urban traffic vulnerability evaluation results indicate that among China's first-tier, new first-tier cities, and second-tier cities, a total of 13 cities (i.e., Shanghai, Nanjing, Suzhou, Chongqing, Harbin, Changchun, Jinan, Yangzhou, Nantong, Changzhou, Wenzhou, Xiamen, and Zhongshan) showed significant correlations. In addition, they were significant in the OLS regression analysis (cities marked in red). These results indicate that there was a correlation between the traffic congestion index and the rainfall intensity for these cities. Therefore, urban traffic was significantly affected by rainfall, and the ability to cope with rainfall events was relatively poor. Hence, the urban traffic was relatively fragile for these cities. Moreover, for these cities, a greater value of the traffic vulnerability index, k , meant that the urban traffic congestion index changed faster with an increase in the rainfall intensity, and the traffic was strongly affected by precipitation. For example, Shanghai (a first-tier city) and Chongqing (a new first-tier city) had relatively large traffic vulnerability index k values; hence, both were more vulnerable to urban traffic (compared with Nanjing and Suzhou) under rainfall conditions. Some second-tier cities, such as Harbin, Changchun, and other northeastern cities had relatively large traffic vulnerability indexes, k , and experienced relatively high traffic vulnerabilities compared with other second-tier cities that passed the significance test (e.g., Jinan, Yangzhou, Nantong, Changzhou, Wenzhou, Xiamen, and Zhongshan). In addition, the remaining 28 cities (cities marked in black) showed no correlation between the traffic congestion index and the rainfall intensity for these cities. For these cities, there was no impact of rainfall on urban traffic, and the ability to cope with rainfall events was relatively strong.

4.2. Analysis of the Correlation between Traffic Vulnerability and Socioeconomic Factors

4.2.1. Economic Factor (GDP)

The gross domestic product (GDP), i.e., the market value of all final products produced in a specific region within a certain period, is often used to measure the economic level and social development of a region. By combining the GDP (as an economic measure) with the traffic vulnerability evaluation index, k , this section further investigates whether the level of socioeconomic development has an impact on the urban traffic vulnerability and whether the level of the urban traffic health develops simultaneously with socioeconomic development [38,39].

Depending on the city tier development, all of the 41 cities were classified into first-tier, new first-tier, and second-tier cities. A GDP-vulnerability index scatter diagram was prepared (Figure 4a), and an OLS regression analysis was performed. We also performed residual normality test QQ plots to evaluate the fit (Figure A2). The main parameters of OLS regression (slope k , intercept α , p -value, and t -value) are summarized in Table A2; we only use parameters of k and p -value there. The results show that there was a positive correlation between the GDP and the vulnerability index, indicating that GDP development had a low degree of improvement on urban traffic vulnerability. The health of urban traffic did not develop simultaneously with GDP development. Urban traffic vulnerability still requires more in-depth investigations.

