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Effect of taxis on emissions and fuel consumption in a city based on license plate recognition data: A case study in Nanning, China

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ABSTRACT

With the rapid increase in urban vehicle ownership, transportation systems have become a major source of air pollution in cities across the globe. Taxis in urban transportation systems contribute to air pollution in two ways: through direct emissions, and through the indirect emissions of other vehicles resulting from increased traffic flow and saturation of the road network caused by vacant taxis. To analyze the differences between emissions in urban road transportation systems with and without taxis quantitatively, this study estimates the on-road emissions and fuel consumption (FC) of vehicles before and during a taxi strike in Nanning, China using license plate recognition data. The spatiotemporal features of the emissions and FC before and during the taxi strike are analyzed, including temporal variations and spatial distributions. The emissions and FC in four typical road segments are also analyzed with and without taxis. The results demonstrate that in the event of a taxi strike, the total emissions and FC decrease to a larger extent compared to the decrease in total travel distance. However, the temporal and spatial patterns of pollutant emissions in the city exhibit no significant change. The amounts of carbon monoxide (CO), hydrocarbons (HC), nitrogen oxides (NOx), particulate matter (PM), FC, and carbon dioxide (CO_2) decrease by 12.54%, 12.98%, 8.01%, 7.80%, 11.33%, and 11.33%, respectively, between 7 a.m. and 1 p.m. during the taxi strike. During the morning peak period (8 a.m.–10 a.m.), the reductions in emissions and FC are significant, i.e., 14.74%, 15.05%, 11.70%, 10.75%, 14.17%, and 14.17% for CO, HC, NOx, PM, FC, and CO_2, respectively. Finally, from the results based on a large dataset, informative insights for improving taxi management systems and reducing emissions and FC are discussed to promote the sustainable development of urban transportation systems.

1. Introduction

The pollution caused by vehicles traveling on urban road networks has become a primary source of air pollution in cities across the globe, particularly with the rapid increase in vehicle ownership in developing countries (Singh et al., 2017; Wang et al., 2015; Zhang and Nian, 2013). Emissions from motor vehicles mainly comprise nitrogen oxides (NOx), carbon monoxide (CO), carbon dioxide (CO_2), hydrocarbons (HC), and particulate matter (PM). For example, Wang et al. (2015) found that the emissions from urban passenger transportation in Beijing in 2012 reached 15 million tons of CO_2, 75.5% of which was from cars. Another study (Wang et al., 2008) showed that the total CO, volatile organic compounds (VOCs), NOx, and PM emissions from vehicles in Shanghai in 2004 were 57.06×10^4, 7.75×10^4, 9.20×10^4, and 0.26×10^4 t, respectively.

Taxis usually comprise only a small percentage of the total number of motor vehicles in a city. In most cities, however, taxis normally account for high daily mileage and long operating times, thereby constituting an important component of urban transportation systems. For example, taxis account for 25% of all traffic flow on roads in Hong Kong (Hong Kong Island and Kowloon) (Yang et al., 2005) and serve approximately 10% of the total passenger transportation volume (Yang et al., 2010). Thus, the effect of taxis on emissions in cities should be investigated. Latham et al. (2008) estimated that taxis contribute 24% of the PM with a diameter of less than 10 μm (PM_{10}) and 12% of the NOx in traffic emissions in central London. In a study in New York City (Gao and Kitirattragarn,

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2008), taxis were considered an opportunity to mitigate air pollution in the city. Wang et al. (2008) estimated that taxis accounted for 18.2% of the total vehicle kilometers traveled, but were responsible for 22.2%, 14.2%, and 10.4% of the CO, VOC, and NOx emissions, respectively. Oliver et al. (2008) showed that taxis accounted for 18% of the total distance traveled in Tianjin, but 33% and 25% of the VOC and CO emissions, respectively. These results indicate that pollutant emissions from taxis represent a severe problem in cities. Moreover, other studies have found that gasoline-based taxi pollutant emissions are higher than those from other vehicle types in cities based on the ratio of emissions to passenger-km traveled. Stead (1999) found that the CO_2, CO, HC, NOx, and PM emissions from taxis were higher than those from private cars traveling at the same speed in Britain based on original data from the 1989/91 National Travel Survey. Reddy et al. (2000) found that the emissions to passenger-km ratio of taxis was higher than that for cars and buses in India. Wang et al. (2015) determined that in terms of the emissions per passenger-km, taxi trips produce more than five times the emissions of bus trips in Beijing. In other words, as a flexible mode of transportation in cities, emissions from taxis are higher per passenger-km owing to their high vacancy ratio (An et al., 2011). Weng et al. (2009) found that the average vacancy rate of taxis in Beijing is greater than 40% based on floating car data. Therefore, taxis are among the major targets for potential reduction of carbon emissions in the transportation sectors of cities.

Emissions from taxis are also influenced significantly by the fuel type. To reduce direct emissions from taxis, several cities have begun to replace the fuel sources for taxis with clean fuels. Some studies have investigated the factors that influence the preference of taxi drivers for clean fuel or vehicle types. Gao and Kitirattragarn (2008) investigated the likelihood that taxi owners in New York City would prefer hybrid electric vehicles, and analyzed the implications of such preferences for emissions. Liu et al. (2012) examined the fuel choice determinants for taxi drivers in Nanjing. A survey of taxi drivers indicated that personal characteristics, vehicle features, and seasonal factors significantly influence the fuel choice of taxi drivers. Based on a survey in the U.S. and South Korea, Park et al. (2014) found that positive factors that can predict driver acceptance of electric taxis are usefulness, services, system quality, and trust, whereas negative factors include perceived risks and costs. Kim et al. (2017) analyzed the implementation potential of electric taxis and determined their socioeconomic benefits. To reduce pollutant emissions and promote the development and use of electric vehicles, the taxi industry has recently been assigned the highest priority for clean fuel replacement over other transportation sectors in major cities in China. For example, nearly all of the taxis in Taiyuan were replaced with electric vehicles in 2016.

Most previous studies on taxi emissions have been based on surveys and statistical data (An et al., 2011; Stead, 1999; Wang et al., 2015). Based on such data, different models can be developed and the average air pollution due to transportation can be estimated. However, detailed pollutant emissions characteristics, such as spatiotemporal features in a city, are difficult to analyze. The development of modern information and communication technology has made it possible to study various fields, such as the environment (Shang et al., 2014; Togawa et al., 2016) and transportation (Klein and Ben-Elia, 2016; Shang et al., 2014). For example, data based on the Global Positioning System (GPS) provides an opportunity to estimate the pollutant emissions of vehicles in combination with detailed speed, acceleration, and deceleration information. Wang et al. (2008) measured the emissions distribution of on-road vehicles in Shanghai with the aid of GPS data. Beckx et al. (2010) estimated the emissions of individual vehicle trips based on second-by-second GPS-based travel data. These studies provide examples of the estimation of vehicle pollutant emissions based on detailed travel behavior information. However, the sample sizes are extremely small and may not be representative of overall citywide vehicle emission patterns. Recently, with the increased popularity of including GPS devices in vehicles, particularly in taxis, the emerging data-driven approach provides new opportunities to investigate the overall impact of taxis on air pollution from the transportation sector (Cai and Xu, 2013; Luo et al., 2017; Yu and Peng, 2013). Cai and Xu (2013) evaluated the effect of plug-in hybrid electric vehicles in a taxi fleet on the life cycle of greenhouse gas emissions based on individual travel patterns derived from real-time trajectory data for 10,375 taxis in Beijing over the course of one week. Yu and Peng (2013) analyzed taxi emissions in Shenzhen based on floating car data for 3000 taxis in May 2008. Luo et al. (2017) used the one-day GPS data record of taxis in Shanghai to analyze their FC and emissions. Through big data analysis and visualization techniques, the results illustrate several interesting characteristics of the spatiotemporal pollutant emissions from taxis in Shanghai.

