

Research Article

Evaluation, Classification, and Influential Factors Analysis of Traffic Congestion in Chinese Cities Using the Online Map Data

Changzhi Bian,^{1,2} Changwei Yuan,³ Wenbo Kuang,² and Dayong Wu⁴

¹ China Academy of Urban Planning and Design, Beijing 100044, China
 ² Institute of Transportation Engineering, Department of Civil Engineering, Tsinghua University, Beijing 100084, China
 ³ School of Economy and Management, Chang'an University, Xi'an, Shaanxi 710064, China
 ⁴ Department of Civil, Environmental and Construction Engineering, Texas Tech University, Lubbock, TX 79409, USA

Correspondence should be addressed to Changwei Yuan; changwei@chd.edu.cn

Received 25 April 2016; Revised 8 August 2016; Accepted 18 August 2016

Academic Editor: Yan-Jun Liu

Copyright © 2016 Changzhi Bian et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

This study proposes a new method to describe, compare, and classify the traffic congestion states in 23 Chinese cities using the online map data and further reveals the influential factors that may affect them. First, the real-time traffic congestion information is obtained from the online map of AutoNavi in a 15-minute interval. Next, a new measuring index is introduced to describe the overall characterization of congestion patterns in each city based on online map data, which is named as the congestion ratio. The next analysis is the cluster analysis based on the temporal distribution of the congestion ratio, which helps to identify groups of the selected cities with similar traffic congestion states. These cities are categorized as four groups according to the severity of traffic congestion: severely congested, less severely congested, amble, and smooth cities. Lastly, multiple linear regression models are developed to identify the primary factors that affect the congestion ratio. The result shows that the influences of per capita road area, car ownership, and vehicle miles traveled (VMT) on the congestion ratio are significant. Sensitivity analyses are also implemented in order to reveal more effective policy measures in mitigating traffic congestion in urban areas.

1. Introduction

Accurate description and classification of traffic congestion states of an urban transportation network will improve our understanding of the performance of an entire country or region's transportation network. And further analysis of the primary factors causing traffic congestion could be used to efficiently ease traffic congestion, in terms of planning, operation, and management.

Over the past 50 years, a lots of studies focused on distinguishing congestion state on certain road links. Researchers have developed a huge number of traffic flow models (see, e.g., reviews [1–3]), including well-known Macroscopic Fundamental Diagram (MFD) [4, 5], and Kerner's three-phase traffic theory [6–10] (see papers of Rehborn et al. [11, 12] about the development of Kerner's theory) is used to distinguish and describe congestion patterns on road links. In practice, level of service (LOS) is applied in the US HCM 2000 using letters A through F to describe it, with A being the best and F being the worst [13]. A standard similar to HCM had been established in China. These standards were mainly based on proximity to other vehicles, travel speed, volume capacity ratio, and so forth. Although road-link based congestion evaluation methods above are detailed and accurate, they can hardly be used to evaluate the traffic congestion condition in the whole wide city and further to compare different cities' congestion circumstances.

Traditional regional congestion measures were mostly based on travel survey data, including travel delay and travel time, like National Household Travel Survey (NHTS) in the US and Person Travel (PT) survey in Tokyo metropolitan area. In recent years, with the popularity of "Big Data," more accurate regional congestion measure became possible. INRIX provided detailed traffic speed data every 800 feet (250 meters) across 4 million miles of roads in 40 countries. Powered by INRIX's data, the Texas Transportation Institute annually developed a measure of traffic congestion for many urbanized areas [14]. However, for most developing countries like China, real-time traffic data is either not published due to restrictions or not collectable owing to lack of devices.