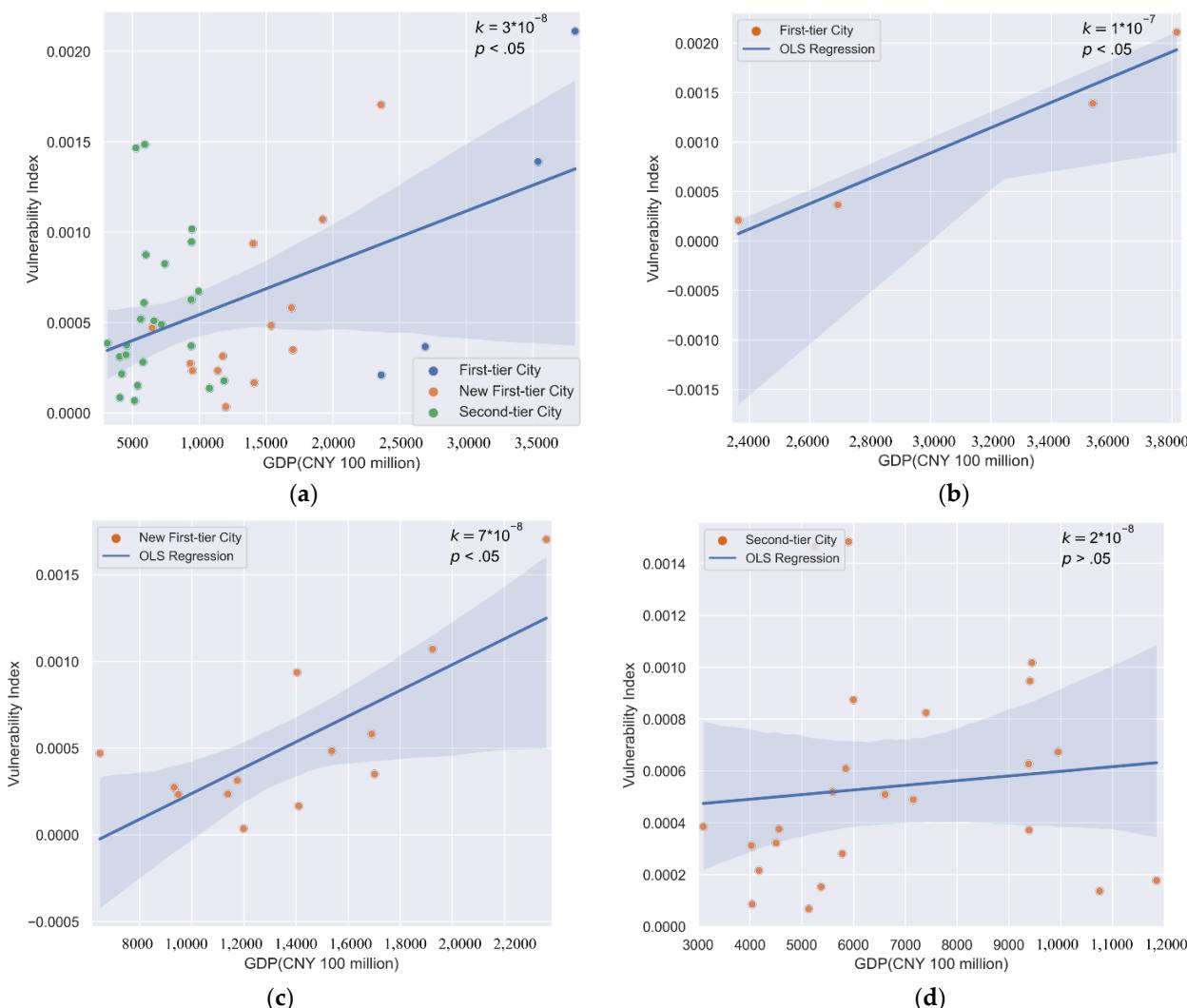


Figure 4. Correlation analysis of the gross domestic product (GDP)-traffic vulnerability indexes: (a) all cities GDP-traffic vulnerability index OLS analysis; (b) first-tier cities GDP-traffic vulnerability index OLS analysis; (c) new first-tier cities GDP-traffic vulnerability index OLS analysis; (d) second-tier cities GDP-traffic vulnerability index OLS analysis.

Correlation analysis of the GDP-traffic vulnerability index was performed for each tier of cities (Figure 4b–d). The results show that GDP growth produced very small improvements in traffic vulnerability. In addition, there was even a trend of GDP growth and vulnerability enhancement for the first-tier and new first-tier cities; this indicated that the development of the economy had not simultaneously produced healthier urban traffic. There is still an opportunity for improvement in the ability of urban traffic to cope with rainfall and other weather conditions, and the vulnerability of urban traffic requires further improvements. A regression analysis of the second-tier cities did not pass the significance test, and the correlation between the GDP and the traffic vulnerability index was weak.

4.2.2. Population Factor (POP)

The urban population refers to the total number of permanent residents in a city, which is an important indicator to measure the level of urban social development. With the development of urbanization, some large cities and even megacities (i.e., cities with more than ten million urban residents) have emerged in China. By the end of 2019, China's megacities included Shanghai, Beijing, Guangzhou, Shenzhen, Tianjin, and Chongqing. Due to an increase in the population, this is bound to result in more travelers and a higher travel demand [40–42]. Therefore, this section utilizes population as an indicator to measure social development and analyzes the impact of urban population growth on traffic vulnerability. An OLS regression analysis was performed, and the main parameters of OLS regression are summarized in Table A3, using only the parameters of k and p -value. We also conducted residual normality test QQ plots to evaluate the fit (Figure A3).

According to the city tier development, all of the 41 cities were divided into first-tier, new first-tier, and second-tier cities, and a population-vulnerability index scatter diagram was plotted (Figure 5a). According to the scatter diagram, it can be seen that the population sizes of the first-tier (blue dots) and new first-tier (orange dots) cities were much higher than those of the second-tier cities (green dots). Among them, Chongqing had the largest population among the new first-tier cities. Chongqing's population includes the residents of the primary urban area, remote Wanzhou, Qianjiang, and other areas. The macro trend showed that the vulnerability of urban traffic increased with an increase in population.