Previous studies (An et al., 2011; Cai and Xu, 2013; Kim et al., 2017; Weng et al., 2009) have verified the importance of taxis in transportation systems. Furthermore, taxis often need cruising or idling time to find passengers, which can be reduced with the help of taxi guidance and dispatching systems. Besides direct pollutant emissions, taxis in a city also contribute indirectly to the air pollution caused by other motor vehicles. In particular, vacant taxis aggravate traffic congestion in saturated or oversaturated traffic conditions, thereby increasing the emissions of all vehicles in the road network. However, owing to limited available data, existing studies lack a comprehensive analysis of the overall effect of taxis on emissions and FC in cities. Based on approximately 3.91 million license plate recognition (LPR) records for three working days in the city of Nanning, this study investigates the total emissions and FC in the transportation sector before and during a taxi strike in the core area of Nanning. The LPR data employed in this study possesses a higher sampling rate, is more detailed, and contains road segment level information compared to aggregate data (survey data). As such, this study also considers spatiotemporal patterns in the emissions and FC before and during a taxi strike and analyzes changes in emissions on four typical road segments.

The remainder of this paper is organized as follows: Section 2 describes the dataset and methods, including the set of LPR data and model for the real-time emission analysis; Section 3 introduces the city for the case study; Section 4 presents the analysis results, discussion, and related implications; and finally, Section 5 concludes the study.

2. Data and methods

The framework of this study is presented in Fig. 1. Data preprocessing is performed to cleanse the data and obtain basic traffic information, such as the traffic volume, travel distance, and average travel speed. The model is implemented based on the COPERT 4 model (Gkatzoflias et al., 2012) to estimate pollutant emissions and FC. The results obtained from the model are subsequently analyzed in the application portion of the study framework. Additional details regarding each step are presented in subsequent sections.

2.1. Data preprocessing

The LPR data used in this study are from Nanning, China. The dataset covers three Tuesdays in 2016: December 6, 13, and 20. The average of the values obtained on December 6 and 13 is used to represent the scenario before the taxi strike. On December 20, 2016, a taxi strike occurred in Nanning to protest the effect of various ride-sharing services. During the strike, 88.9% of the taxis in the city

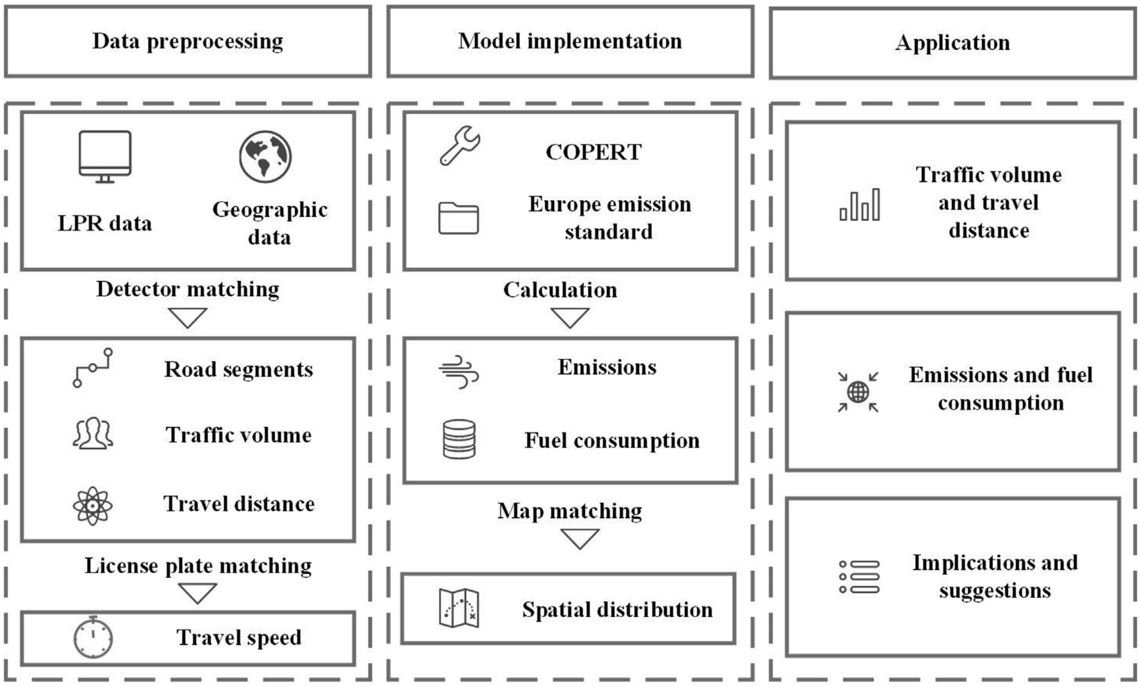

Fig. 1. Proposed study procedure.

were not on the road from morning until noon. The LPR dataset includes approximately 2.68 million records and 1.23 million records obtained between 7 a.m. and 1 p.m. before and during the taxi strike, respectively. The records comprise 173 locations (signalized intersections and road segments). At the end of the detector-matching process, 2.40 million and 1.08 million data records corresponding to scenarios before and during the taxi strike, respectively, remain. Each LPR data record includes the information listed in Table 1. A record without a vehicle plate number (unique ID) still represents a vehicle that passed the stop line or road segment, even though its plate number was not recognized by the camera. Thus, the traffic flow volume can be obtained relatively accurately. Conducting a series of data preprocessing steps is possible based on the information provided by the LPR data. First, the data is cleaned by removing invalid records caused by data recording or transmission errors. Second, the traffic flow volume is calculated from the number of records on a road segment during a time unit. Finally, match processing based on the vehicle plate number is performed to obtain the travel time on a road segment, and thus calculate the average travel speed. Thus, the FC and pollutant emissions can be calculated on the road segment level.

2.2. Estimation methodology for emissions and fuel consumption

The typical methodology for estimating on-road vehicle emissions involves multiplying the emission factors (e.g., NOx emissions in g/L) by 100 km of FC (e.g., L/100 km) (An et al., 2011; Wang et al., 2015) or multiplying the emission factors (e.g., NOx emissions in g/km) by the vehicle activities (e.g., vehicle miles traveled, VMT) (An et al., 2011; Kim et al., 2017; Singh et al., 2017). To calculate the actual emissions in a road segment or road network within a certain period, the major challenge is finding a method to obtain accurate data for the vehicle volume, vehicle type, and vehicle operation status. In this study, the traffic flow volume and average speed on a road segment can be obtained from the LPR data; thus, the latter methodology is used.