Previous researches studied several factors related to congestion. Generally, there are three ways to analyze factors which influence urban traffic status. Firstly, some researchers tried to build spatial interaction model and solved it mathematically. Tsekeris and Geroliminis [15] applied Macroscopic Fundamental Diagram (MFD) in a monocentric city model to analyze the relationship between land use and traffic congestion. The findings reinforced the "compact city" hypothesis, by favoring a larger mixed-use core area compared to the peripheral area. Safirova [16] developed a fully closed general equilibrium model of a monocentric city to analyze the effects of telecommuting on the urban economy and traffic congestion. The study concluded that, under certain conditions, telecommuting increased the city size and the average transport costs of commuters. Gubins and Verhoef [17] considered a monocentric city model with a traffic bottleneck. Instead of building the standard monocentric model of urban land use, Anas and Xu [18] built a fully closed computable general equilibrium model with endogenous traffic congestion and then discussed the relationship between congestion, land use, and job dispersion. While these models above were based on several assumptions, such as simplified geometrical city shape and hypothetical traveler behaviors, urban transportation system is a highly complex system. As a result, there are inevitably mismatches between the reality and theoretical models. Statistical analysis is another way that researchers used in this field. Sarzynski et al. [19] examined the relationship between 7 distinct aspects of land use in 1990 and 3 measures of transport congestion in 2000, using data from a nationally representative sample of 50 of the 100 largest US urban areas as of 1990. They reveal most measures of land use in 1990 were significantly related to traffic congestion levels in 2000. Scharank et al. [14] used real data and theoretical assumptions to illustrate that bigger public transportation ridership, more roadways in critical corridors, and better traffic flow condition can relieve the congestion. Cervero [20] employed a path model to causally sort out the links between freeway investments and traffic increased, using data for 24 California freeway projects across 15 years. The research confirmed the presence of induced travel, new travel spurred by roadway investments. Nasri and Zhang [21] examined the changes in vehicle miles traveled (VMT) in order to analyze the effectiveness of transit-oriented development (TOD) on less driving using Washington DC and Baltimore's case. Although the research did not directly discuss traffic congestion, it pointed out how VMT which significantly affects congestion was influenced by TOD. The third method is case study. Sim et al. [22] used Singapore as an example to illustrate how integrating land use and transport planning reduced work-related travel. Findings from related surveys showed that there was a great potential in reducing work-travel and reliance on the car so as to alleviate traffic congestion through decentralization of commercial activities. These studies above were generally based on data in developed countries, while

quantitative factor analyses in developing counties including China are limited.

Due to lack of published data in a large number of developing countries such as China, this study utilizes the integrated online map data provided by AutoNavi for road congestion state description (Section 2). Next, a novel method to evaluate the congestion state of a city is proposed using the online map data and classification of traffic congestion in Chinese cities is performed (Section 3). Moreover, influential factors of traffic congestion in Chinese cities are discussed based on the online map data (Section 4). The major findings and limitations of this study could be found in Section 5.

2. Description of Traffic Congestion Using the Online Map Data

2.1. The Selection of Data Source. Map service providers, like AutoNavi, Google, and Baidu, collect data from various intelligent traffic detection means, such as video, coil, and floating cars. They integrate the data from all these sources to determine the real-time urban road traffic conditions and present them in different colors. This study uses the online map data from AutoNavi. The real-time traffic information from AutoNavi denotes road state as congestion, amble, and smooth with three colors, red, yellow, and green, respectively. Through the on-road test in Beijing, the corresponding speed ranges for different colors are estimated. For expressway, average speeds on red, yellow, and green road links are 0-20 km/h, 20-40 km/h, and more than 40 km/h, respectively. For major and minor arterials, average speed on red road links is 0-15 km/h, while it is 15-35 km/h and more than 35 km/h on yellow and green road links, respectively. Based on the map consisting with roads in different colors representing different traffic conditions, this study proposes an indicator that denotes the proportion of congested roads on the map, which is used to describe each city's traffic running state at different times.

This research chooses 23 cities in China, taking their urban zones as the research objects. These 23 cities include Beijing, Changchun, Shenyang, Shanghai, Guangzhou, Hangzhou, Dalian, Tianjin, Qingdao, Chengdu, Chongqing, Wuhan, Changsha, Nanchang, Wuxi, Changzhou, Xiamen, Ningbo, Xi'an, Kunming, Xining, Fuzhou, and Shenzhen. The reason to choose these cities is twofold. First, they represent major large cities in China. Second, traffic congestion has become one of the most serious urban problems in most of them.

2.2. Access to the Map Image Information on the Web. Map images on the web are composed of different layers: the bottom layer displays basic geographic information; the middle layer shows names, comments, and other information of different venues; the upper layer, which is utilized in this study, contains traffic information depicted with colors red, yellow, and green. Using MATLAB 7.11.0 (R2010b), we download all the blocks of the upper layer and splice them according to their naming rules, to generate a map containing the real-time network running state for a certain area. This process is shown in Figures 1 and 2.