The correlations between population and the traffic vulnerability index among the cities of each tier were also analyzed (Figure 5b–d). The results demonstrate that first-tier, new first-tier, and second-tier cities all exhibited a trend in population growth and an enhancement in the urban traffic vulnerability. The following conclusions can be drawn. The traffic vulnerabilities of China's main first-tier, new first-tier, and second-tier cities are significantly affected by the urban populations. The first-tier cities are megacities with high-density urban populations. The greater the urban population, the greater the travel demand, and the impact of rainfall on the traffic vulnerability is more profound. For the second-tier cities, the population densities were relatively low, and the travel demand was also lower than that of the first-tier cities. However, as the population increased, the traffic vulnerability index also increased. Therefore, controlling the urban population can alleviate the traffic vulnerability of megacities to a certain extent and improve the traffic vulnerability of first-tier and new first-tier cities. Additionally, the construction of transport infrastructure in the second-tier cities is still incomplete, so there is an opportunity for improvement in the capacity of the urban traffic to carry more people.

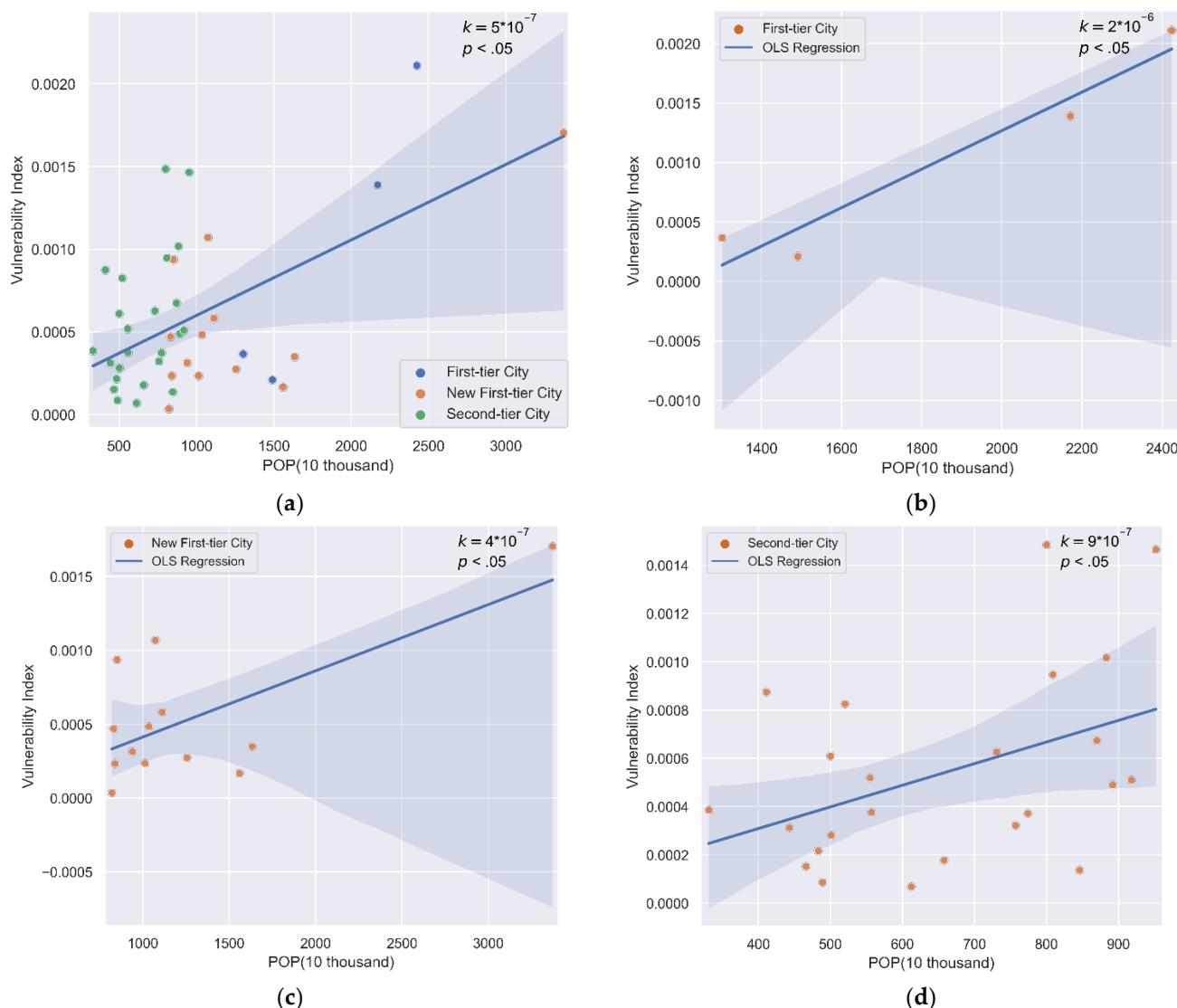


Figure 5. Correlation analysis of all the city's population-traffic vulnerability indexes: (a) all cities population (POP)-vulnerability index OLS analysis; (b) first-tier cities POP-vulnerability index OLS analysis; (c) new first-tier cities POP-vulnerability index OLS analysis; (d) first-tier cities POP-vulnerability index OLS analysis.