Several practical tools for calculating transportation emissions have been developed including COPERT (Computer Programme to Calculate Emissions from Road Transport) (Ntziachristos et al., 2009), MOBILE6 (Mobile Source Emission Factor Model) (Brzezinski and Newell, 1998), MOVES (Motor Vehicle Emission Simulator) (Koupal et al., 2008), and CMEM (Comprehensive Modal Emission Model) (Feng et al., 1997). Previous studies (Cai and Xie, 2010; Xu et al., 2014) have suggested that COPERT is more suitable for calculating the transportation emissions in China because the motor vehicle emission standards in China are similar to those in Europe. Thus, the COPERT 4 model and Euro emission standards were used in this study to estimate the vehicular emissions and FC in the case study city. This study considered CO, HC, NOx, PM (i.e., $PM_{2.5}$), FC, and CO_2. It should be noted that the type of each

Table 1
Description of LPR data.

Fields	Description
Vehicle license plate number (unique ID)	Unique anonymized identifier for each vehicle
Intersection or road segment ID	Unique identifier for each intersection or road segment in Nanning, marked with numbers from "1″ to "173″
Passing time	Time at which each vehicle passes the detector (example: "20161213105234″)
Approach	Approach information, including northbound, southbound, westbound, and eastbound directions
Lane number	Identifiers for each lane, with "1″ denoting the lane closest to the centerline, "2″ denoting the lane second closest to the centerline, etc.

detected vehicle is unknown; thus, all vehicles are assumed to be of the same type, i.e., gasoline-based light passenger cars, which account for over 90% of the traffic volume in the central area of Nanning.

The expression (Gkatzoflias et al., 2012) used to estimate CO, HC, NOx, PM, and FC is as follows:

$$E_{hot:i} = \sum_{r,j} \lambda_j \times N_r \times D_r \times e_{hot:i,j,r}, \quad (1)$$

where $E_{hot:i}$ (g) is the hot exhaust emission of pollutant i or the FC in a road network during a certain period, λ_j is the percentage of vehicles under the Euro $j(j = 1, 2, 3, 4, 5)$ emission standard, N_r is the number of vehicles on road segment r during a certain period, D_r (km) is the length of road segment, and $e_{hot,i,j,r}$ (g/km) is the hot emission factor for pollutant i and FC under the Euro j standard on road segment r.

The emission factors of various pollutants for gasoline passenger cars under different emission standards can be calculated as functions of the vehicle speed. The generic functions used in this study are given in Eqs. (2)–(5) (Gkatzoflias et al., 2012):

$$e_{hot,i,j,r} = (a + c \times V_r + e \times V_r^2) \Big/ (1 + b \times V_r + d \times V_r^2), \quad (2)$$

$$e_{hot,i,j,r} = a \times V_r^5 + b \times V_r^4 + c \times V_r^3 + d \times V_r^2 + e \times V_r + f, \quad (3)$$

$$e_{hot,i,j,r} = (a + c + e \times V_r^2 + f/V_r) \Big/ \quad (4)$$

$$e_{hot,i,j,r} = a \times V_r^b + c \times V_r^d, \quad (5)$$

where a, b, c, d, e, f are coefficients, and V_r is the average travel speed on road segment r. Coefficients a, b, c, d, e, f were obtained from the COPERT 4 model. In the COPERT 4 model, the emission factors for the different emission standards and pollutants are represented by various equations and coefficients.

In accordance with the COPERT 4 model (Gkatzoflias et al., 2012), CO_2 is estimated based on the FC, which is calculated using Equation (6) as follows;

$$E_{CO_2,m} = \sum_{r,j} 44.011 \times \frac{\lambda_j \times FC_{m,j,r}}{12.011 + 1.008 r_{H:C,m} + 16.000 r_{O:C,m}}, \quad (6)$$

where $E_{CO_2,m}$(g) is the CO_2 emissions in a road network when combusting fuel m, $FC_{m,j,r}$ (g) is the FC on road segment r when combusting fuel m under the Euro j standard, $r_{H:C,m}$ is the ratio of hydrogen to carbon for fuel m (1.80 when m is gasoline), and $r_{O:C,m}$ is the ratio of oxygen to carbon for fuel m (0 when m is gasoline). In this study, gasoline is considered as the fuel.

3. Case description

Nanning is the capital of the Guangxi Zhuang autonomous region, which is located in southern China. Nanning is situated in the southeast Asian economic circle; thus, it is an important economic center along the coast of the Beibu gulf. As the representative city of China in the Association of Southeast Asian Nations, Nanning has undergone rapid development in the past decade. Nanning has an administrative area of 22,293 km^2, which consists of seven administrative districts and five counties. As of 2016, the permanent population of Nanning was 7.06 million. The study area is the central city area including parts of Xixiangtang, Xingning, Qingxiu, and Jiangnan districts, where the population density and traffic activities are high.

In 2005–2016, the gross domestic product (GDP) of Nanning increased from 72.8 billion CNY to 370.3 billion CNY, with an annual growth rate of 15.9%. As a result of this rapid economic development, the traffic demand in Nanning has also increased rapidly. The number of private cars in Nanning increased from 0.21 million to 0.8 million from 2009 to 2015, with an annual growth rate of over 24%. This increase in travel demand contributes to air pollution, which has significant adverse effects on human health. The Nanning Comprehensive Transport Annual Report (Nanning, 2015) indicated that the air quality in Nanning worsened as a result of the increasing vehicle traffic demand. From 2009 to 2013, the annual occurrence of good air quality (air pollution index < 100) decreased from 99.18% to 83.84%.

There were 6720 taxis in Nanning in 2015, accounting for only 0.84% of private cars. According to the Comprehensive Transport Annual Report, the average daily driving distance of a taxi in Nanning was 296.05 km in 2015, with 28.9% (85.7 km) vacant driving distance. Taxis are an important part of the urban transportation system in Nanning. The overall difference in traffic conditions and traffic emissions before and during a taxi strike can be analyzed based on the collected data.

4. Results and implications

4.1. Overall effect on traffic conditions and emissions

The emissions and FC of vehicles are determined by two important factors: the first factor is the travel distance, which is affected by the traffic volume to certain extent; and the second factor is the emission factor, which is related to the travel speed. This subsection discusses the changes in these two important factors in the event of a taxi strike and analyzes the resulting changes in emissions and FC.

4.1.1. Effect on traffic volume and travel distance

As the basis for estimating emissions and FC, the traffic volume and travel distance are first analyzed. The hourly traffic volume is calculated as the sum of valid vehicle records detected in the study area in an hour. The hourly travel distance is the sum of the travel distance of detected vehicles in the study area in an hour.