Mathematical Problems in Engineering



FIGURE 1: Bottom, middle, and upper layers in AutoNavi map.



FIGURE 2: Splicing processes for the real-time network traffic state map.

0.4

2.3. Structuration of Unstructured Data. The real-time network state map acquired through the abovementioned steps is a typical type of unstructured data; however, further analysis in this research requires structured information. Hence, the image recognition function capsulated in MATLAB is used to analyze the color of each pixel in Figure 3. By setting the RGB threshold of the three colors, red, yellow, and green, the area ratios of all the three colors are extracted from the figure, equal to the proportion of each color.

Using the abovementioned information extraction module, the quantitative description of different cities' real-time traffic conditions is obtained. This research utilizes the realtime traffic information for the selected 23 cities in China. The data was collected every 15 minutes from March 3rd, 2014, to April 3rd, 2014.

3. Evaluation and Classification of Congestion Using Cluster Analysis

0.35 0.3 Congestion ratio 0.25 0.2 0.15 0.1 0.05 0 ***** 10:00 12:00 14:00 16:00 20:00 24:00 00:0 2:00 00: 5:00 8:00 22:00 18:00Time Weekday Weekend

FIGURE 3: Congestion ratio in each time period in March 2014, Beijing.

3.1. Variables Selection. The congestion ratio is defined as the sum of congested and amble state ratios in the whole network. In Figure 3, red points display the congestion ratio in weekdays in Beijing. Compared to the travel temporal distribution of Beijing from travel survey in 2010 in Figure 4 [23],

the congestion ratio collected from AutoNavi is corresponding to residents' travel behaviors. It is an appropriate substitution for evaluation and comparison of traffic congestion between different cities.

Travel characteristics on weekdays have significant differences from those on weekends. This results in significant



FIGURE 4: Travel temporal distribution from Beijing travel survey 2010.

difference in the urban traffic condition between weekdays and weekends, as shown in Figure 3. Therefore, this study divides structured data into two groups: the weekday group and the weekend group. For each group, the congestion ratio during each period (length: 15 min) is chosen as the variable for the following cluster analysis.

3.2. Data Preprocessing. As discussed in the previous section, the targeted variables are determined as the summation of the congestion ratio during each time period. For further cluster analysis, we need to preprocess original data. The objective matrix is shown below. Each row indicates a city, when each column stands for a time period which is 15 minutes. There are 23 rows and 96 columns in objective matrix, as we divide one day time into 96 periods:

$$\begin{bmatrix} \xi_{1,1} & \xi_{1,2} & \cdots & \xi_{1,95} & \xi_{1,96} \\ \xi_{2,1} & \xi_{2,2} & \cdots & \xi_{2,95} & \xi_{2,96} \\ \cdots & \cdots & \cdots & \cdots \\ \xi_{22,1} & \xi_{22,2} & \cdots & \xi_{22,95} & \xi_{22,96} \\ \xi_{23,1} & \xi_{23,2} & \cdots & \xi_{23,95} & \xi_{23,96} \end{bmatrix}$$
(1)
$$\xi_{\text{city},t} = \frac{1}{\text{day}_t} \sum_{d=1}^{\text{day}_t} \xi_{\text{city},t,d}$$

 $\xi_{\text{city},t,d}$ represents the congestion ratio at the *t*th period on the *d*th day; day_t represents the amount of date that contains the *t*th period's data in our dataset. As a result, $\xi_{\text{city},t}$ is the average congestion ratio of the certain city in the *t*th period.

3.3. Cluster Methodology. As it is hard to accurately estimate the number of cluster groups in city congestion classification, instead of k-means cluster method, hierarchical cluster by using median clustering agglomerative method (HMC) is performed in this study. Since the physical meaning of all the variables stays consistent, there is no need to standardize the variables. There are several basic parameters in HMC model. Euclidean distance between sample city i and sample city j is denoted as d_{ij} by the following formulation:

$$d_{ij} = \sqrt{\sum_{t=1}^{96} \left(\xi_{i,t} - \xi_{j,t}\right)^2}.$$
 (2)

In HMC model, the distance between cluster G_p and cluster G_q denoted as $D_M(p,q)$ is defined as the average value of the distances between each sample city *i* in cluster G_p and each sample city *j* in cluster G_q , as follows:

$$D_{M}(p,q) = \frac{1}{pq} \sum_{i \in G_{p}} \sum_{i \in G_{q}} d_{ij}^{2}.$$
 (3)

The minimum value of $D_M(p,q)$ is denoted as S_0 , which is the distance between cluster G_p and cluster G_q :

$$S_0 = \min\{D_M(p,q)\}.$$
 (4)

HMC model contains 4 steps.