4.2.3. The Car Ownership Factor

As an indicator to measure the level of social development, car ownership is closely related to the level of economic development level and the population of a city [43–45]. According to the Statistical Communique of the People's Republic of China on the 2019 National Economic and Social Development, there were 30 cities with more than two million vehicles in China in 2019. Among them, 11 cities (i.e., Beijing, Chengdu, Chongqing, Suzhou, Shanghai, Zhengzhou, Shenzhen, Xi'an, Wuhan, Dongguan, and Tianjin) had more than three million vehicles [35].

This section analyzes whether car ownership has an impact on traffic vulnerability. For the 41 first-tier, new first-tier, and second-tier cities, the scatter plots of car ownership and the traffic vulnerability index of each city were plotted, the OLS correlation analysis was performed on the scattered points (Figure 6a), and the main parameters of OLS regression are summarized in Table A4; we also conducted residual normality test QQ plots to evaluate the fit (Figure A4).

The results demonstrate that car ownership was correlated with the degree of urban traffic vulnerability.

An OLS regression analysis was also performed on car ownership and the traffic vulnerability index for first-tier, new first-tier, and second-tier cities (Figure 6b–d). The results indicate that there were no obvious correlations between car ownership and the traffic vulnerability index in all tiers of cities. Therefore, car ownership had little impact on the vulnerability of urban traffic in response to rainy weather. In addition, some urban traffic restrictions had some impact on the results of this study to some extent.