As illustrated in Fig. 2, the hourly traffic volume and hourly travel distance before and during the taxi strike exhibit similar temporal variation trends, i.e., they both reach a peak value at approximately 8 a.m. and then decrease. Between 7 a.m. and 1 p.m., the cumulative traffic volumes before and during the strike are 1.20 million pcu (passenger car units) and 1.08 million pcu, respectively, whereas the cumulative travel distances are 1.47 million km and 1.36 million km, respectively. The cumulative travel volume and travel distance decrease by 10.17% and 7.78%, respectively, during the taxi strike. Compared to the values before the taxi strike, the hourly traffic volume and hourly travel distance during the taxi strike exhibit a significant decreasing trend between 7 a.m. and 10 a.m., with reductions from 6.63% to 25.18%. Between 10 a.m. and 1 p.m., however, the hourly traffic volume and travel distance before and during the taxi strike are nearly the same. There are several possible reasons for these changes. First, the taxi strike eliminated taxi-based traffic volume and travel distances. The taxi strike also affected the behavior of taxi passengers. At the beginning of the taxi strike, i.e., between 7 a.m. and 10 a.m., there was minimal time for the original taxi passengers to react because no strike information was announced in advance. Thus, some passengers chose public transit or (electric) bikes during this period. Thus, a significant

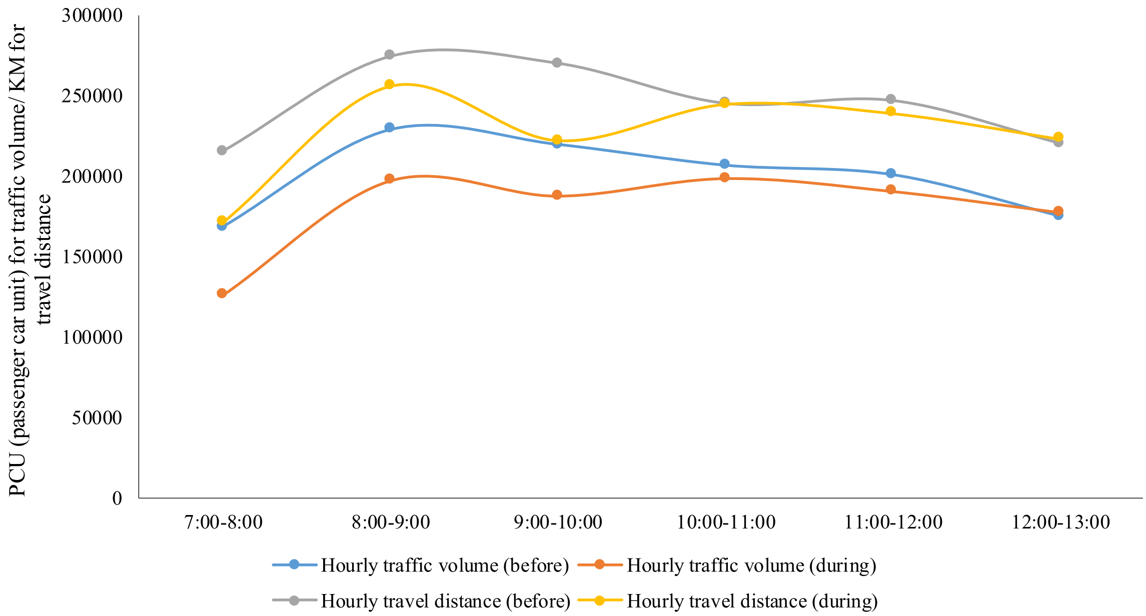

Fig. 2. Variation in traffic volume and travel distance before and during the taxi strike.

decrease in vehicle traffic volume and travel distance was observed. However, abundant time was available for the original taxi passengers to react to the taxi strike 3 h later. Thus, between 10 a.m. and 1 p.m., some original taxi passengers found alternative transport modes similar to taxis, such as borrowing or booking a car via mobile applications. Furthermore, taxi drivers typically pause operation at noon to have lunch. Therefore, even without a taxi strike, many taxis may still have been parked at certain locations at noon. The impact of the taxi strike on the traffic volume and travel distance is thus reduced during the lunch break of taxi drivers between 11 a.m. and 1 p.m.; as a result, changes in traffic volume and travel distance are not apparent during this period.

4.1.2. Effect on travel speed and emission factor

The emission factor is a function of the average travel speed. The changes in travel speed should thus be analyzed during a taxi strike. The average travel speed on the road segment level can be obtained from the data processing procedure. Fig. 3 presents the distribution of the road segment level average travel speed between 7 a.m. and 1 p.m. before and during the taxi strike. A general improvement in

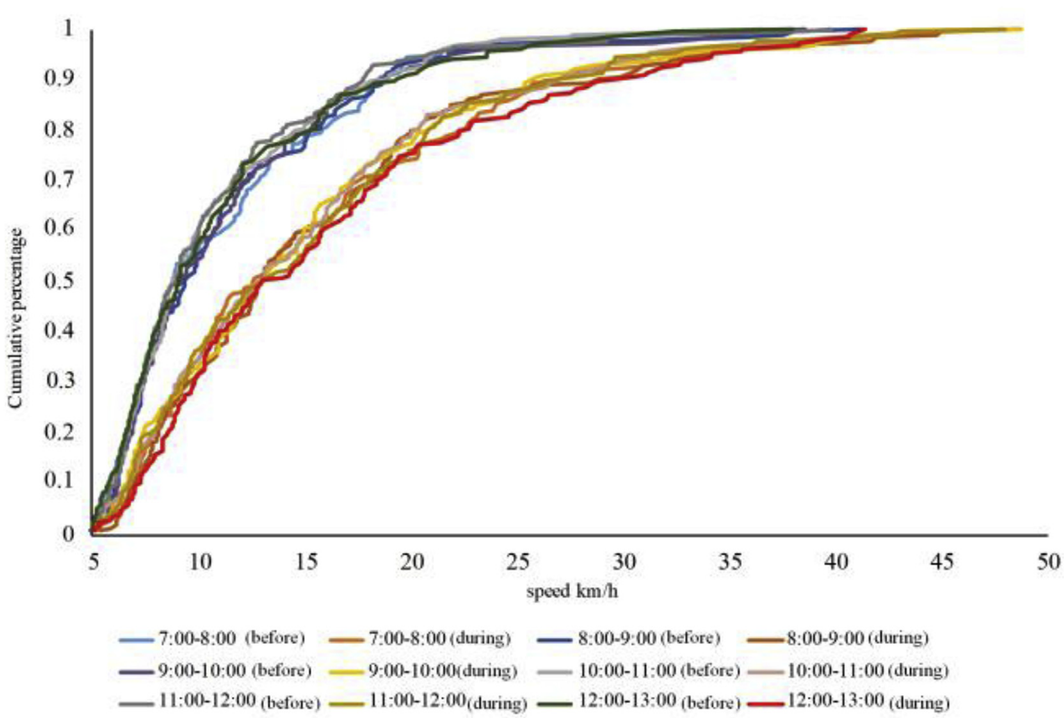

Fig. 3. Distributions of the average travel speed on road segments before and during the taxi strike.