Step 1. Each sample city belongs to its own cluster; that is, the number of clusters is equal to the amount of sample cities.

Step 2. Calculate the distances between each two clusters as $D_M(p,q)$ and find out S_0 .

Step 3. Combine G_p and G_q as a new cluster $G_m \cdot G_m = G_p \cup G_q$.

Step 4. Iterate Steps 2 and 3 until all sample cities are in one cluster.

After getting the hierarchical cluster results, determining the number of clusters is requisite. However, there are no satisfactory rules determining the exact number of clusters in hierarchical cluster analysis. Milligan and Cooper [24] conducted 30 procedures for determining the number of clusters. Their results showed that the pseudo *F* statistic, pseudo t^2 statistic developed by Duda and Hart [25], and the cubic clustering criterion (CCC) perform better.

Cluster process is conducted in SAS 9.2 and the cluster results are concluded by four statistics, that is, local peak of the CCC, large difference between the R^2 statistics in this step and the next cluster fusion, a large pseudo *F* statistic, and a small value of pseudo t^2 statistic combined with a large pseudo t^2 statistic in next cluster iteration.

3.4. Results and Discussions

3.4.1. Cluster Analysis Results for the Weekday Group. The cluster analysis statistical indexes, the R^2 value, the CCC value, the pseudo F statistic, and the pseudo t^2 statistic, indicate that the cities should be divided into four clusters, as shown in Table 1. The cluster tree is shown in Figure 5; the congestion characteristics for each group are shown in Figure 6.

The first category is severely congested cities. This group represented by Beijing has a very lasting and extensive



FIGURE 5: Cluster trees for weekdays.

TABLE 1: HMC model statistics for weekdays.

The number of clusters	CCC	Pseudo F	Pseudo t^2	R^2
5	_	8.7	2.2	0.658
4	-1.5	10.5	1.4	0.623
3	-2.5	8.8	8.7	0.468
2	-0.97	13.4	2.9	0.390



FIGURE 6: Congestion characteristics classification for weekdays.

congestion, with low travel efficiency. It is not yet common in present China.

The second category is less severely congested cities. Represented by Guangzhou and Wuhan, this group of cities shares a relatively flat morning peak, an obvious peak at noon, and a very lasting and highly congested evening peak. This group also includes Fuzhou, Xi'an, and Xining. These cities should further examine the congested period of time and section of roads and take actions towards these targeted range of time and area, in case the jams are getting worse.

The third category is amble cities. Cities such as Shanghai, Changchun, Dalian, Ningbo, Shenyang, Chengdu, Changsha, Shenzhen, Kunming, Hangzhou, Tianjin, Qingdao, Nanchang, and Chongqing belong to this group, of which the morning and evening peaks are obvious, but overall traffic conditions are moderate. Congestion is only limited to local road network in a relatively short time period. It is the most common traffic condition for large and medium-sized cities in present China.

The fourth category is smooth cities. Represented by Wuxi, Changzhou, and Xiamen, cities in this category share a smooth traffic condition throughout the whole time.

3.4.2. Cluster Analysis Results for the Weekend Group. The cluster analysis statistical indexes indicate that it is proper to divide cities into five categories, which is shown in Table 2. It is shown in Figure 7 that the fifth category only contains Dalian. The reason for Dalian's heterogeneity is that the morning peak in Dalian is a lot earlier than other cities. The peak starts about 2 hours before other cities, while it ends 2 hours earlier as well. Considering obvious similarities between Dalian and amble cities group on congestion duration and peak value, we classify Dalian as a city in the amble city group.

Generally speaking, the traffic condition on weekends is significantly smoother than that on weekdays, and the peak value of rush hour is also significantly lower. The starting time of morning peak on weekends has a 2-hour delay compared to that on weekdays. The congestion characteristics for each weekend's group are shown in Figure 8.



FIGURE 7: Cluster trees for weekends.