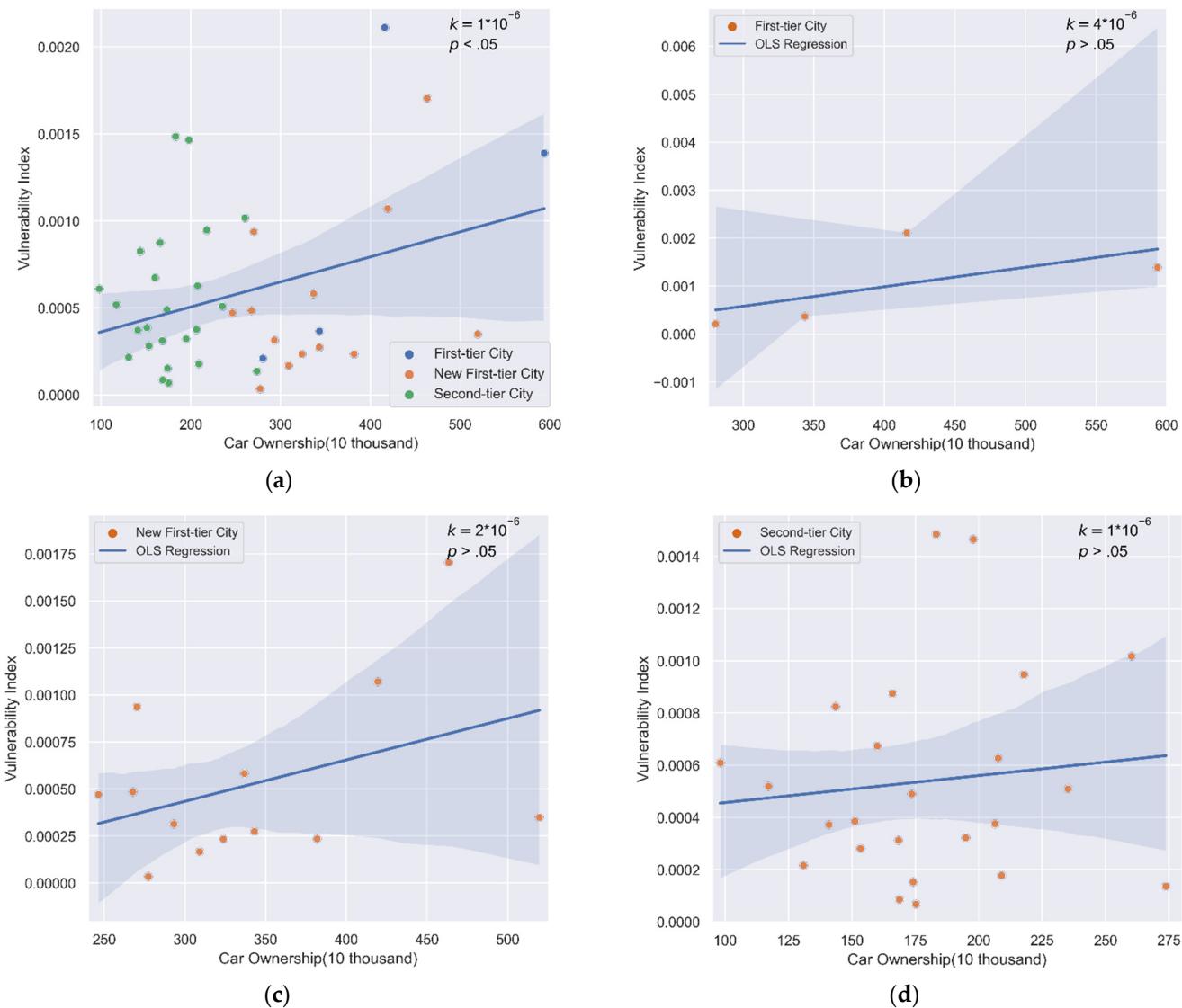


Figure 6. Correlation analysis of all the cities car ownership-traffic vulnerability indexes: (a) all cities car ownership-vulnerability index OLS analysis; (b) first-tier cities car ownership-vulnerability index OLS analysis; (c) new first-tier cities car ownership-vulnerability index OLS analysis; (d) second-tier cities car ownership vulnerability Index OLS analysis.

5. Discussion

In this study, we used two-year daily precipitation and hourly traffic data from 41 cities. The amount of data is statistically sufficient. We focused on working days, excluding the influence of holidays and weekends. All of these guarantee the robustness of the research results. We proposed an urban traffic vulnerability evaluation index under rainy weather and combined it with socio-economic factors to understand traffic vulnerability. The study enriches the content of urban physical examinations and provides some theoretical basis for

urban health and sustainable development. It is also of great significance when planning the construction of sponge and resilient cities.

There are several research topics that can be explored in the future. First, traffic vulnerability of working days was used for the evaluation. Therefore, future studies could evaluate the traffic vulnerability of weekends and holidays. Furthermore, the vulnerability due to precipitation of urban traffic in morning and evening peak conditions of working days could be evaluated in the future. Second, the evaluation method could be extended to other cities.

6. Conclusions

This study established a set of urban traffic vulnerability evaluation indices to evaluate the traffic vulnerability of 41 cities in China. The results suggest that there were 13 cities (i.e., Shanghai, Nanjing, Suzhou, Chongqing, Harbin, Changchun, Jinan, Yangzhou, Nantong, Changzhou, Wenzhou, Xiamen, and Zhongshan) whose traffic was significantly affected by rainfall, while the traffic of the remaining 28 cities was not.

The impact of these socio-economic factors on urban traffic vulnerability was analyzed as well. The following conclusions were made. First, the GDP had a limited effect on improving the traffic vulnerability. For the first-tier and new first-tier cities, the traffic vulnerability became serious with GDP growth. For the second-tier cities, the traffic vulnerability was less affected by the GDP. Second, the size of the urban population had a significant impact on urban traffic vulnerability. For the first-tier and new first-tier cities, the size of the population had a greater impact on the traffic vulnerability; for the second-tier cities, they can improve the capacity of urban traffic by transport infrastructure construction to carry more people. Third, urban car ownership had little impact on urban traffic vulnerability.