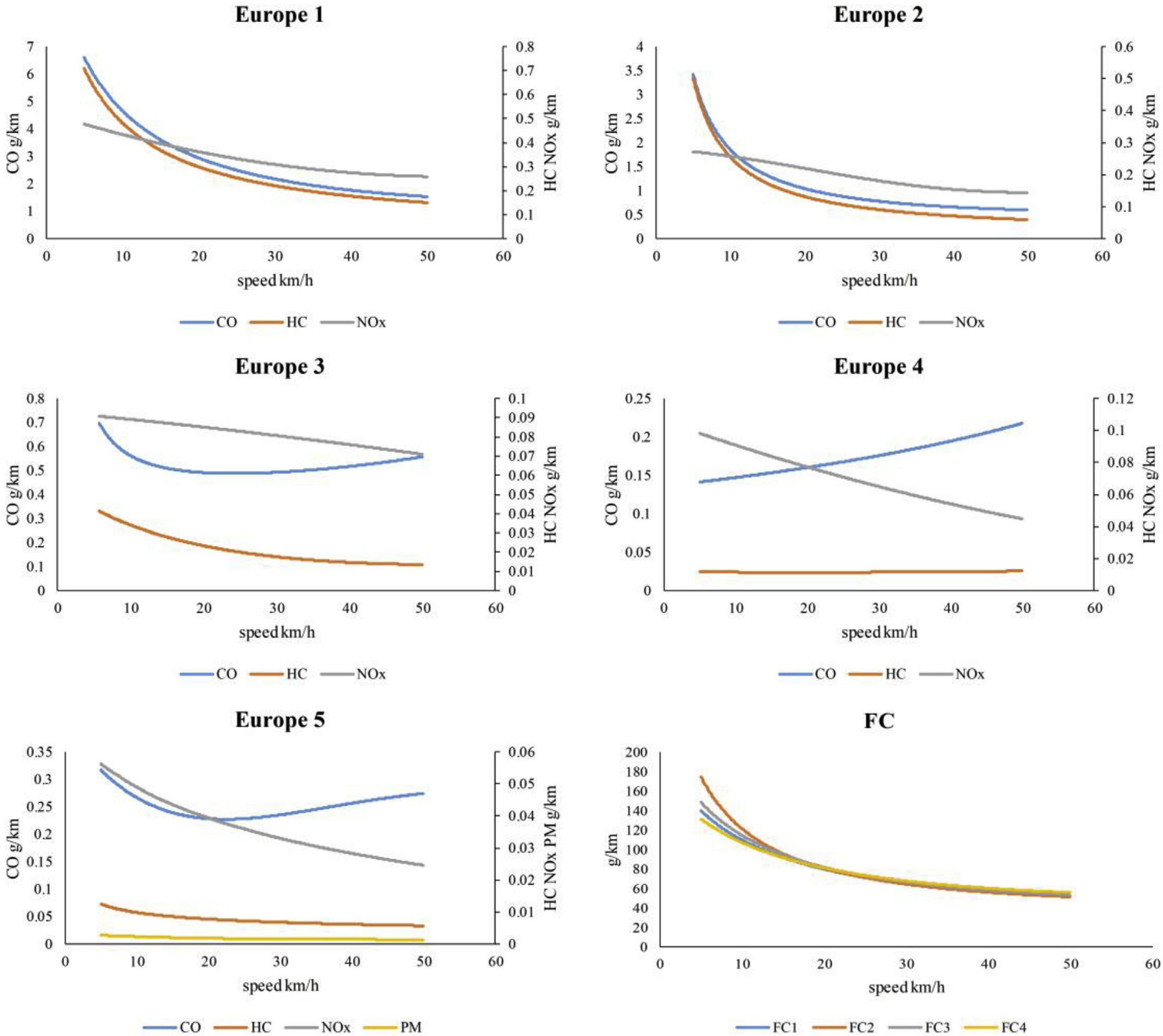

Fig. 4. Relationships between the emission factors and average travel speed under different standards.

the average travel speed is observed during the taxi strike, indicating that at the same cumulative percentage, a higher average travel speed can be observed during the taxi strike.

Along with the traffic volume for each road segment provided by the LPR data, the average travel speed during a certain period can be calculated for the entire study area using Eq. (7):

$$v = \frac{\sum_r N_r \times v_r}{\sum_r N_r}, \tag{7}$$

where v is the average travel speed in the study area during a certain period, N_r is the number of vehicles detected during a certain period on road segment r, and v_r is the average travel speed on road segment r during a certain period. In the event of a taxi strike, the average speed on the entire road network between 7 a.m. and 1 p.m. increased by 13.74%, thereby making the average traffic conditions better than before the taxi strike.

The average travel speed directly determines the emission factors. The relationship between the emission factors and average travel speed is shown in Fig. 4. Most of the emission factors decrease monotonically with increasing average travel speeds from 5 to 50 km/h. However, the CO emission factor under the Euro 3 and 5 emission standards and the HC emission factor under the Euro 4 emission standard initially decrease and then increase with increasing average travel speed. Concurrently, the CO emission factor under the Euro 4 emission standard steadily increases with the average travel speed.

4.1.3. *Effect on emissions and fuel consumption*

During the taxi strike, with 88.9% of the taxis (accounting for less than 1% of private individual vehicles) not on the road, the cumulative emissions of CO, HC, NOx, PM, and FC between 7 a.m. and 1 p.m. were reduced by 12.54%, 12.98%, 8.01%, 7.80%, and 11.33%, respectively. The emission of CO_2 is proportional to that of FC; thus, FC and CO_2 are changed by the same percentage of 11.33%.

Table 2
Emissions and fuel consumption during morning peak hours.

Period	Standard	Euro 1					
	pollutants	CO	HC	NOx	PM	FC	CO_2
before	emissions (g)	2418552	256906.1	289315.5	2256.341	58325123	1.86E+08
	average emission factor (g/km)	3.451489	0.366628	0.412879	0.00322	83.23516	264.9661
during	emissions (g)	2052078	218653.4	255944.3	2014.413	50082603	1.59E+08
	average emission factor (g/km)	3.280206	0.349513	0.409122	0.00322	80.05607	254.846
Period	Standard	Euro 2					
	pollutants	CO	HC	NOx	PM	FC	CO_2
before	emissions (g)	1029168	142284.1	115609	2256.341	65220962	2.08E+08
	average emission factor (g/km)	1.468715	0.203052	0.164984	0.00322	93.07614	296.2933
during	emissions (g)	872047.9	120053	103609	2014.413	55718093	1.77E+08
	average emission factor (g/km)	1.393952	0.191902	0.165617	0.00322	89.06429	283.5222
Period	Standard	Euro 3					
	pollutants	CO	HC	NOx	PM	FC	CO_2
before	emissions (g)	313146.3	17793.51	48101.78	896.9306	60885635	1.94E+08
	average emission factor (g/km)	0.446888	0.025393	0.068646	0.00128	86.88924	276.5983
during	emissions (g)	273029.4	15212.5	42048.18	800.7604	52230652	1.66E+08
	average emission factor (g/km)	0.436432	0.024317	0.067213	0.00128	83.48968	265.7764
Period	Standard	Euro 4					
	pollutants	CO	HC	NOx	PM	FC	CO_2
before	emissions (g)	79297.08	6293.81	48004.9	896.9306	56919931	1.81E+08
	average emission factor (g/km)	0.113164	0.008982	0.068507	0.00128	81.22982	258.5824
during	emissions (g)	72805.89	5533.889	41504.11	800.7604	48990973	1.56E+08
	average emission factor (g/km)	0.116379	0.008846	0.066344	0.00128	78.31112	249.2912
Period	Standard	Euro 5					
	pollutants	CO	HC	NOx	PM	FC	CO_2
before	emissions (g)	145370.2	5307.209	25923.56	1157.28	–	–
	average emission factor (g/km)	0.207456	0.007574	0.036995	0.002331	–	–
during	emissions (g)	127018.9	4579.602	22364.07	1029.33	–	–
	average emission factor (g/km)	0.203037	0.00732	0.035749	0.001645	–	–
Period	Pollutants	CO	HC	NOx	PM	FC	CO_2
before	total emission (g)	790499.4	85815.61	107599.1	1466.73	59654316.5	1.9E+08
during	total emission (g)	673974.7	72901.91	95007.95	1309.08	51202659	1.63E+08