TABLE 2: HMC model statistics for weekends.

The number of clusters	CCC	Pseudo F	Pseudo t^2	R^2
6	_	8.0	2.2	0.703
5	—	8.3	2.4	0.648
4	-3.6	6.2	9.0	0.496
3	-2.7	7.3	2.2	0.422
2	-3.5	3.8	9.3	0.152



FIGURE 8: Congestion characteristics classification for weekends.

The first category is severely congested cities. This group represented by Beijing still experience very lasting and extensive congestion as the situation on weekdays. The second category is less severely congested cities. This group of cities includes Guangzhou, Wuhan, Fuzhou, and Xi'an. The third category is amble cities. In China, most cities including Shanghai, Changchun, Dalian, Ningbo, Shenyang, Chengdu, Changsha, Shenzhen, Kunming, Hangzhou, Tianjin, Qingdao, Xining, Nanchang, and Chongqing belong to this group. The congestion ratio in these cities is below 15% for most of the time. The fourth category is smooth cities. This category is represented by Wuxi, Changzhou, and Xiamen. Cities belong to this category have very smooth traffic condition throughout the whole weekends.

4. Primary Factors Influencing Congestion and Sensitivity Analyses

4.1. *Methodology and Data*. This study uses multiple linear regression to identify the primary factors influencing the traffic congestion:

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n, \tag{5}$$

where the dependent variable Y is the congestion level. It is calculated as the 15th percentile of the summation of congestion ratio as an evaluation index for congestion. In addition, considering heterogeneity between weekdays and weekends, two models are developed to represent the cases during weekdays or weekends separately. Figure 9 shows 15th percentile of the congestion ratio for the selected 23 cities.

The independent variables X_1, X_2, \ldots, X_n are primary factors influencing congestion, and $\beta_1, \beta_2, \ldots, \beta_n$ are the corresponding coefficients. We hold that the emergence of congestion is related to the supply of network facilities and the volume of vehicles used. The supply of facilities could be measured using per capita urban road area, and the volume of vehicle used is codetermined by the vehicle ownership and usage. And the vehicle usage could be further represented as average daily Vehicle Mileage Traveled (VMT)

TABLE 3: Multiple regression analysis statistics.

	Weekdays			Weekends			
	Coefficient	Standardized coefficient	<i>t</i> -value (prob.)	Coefficient	Standardized coefficient	<i>t</i> -value (prob.)	
X _α	0.498	0.364	2.17 (0.042)	0.422	0.336	1.96 (0.064)	
X_q	0.000	0.220	1.65 (0.114)	0.000	0.214	1.57 (0.133)	
X_m	0.001	0.413	1.97 (0.063)	0.001	0.446	2.08 (0.050)	
F statistic (prob.)	prob.) 118.65 (<0.0001)			113.2 (<0.0001)			
R^2	0.947			0.944			



FIGURE 9: 15th percentile of the congestion ratios for 23 sample cities.

(or Vehicle Kilometer Traveled (VKT)), which is associated with residents' driving preference and further related to the urban scale. According to the analysis above, the following model is proposed:

$$Y = \alpha + \beta_{\alpha} X_{\alpha} + \beta_{q} X_{q} + \beta_{m} X_{m}, \tag{6}$$

where α is the estimable intercept term, which equals zero; X_{α} is the 1/per capita road area; X_q represents the vehicles per 1,000 people; X_m is the daily Vehicle Mileage Traveled (VMT); β_{α} , β_q , and β_m are the estimable coefficient vectors of X_{α} , X_q , and X_m .

When the supply of infrastructure denoted as per capita road area is considerably large, X_{α} is limited to 0. Meanwhile, while there is no vehicle in the city, X_q and X_m equal zero. In this circumstance that there is plenty of road supply with no traffic demand, there should be no congestion at all; that is, the congestion ratio Y is zero. Therefore, the estimable intercept term α should keep 0 in the regression model.

The 23 cities' per capita road area and vehicles per 1,000 people are quoted from [26]. The direct acquisition of daily VMT is rather difficult, so we used the internet platform to launch a nationwide survey on vehicle usage in February 2014 [27], to discover the driving patterns in different cities in China. 4,000 questionnaires were issued, and the total number of valid returns was 2130, covering 29 provinces. Among these provinces, Shanghai, Guangdong, and Beijing returned most questionnaires, which had 293, 289, and 232 valid samples, respectively. The distribution of valid returns is shown in Figure 10. The values of daily VMT are acquired through this survey.