Policy recommendations to improve urban traffic vulnerability in response to rainfall are proposed. First, we need to pursue economic growth and the healthy development of transportation simultaneously and shift construction of transportation infrastructure from large-scale development to structural optimization. In addition, the development of smart and digital transportation modes should be pursued [46]. Second, we should control the population size of megacities. Relocating the population of megacities to the surrounding second-tier cities and increasing the construction of the second-tier cities' transportation infrastructure could enhance the traffic resilience of China's megacities and help promote the balanced and coordinated development of a region [47]. For example, in the Yangtze River Delta region of China, the population can be diverted from Shanghai to neighboring places (e.g., Jiaxing, Wuxi, Jinhua, Shaoxing, and Taizhou). In the Pearl River Delta region of China, the population can be diverted from Shenzhen to neighboring cities (e.g., Dongguan, Huizhou, and Foshan).

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. Summary of OLS Regression

Table A1. Summary of OLS regression analysis used in the traffic vulnerability evaluation index.

City Name	<i>k</i>	δ	<i>p</i>	<i>t</i>
Beijing	0.0014	1.4581	0.2780	1.1151
Shanghai	0.0021	1.3048	0.0027	3.1925
Guangzhou	0.0002	1.3753	0.6306	0.4841
Shenzhen	0.0004	1.2857	0.1661	1.4107
Shenyang	0.0005	1.3014	0.5116	0.6658
Tianjin	0.0002	1.3024	0.7588	0.3109
Qingdao	0.0003	1.2099	0.4993	0.6856
Zhengzhou	0.0002	1.2558	0.7375	0.3387
Xi'an	0.0003	1.3069	0.7609	0.3075
Nanjing	0.0009	1.2751	0.0033	3.1708
Suzhou	0.0011	1.1300	0.0026	3.2321
Chengdu	0.0004	1.2803	0.1228	1.5801
Wuhan	0.0006	1.2880	0.1078	1.6544
Hangzhou	0.0005	1.3155	0.1339	1.5265
Ningbo	0.0000	1.1374	0.6817	0.4132
Chongqing	0.0017	1.3686	0.0142	2.5761
Dongguan	0.0002	1.2566	0.2623	1.1352
Harbin	0.0015	1.3694	0.0017	3.5083
Changchun	0.0015	1.3611	0.0120	2.6949
Taiyuan	0.0003	1.2471	0.7989	0.2579
Jinan	0.0010	1.2500	0.0347	2.2583
Xuzhou	0.0005	1.2617	0.2115	1.2759
Yangzhou	0.0006	1.1103	0.0204	2.4371
Nantong	0.0006	1.0944	0.0251	2.3473
Hefei	0.0009	1.2778	0.0590	1.9498
Changzhou	0.0008	1.0686	0.0035	3.1573
Wuxi	0.0002	1.1243	0.5085	0.6685
Jiaxing	0.0002	1.1002	0.7128	0.3708
Shaoxing	0.0003	1.1160	0.2204	1.2444
Jinhua	0.0004	1.0804	0.1341	1.5282
Nanchang	0.0005	1.2214	0.0774	1.8100
Taizhou	0.0001	1.1554	0.3086	1.0307
Wenzhou	0.0005	1.1585	0.0341	2.1891
Guiyang	0.0001	1.4077	0.8110	0.2408
Fuzhou	0.0004	1.2907	0.4845	0.7051
Quanzhou	0.0007	1.2209	0.0667	1.8851
Xiamen	0.0009	1.2673	0.0429	2.0946
Huizhou	0.0002	1.2170	0.1346	1.5236
Foshan	0.0001	1.2998	0.6547	0.4502
Nanning	0.0003	1.3267	0.3509	0.9458
Zhongshan	0.0004	1.1960	0.0341	2.1849

k, coefficients of OLS; δ , intercept of OLS. *p*, *p*-value of the significance test; *t*, *t*-value of significance test.

Table A2. Summary of OLS regression analysis between traffic vulnerability index and GDP.

City Level	<i>k</i>	δ	<i>p</i>	<i>t</i>
first-tier	1.28×10^{-7}	-2.95×10^{-3}	0.0214	6.7251
new first-tier	7.43×10^{-8}	-5.05×10^{-4}	0.0036	3.6783
second-tier	1.80×10^{-8}	4.19×10^{-4}	0.6066	0.5225
all city	2.86×10^{-8}	2.57×10^{-4}	0.0014	3.4527

k, coefficients of OLS; δ , intercept of OLS. *p*, *p*-value of the significance test; *t*, *t*-value of significance test.

Table A3. Summary of OLS regression analysis between traffic vulnerability index and POP.