Based on these results, the overall contribution of taxis to pollutant emissions and FC in Nanning could be roughly estimated to account for at least 8.77%–14.60% of the total emissions of pollutants and FC. Additionally, based on the proportion of the number of taxis and their corresponding emissions, it can be inferred that taxis, in general, account for higher average emissions and greater FC (also longer average travel distances) compared to typical private vehicles during a day; this result is consistent with those reported in previous studies in other cities (Gao and Kitirattragarn, 2008; Wang et al., 2008).

The taxi strike exerted a considerable effect on the taxi passengers during the morning peak hours (8 a.m.–10 a.m.). Thus, the effects on emissions and FC during the morning peak hours during the taxi strike are discussed here. Table 2 lists the total emissions and FC under different standards during the morning peak hours before and during the taxi strike. The different emission standards indicate the various emissions and FC for the same traffic demand and conditions owing to the improvement in engine technology with the strict increase in the standards. As listed in Table 2, all of the total emissions and FC under different emission standards exhibit a 5.54%–15.62% decline in the morning peak hours during the taxi strike. The maximum decrease in HC emissions (15.62%) during the taxi strike is achieved under the Euro 2 emission standard, whereas the minimum decrease in PM emissions (5.54%) is attained under the Euro 5 emission standard. Concurrently, the average emission factor related to the average travel speed is also calculated. The average emission factor for CO under the Euro 4 emission standard increases by 2.84% during the taxi strike owing to its monotonically increasing relationship with the travel speed. All of the other average emission factors either remain the same or decrease by 0.91%–5.49% during the taxi strike.

The percentage of vehicles under the Euro 1, Euro 2, Euro 3, Euro 4, and Euro 5 emission standards in Nanning are approximately 20%, 20%, 20%, 30%, and 10%, respectively. No equation is provided for calculation of the FC and CO_2 emissions under the Euro 5 emission standard in the applied COPERT 4 model; thus, 10% Euro 5 emission standard vehicles are added to the Euro 4 emission standard when estimating the FC and CO_2 emissions. The calculated total emissions and FC are listed in Table 2. All of the emissions and the FC decrease during the taxi strike, with CO, HC, NOx, PM, FC, and CO_2 reduced by 14.74%, 15.05%, 11.70%, 10.75%, 14.17%, and 14.17%, respectively.

4.2. Spatiotemporal features of emissions and fuel consumption

4.2.1. Temporally varying features

The temporally varying features of the emissions and FC can be further analyzed based on the hourly travel distance and average travel speed for each road segment, as illustrated in Fig. 5. The emissions and FC are proportional to the travel distance. Thus, the temporal variation in the emissions is similar to that of the travel distance.

Before the taxi strike, the peak values of CO, HC, FC, and CO_2 occur between 8 a.m. and 10 a.m., whereas the peak values of NOx and PM are observed between 8 a.m. and 9 a.m. After reaching the peak values, all of the pollutants gradually decrease. During the taxi strike, the peak values of all of the emissions and the FC occur between 8 a.m. and 9 a.m., and reductions are observed between 9 a.m. and 10 a.m. After 10 a.m., the emissions and FC fluctuate within a small range.

Compared to the emissions before the taxi strike, a significant decrease in CO, HC, NOx, PM, FC, and CO_2 is observed between 7 a.m. and 10 a.m. during the taxi strike. From 10 a.m. to 11 a.m. and 12 p.m.–1 p.m., there is no apparent decrease in CO, HC, FC, and CO_2