4.2. *Results and Discussions*. The statistical software SAS 9.2 is used to perform the regression analysis. The fitting results of the regression model are as follows.

Congestion Ratio for Weekdays

$$Y_{\text{weekdays}} = 0.49777 \times X_{\alpha} + 0.00012906 \times X_{q} + 0.00137 \times X_{m}.$$
(7)

Congestion Ratio for Weekends

$$Y_{\text{weekends}} = 0.42175 \times X_{\alpha} + 0.00011507 \times X_q$$

+ 0.00136 × X_m . (8)

Table 3 shows that regression model is significant for both weekdays and weekends groups under 85% confidence level. Specifically, all the coefficients, β_{α} , β_{q} , and β_{m} , are positive, which indicates that the reciprocal of per capita road area, the vehicles per 1,000 people, and VMT are all positively correlated to the congestion ratio. The smaller value of per capita road area, the more vehicles per 1,000 people, and the more VMT lead to higher congestion ratio. It conforms to our common sense that if road supply was increased and travel demand was reduced, then the road condition would be smoother.

There is a multicollinearity issue that needs to be further discussed in this regression model. According to Downs [28], the increase of road supply may promote the use of vehicle and result in more serious congestion, introducing multicollinearity problems into the model. In fact, the car ownership mainly depends on the level of economic development instead of infrastructure supply. Stares and Liu [29] reviewed autoownership researches from 1970s and made a conclusion that the number of vehicles per 1,000 people is related to many factors such as economy, culture, and geography, but the per capita income is still the most important factor influencing car ownership.

4.3. Sensitivity Analyses

4.3.1. Single Factor Sensitivity Analysis. Let the variables per capita road area and vehicles per 1,000 people be uncertainties



FIGURE 10: The distribution of valid returns in nationwide vehicle usage survey.

TABLE 4: Single factor sensitivity analysis result on weekdays and weekends.

Uncertainties	Rate of change					
	20%	10%	0	-10%	-20%	
Weekdays						
Per capita road area	-5.60%	-3.06%	0.00%	3.73%	8.40%	
Vehicles per 1,000 people	4.60%	2.30%	0.00%	-2.30%	-4.60%	
		Weekends	6			
Per capita road area	-5.16%	-2.81%	0.00%	3.44%	7.73%	
Vehicles per 1,000 people	4.46%	2.23%	0.00%	-2.23%	-4.46%	

and their range ability be $\pm 10\%$ and $\pm 20\%$, respectively. The changing rates of congestion ratio are indicated in Table 4. This study takes the mean value of X_{α} , X_{q} , and X_{m} as the base for corresponding variables.

For both weekdays and weekends, the changes from two factors, per capita road area and vehicles per 1,000 people, have obvious impacts on the congestion ratio. Currently, cities in China have taken a variety of approaches to ease the congestion. Megacities such as Shanghai, Beijing, and Guangzhou mainly use auction practice of private car license plates or license-plate lottery to restrict the growth of car ownership, while medium and small-sized cities largely improve their infrastructure to ease traffic pressure. Through the sensitivity analysis results we could find, constructing more roads in the main urban area might have a more

TABLE 5: Multifactor sensitivity analysis on weekdays and weekends.

		Changing rate of per capita road area				
		20%	0	-20%		
Weekdays						
Changing auto of	20%	-1.00%	4.60%	13.01%		
vehicles per 1 000 people	0	-5.60%	0.00%	8.40%		
· · · · · · · · · · · · · · · · · · ·	-20%	-10.20%	-4.60%	3.80%		
Weekends						
Changing auto of	20%	-0.70%	4.46%	12.19%		
vehicles per 1,000 people	0	-5.16%	0.00%	7.73%		
· · · · · · · · · · · · · · · · · · ·	-20%	-9.61%	-4.46%	3.28%		

significant effect on the control of congestion than restricting car ownership. But obviously, in large cities with dense road networks already being constructed, building more roads is fairly difficult.

4.3.2. Multifactor Sensitivity Analysis. The multifactor sensitivity analysis also uses the variables per capita road area and vehicles per 1,000 people as the changing variables. The results are present in Table 5.