City Level	k	δ	p	t
first-tier	1.62×10^{-6}	-1.97×10^{-3}	0.0328	5.3866
new first-tier	4.49×10^{-7}	-3.62×10^{-5}	0.0121	3.0009
second-tier	8.96×10^{-7}	-4.95×10^{-5}	0.0378	2.2102
all city	4.57×10^{-7}	1.42×10^{-4}	0.0002	4.1637

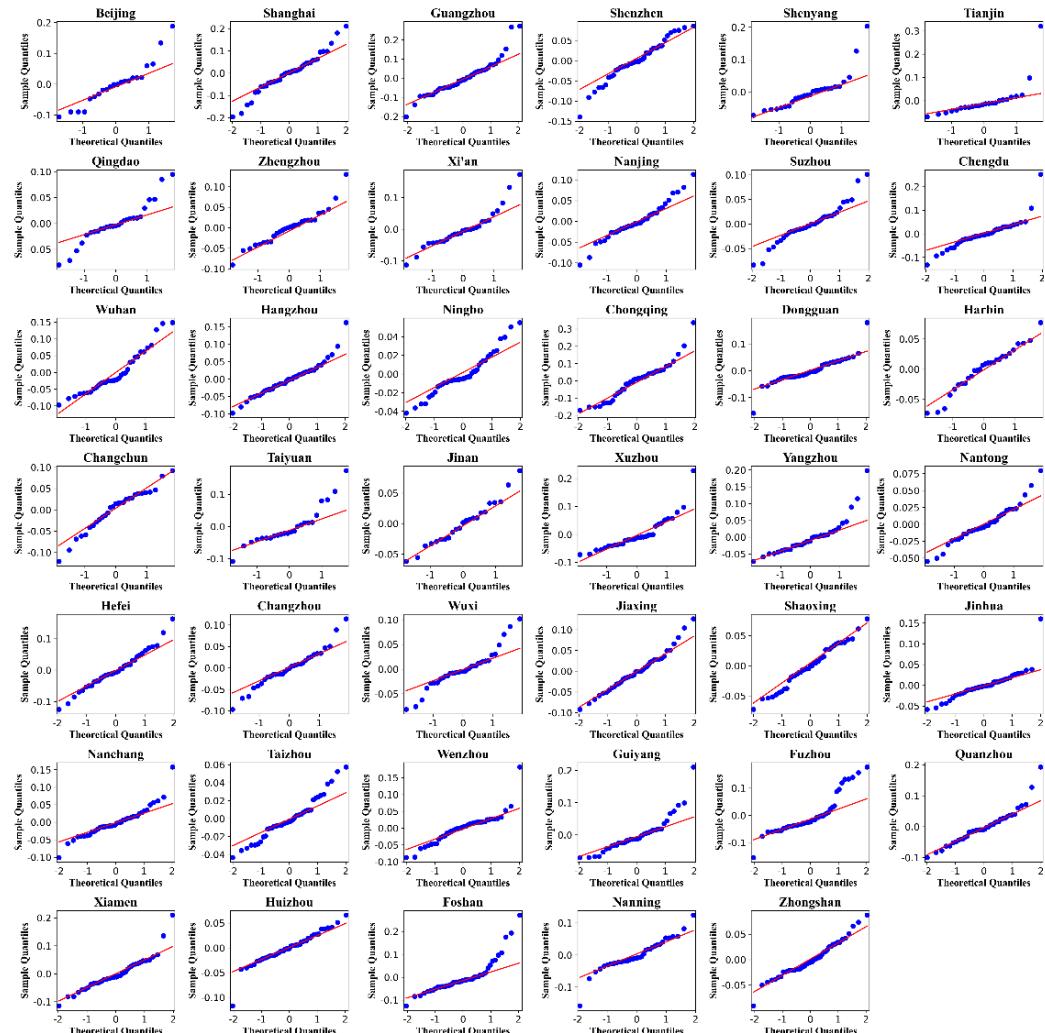
k , coefficients of OLS; δ , intercept of OLS. p , p -value of the significance test; t , t -value of significance test.

Table A4. Summary of OLS regression analysis between traffic vulnerability index and car ownership.

City Level	k	δ	p	t
first-tier	4.06×10^{-6}	-6.36×10^{-4}	0.3879	1.0948
new first-tier	2.20×10^{-6}	-2.27×10^{-4}	0.1816	1.4261
second-tier	1.04×10^{-6}	3.53×10^{-4}	0.6071	0.5217
all city	1.44×10^{-6}	2.18×10^{-4}	0.0327	2.2146

k , coefficients of OLS; δ , intercept of OLS. p , p -value of the significance test; t , t -value of significance test.