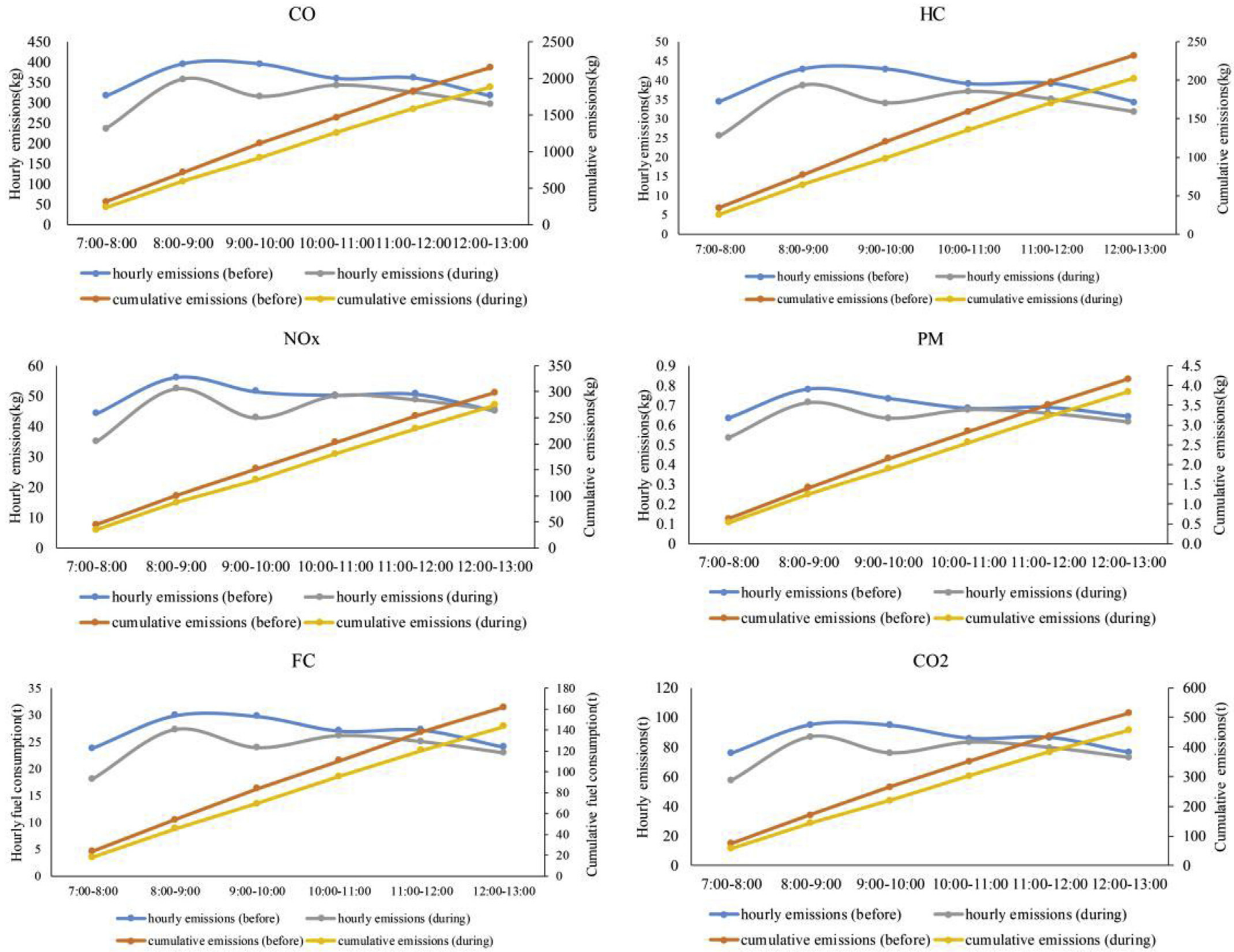

Fig. 5. Temporal variation in the emissions and fuel consumption before and during the taxi strike.

during the taxi strike, while a decrease of 7.97%–10.32% is observed between 11 a.m. and 12 p.m. For NOx and PM, the emission changes are within 5% between 10 a.m. and 1 p.m. during the taxi strike. Thus, after 10 a.m., the percentage decrease in emissions and FC is smaller than that before 10 a.m., which corresponds to the observed temporal variation in the travel distance.

4.2.2. Overall spatially varying features

From a spatial perspective, the distributions of cumulative emissions and FC between 7 a.m. and 1 p.m. before and during the taxi strike are shown in Fig. 6. All of the figures exhibit very similar spatial distributions for the different pollutants and FC before and during the taxi strike. It should be noted that the areas that lack detectors usually exhibit zero emissions, which does not precisely represent the real situation. The emissions and FC are mainly concentrated in four core areas: namely, areas A, B, C, and D. Areas A and C comprise several bridges across the Yongjiang River in Nanning, which connect the north and south parts of the city and carry considerable daily traffic volume. Area B is the CBD (central business district) of the city. Area D is an important expressway that connects the central area of the city to the suburban areas. The reasons for the similar spatial distributions before and during the taxi strike may be explained as follows. First, the emissions and FC are proportional to the total travel distance of all vehicles; thus, the different pollutants exhibit similar distributions. Second, a taxi strike does not change the spatial patterns of a certain travel demand. For example, Nanning city is divided into two parts by the Yongjiang River, and the two parts are closely connected. The traffic volume on the Zhongxing bridge (in area C) only decreases by 0.89% during the morning peak hours during the taxi strike, thereby indicating that the vehicle traffic demand in certain areas is stable and will not change even if a taxi strike occurs. Thus, certain main emission areas will not vary considerably during a taxi strike.

4.2.3. Spatiotemporal features

The impact of the taxi strike on the emissions and FC varies in different periods and spaces; thus, their spatiotemporal features should be analyzed. This study selects the CO emissions as a typical pollutant to explore these spatiotemporal features, as shown in Fig. 7. Considering the similarity between emissions and FC, the features of the other emissions and the FC are not repeated.

A taxi strike only changes the travel mode, rather than the basic travel demand, of residents used to commuting by taxi. As such, changes in the spatiotemporal trends with time are, for the most part, similar before and during the taxi strike. Areas A, B, C, and D depicted in Fig. 7 are analyzed here.

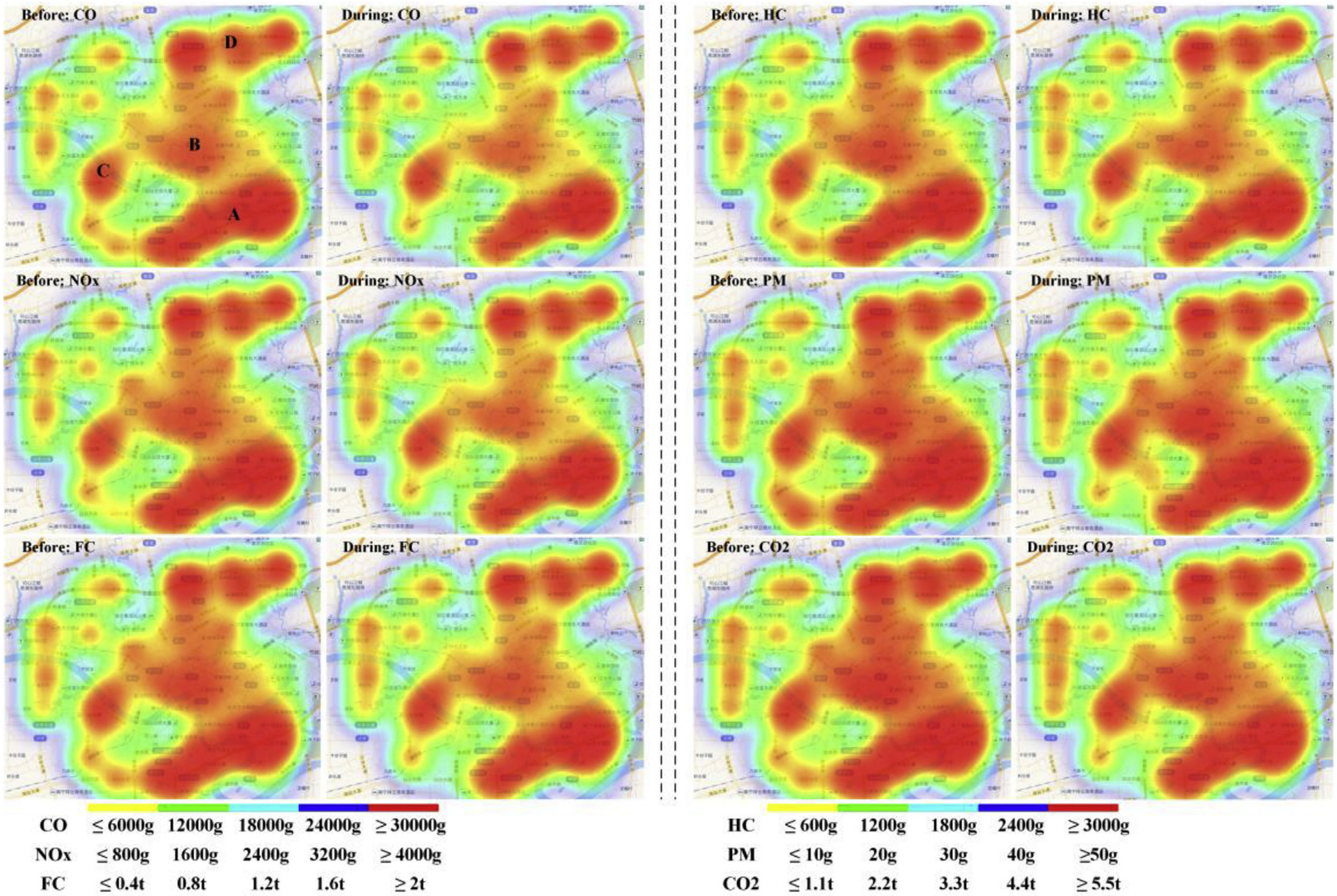

Fig. 6. Spatial variation in the emissions and fuel consumption before and during the taxi strike.