The multifactor sensitivity analysis shows, under the assumption that daily VMT stays constant, that if we increase the values of per capita road area and vehicles per 1,000 people by 20%, the congestion ratios on weekdays and weekends will decrease by 1.0% and 0.7%, respectively. Thus, if governments only intensify the construction of road infrastructure and

do not take actions to guide the growth of car ownership, congestion situation can hardly be alleviated. On the other hand, if per capita road area is increased and the car ownership is controlled by the government, the congestion situation can be reduced significantly. Then, the congestion ratios on weekdays and weekends are witnessed to have a significant reduction of 5.6% and 5.16%, respectively.

It must be added, however, that guiding and controlling the growth of car ownership are only a means for easing traffic congestion, rather than a purpose. To alleviate congestion, the key point still lies in reducing the use of cars. Controlling the car ownership is just one way to reduce car travel. Other strategies such as constructing an impeccable public traffic system or nonmotorized transportation could also play a positive role in easing traffic congestion.

5. Conclusions

One of the main contributions of this study is that it provides a feasible way for researchers, especially for those in countries with limited standard traffic data, to analyze traffic congestion from the online map data. Comparing with the results from travel survey in Beijing, this research confirms that the congestion ratio derived from the congestion status denoted as different colors on online maps is a reliable index to describe and compare different cities' congestion states.

Based on the real-time congestion ratio data, cluster analysis is proposed for the selected 23 Chinese cities. The result indicates that the selected cities can be divided into four categories according to their congestion pattern. Furthermore, by multiple linear regression analysis, this study finds that per capita road area, car ownership per thousand people, and VMT per day can significantly affect the congestion ratio. Sensitivity analyses upon influential factors indicate that it is more efficient to reduce congestion when increasing per capita road area and restricting vehicles per 1,000 people simultaneously.

This research holds some limitations as well. Firstly, the congestion status data is only gotten from AutoNavi; comparison with other online maps such as Baidu is needed in order to improve the quality of data. Secondly, congestion and amble state are both considered to be the congestion state in this research; these two states could be distinguished in future works. Moreover, in the regression model, the parameter daily VMT is obtained from questionnaires. A larger sample size can potentially increase the estimation accuracy. Lastly, a more detailed look at the urban shape and household activity within the cities and creating a classification system for predicting congesting levels are very necessary.

Competing Interests

The authors declare that there is no conflict of interests regarding the publication of this article.

Acknowledgments

This research was supported by National Natural Science Foundation of China (Grant no. 51278057), Fok Ying-Tong Education Foundation, China (Grant no. 151075), and Science and Technology Program of Beijing, China (Grant no. Z121100000312101).