Appendix B. QQ Plots for OLS Regression

**Figure A1.** The QQ plots for OLS regression (traffic vulnerability evaluation index).

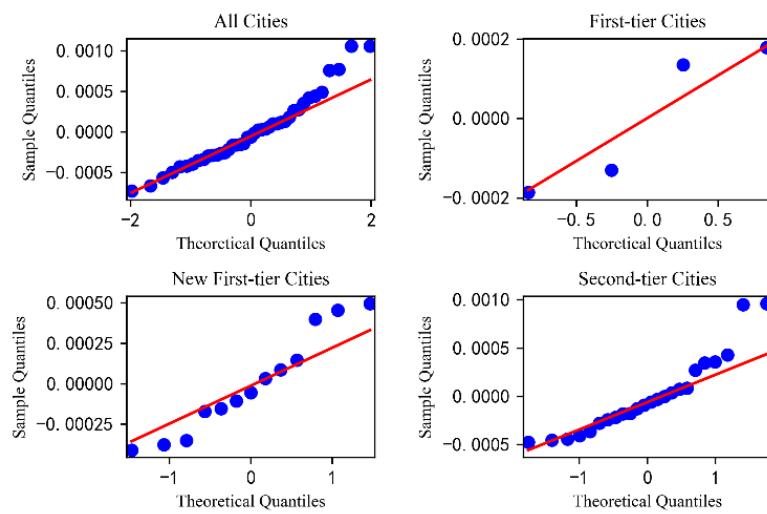


Figure A2. The QQ plots for OLS regression between traffic vulnerability index and GDP.

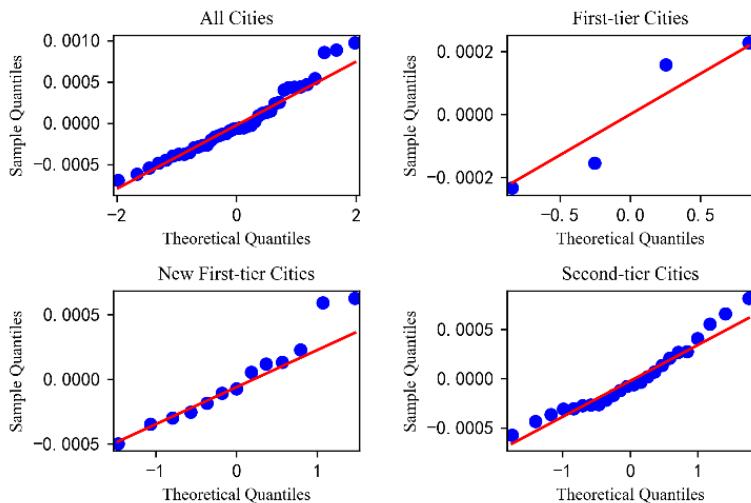


Figure A3. The QQ plots for OLS regression between traffic vulnerability index and POP.

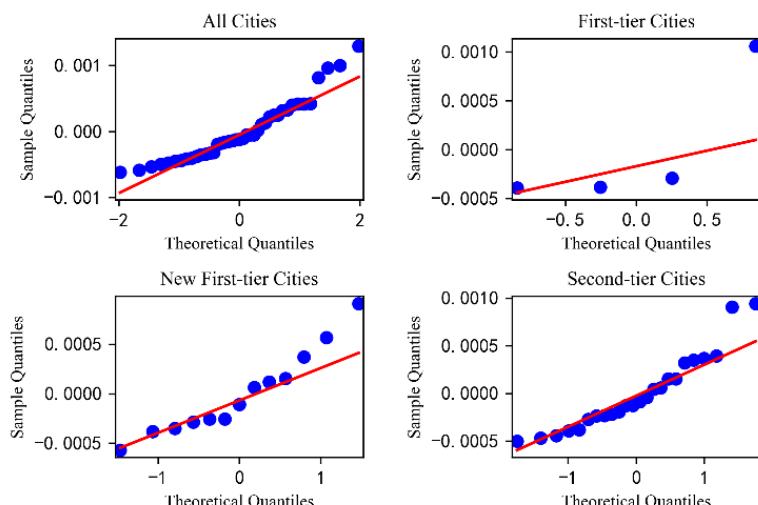


Figure A4. The QQ plots for OLS regression between traffic vulnerability index and car ownership.

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