References

- N. H. Gartner, C. J. Messer, and A. K. Rathi, Eds., *Traffic Flow Theory*, Transportation Research Board, Washington, DC, USA, 2001.
- [2] D. C. Gazis, Traffic Theory, Springer, Berlin, Germany, 2002.
- [3] L. Elefteriadou, An Introduction to Traffic Flow Theory, vol. 84 of Springer Optimization and Its Applications, Springer, New York, NY, USA, 2014.
- [4] C. F. Daganzo, "Urban gridlock: macroscopic modeling and mitigation approaches," *Transportation Research Part B: Methodological*, vol. 41, no. 1, pp. 49–62, 2007.
- [5] N. Geroliminis and C. F. Daganzo, "Existence of urban-scale macroscopic fundamental diagrams: some experimental findings," *Transportation Research Part B: Methodological*, vol. 42, no. 9, pp. 759–770, 2008.
- [6] B. S. Kerner, "Congested traffic flow: observations and theory," *Transportation Research Record*, vol. 1678, pp. 160–167, 1999.
- [7] B. S. Kerner, The Physics of Traffic: Empirical Freeway Pattern Features, Engineering Applications and Theory, Springer, Berlin, Germany, 2004.
- [8] B. S. Kerner, *Introduction to Modern Traffic Flow Theory and Control*, Springer, Berlin, Germany, 2009.
- [9] B. S. Kerner, "Failure of classical traffic flow theories: a critical review," *Elektrotechnik und Informationstechnik*, vol. 132, no. 7, pp. 417–433, 2015.
- [10] B. S. Kerner, "Failure of classical traffic flow theories: stochastic highway capacity and automatic driving," *Physica A*, vol. 450, pp. 700–747, 2016.
- [11] H. Rehborn, S. L. Klenov, and J. Palmer, "An empirical study of common traffic congestion features based on traffic data measured in the USA, the UK, and Germany," *Physica A: Statistical Mechanics and Its Applications*, vol. 390, no. 23-24, pp. 4466–4485, 2011.
- [12] H. Rehborn and M. Koller, "A study of the influence of severe environmental conditions on common traffic congestion features," *Journal of Advanced Transportation*, vol. 48, no. 8, pp. 1107–1120, 2014.
- [13] National Research Council, *Highway Capacity Manual 2000*, Transportation Research Board, Washington, DC, USA, 2000.
- [14] D. Scharank, B. Eisele, and T. Lomax, *TTI's 2012 Urban Mobility Report*, Texas A&M Transportation Institute, 2012.
- [15] T. Tsekeris and N. Geroliminis, "City size, network structure and traffic congestion," *Journal of Urban Economics*, vol. 76, no. 1, pp. 1–14, 2013.
- [16] E. Safirova, "Telecommuting, traffic congestion, and agglomeration: a general equilibrium model," *Journal of Urban Economics*, vol. 52, no. 1, pp. 26–52, 2002.
- [17] S. Gubins and E. T. Verhoef, "Dynamic bottleneck congestion and residential land use in the monocentric city," *Journal of Urban Economics*, vol. 80, pp. 51–61, 2014.
- [18] A. Anas and R. Xu, "Congestion, land use, and job dispersion: a general equilibrium model," *Journal of Urban Economics*, vol. 45, no. 3, pp. 451–473, 1999.
- [19] A. Sarzynski, H. L. Wolman, G. Galster, and R. Hanson, "Testing the conventional wisdom about land use and traffic congestion:

the more we sprawl, the less we move?" *Urban Studies*, vol. 43, no. 3, pp. 601–626, 2006.

- [20] R. Cervero, "Road expansion, urban growth, and induced travel: a path analysis," *Journal of the American Planning Association*, vol. 69, no. 2, pp. 145–163, 2003.
- [21] A. Nasri and L. Zhang, "The analysis of transit-oriented development (TOD) in Washington, D.C. and Baltimore metropolitan areas," *Transport Policy*, vol. 32, pp. 172–179, 2014.
- [22] L. L. Sim, L. C. Malone-Lee, and K. H. L. Chin, "Integrating land use and transport planning to reduce work-related travel: A Case Study of Tampines Regional Centre in Singapore," *Habitat International*, vol. 25, no. 3, pp. 399–414, 2001.
- [23] Beijing Municipal Commission of Transport, Report of the Fourth Travel Survey of Residents in Beijing 2010, Beijing Transportation Research Center, Beijing, China, 2012 (Chinese).
- [24] G. W. Milligan and M. C. Cooper, "An examination of procedures for determining the number of clusters in a data set," *Psychometrika*, vol. 50, no. 2, pp. 159–179, 1985.
- [25] R. O. Duda and P. E. Hart, Pattern Classification and Scene Analysis, John Wiley & Sons, New York, NY, USA, 1973.
- [26] National Bureau of Statistics of the People's Republic of China, *China City Statistics Yearbook 2013*, China Statistics Press, Beijing, China, 2014 (Chinese).
- [27] Vehicle Usage Survey in China on the internet in February, 2014, http://www.sojump.com/jq/3067915.aspx.
- [28] A. Downs, Stuck in Traffic: Coping with Peak-Hour Traffic Congestion, The Brookings Institution, Washington, DC, USA, 1992.
- [29] S. Stares and Z. Liu, "Motorization in Chinese cities: issues and actions," in *China's Urban Transport Development Strategy: Proceedings of a Symposium in Beijing*, pp. 43–104, World Bank, Washington, DC, USA, 1995.





World Journal







Journal of Applied Mathematics

Hindawi

Submit your manuscripts at http://www.hindawi.com



Journal of Probability and Statistics



International Journal of Differential Equations





Journal of Complex Analysis



International Journal of Mathematics and **Mathematical** Sciences







Mathematical Problems

Journal of **Function Spaces**



Abstract and **Applied Analysis**



International Journal of Stochastic Analysis



Discrete Dynamics in Nature and Society