Each area possesses its own specific characteristics. Area A is mostly residential with several primary schools, and the travel demand (usually for commuting) in such areas is largely rigid and remains reasonably unaffected by taxis going on strike. Thus, pollutant emission levels in area A remain rather high from morning to noon before and during the taxi strike. In contrast, area B mainly comprises some businesses (shopping malls), administration buildings (government offices), and public service facilities (hospitals, parks, and universities), and these areas can be considered hotspot destinations for people hiring taxis (Chen et al., 2018; Si et al., 2013). Consequently, the emissions in area B are observed to decrease significantly in the early morning hours during the taxi strike, followed by a gradually attained peak level during the day. At noon, lower emission levels in area B are observed compared to the levels observed early in the morning on days without a strike. In contrast, the emission levels at noon during the strike remain rather high. This can, in part, be attributed to a large number of morning trips being postponed by the taxi strike, thereby resulting in increased emissions at noon. As for areas C and D, they contain several important transportation corridors carrying a certain proportion of fixed travel demand. The taxi strike, therefore, does not have a major impact on the relative concentration of emissions in these areas.

4.3. Road-level variation

In Sections 4.1 and 4.2, the impacts of a taxi strike on the entire road network were discussed. The emissions and FC depend on the traffic demand and conditions, which vary considerably in different road segments. In this study, four typical road segments from the four main areas are selected, as illustrated in Fig. 8, to investigate the effect of the taxi strike on different road segments. Road segments A and D are segments of the expressway located on the border of the study area. Road segments B and C are segments of urban roads, of which road segment C is a bridge across the Yongjiang River.

The changes in the traffic volume and travel speed distribution in the four road segments are presented in Table 3 and Fig. 9. The conditions during the taxi strike are similar to those during traffic restrictions, and the impacts of the former vary with the road segment (Li and Guo, 2016). On road segment A, a significant decrease in the traffic volume is observed between 7 a.m. and 1 p.m. during the taxi strike, as can be seen in Table 3. With the decreasing traffic volume, the 15th-percentile to 85th-percentile travel speed on road segment A increases by over 100%, as shown in Fig. 9. Road segment B is located in the CBD; hence, the impact of the taxi strike is similar to that in area B. On road segment B, the traffic volume is reduced between 7 a.m. and 11 a.m. and an increase occurs between 11 a.m. and 1 p.m. during the taxi strike. The travel speed distribution on road segment B indicates that the 15th-percentile to 85th-percentile travel speed increase by 40%–50% during the taxi strike. On road segment C, the traffic volume and travel speed fluctuate within a normal range during the taxi strike. Road segment C is a bridge across the Yongjiang River with a high and stable traffic demand; thus, the taxi strike has nearly no effect on the traffic volume and travel speed on road segment C. On road

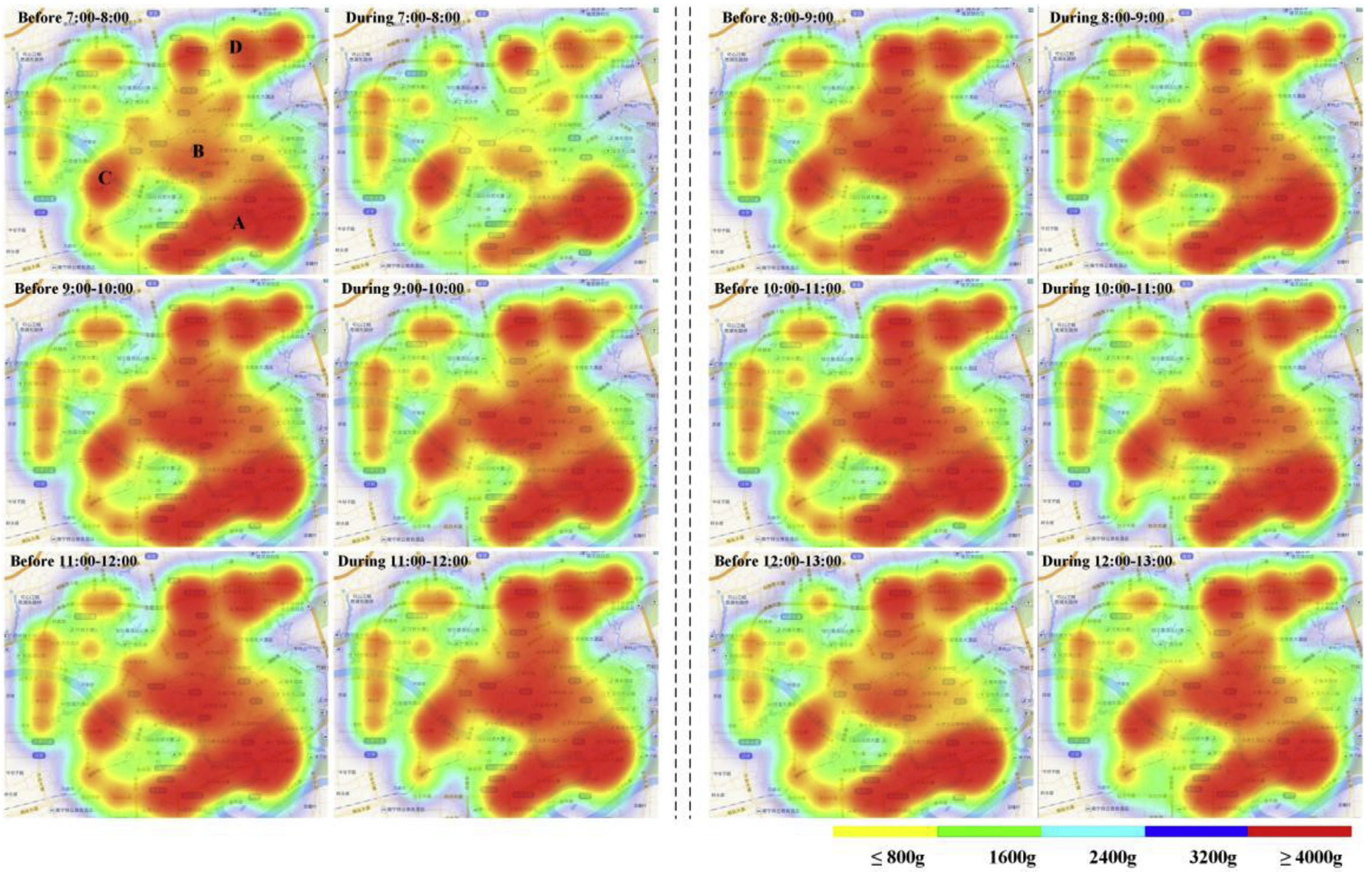

Fig. 7. Spatiotemporal variation in CO emissions before and during the taxi strike.

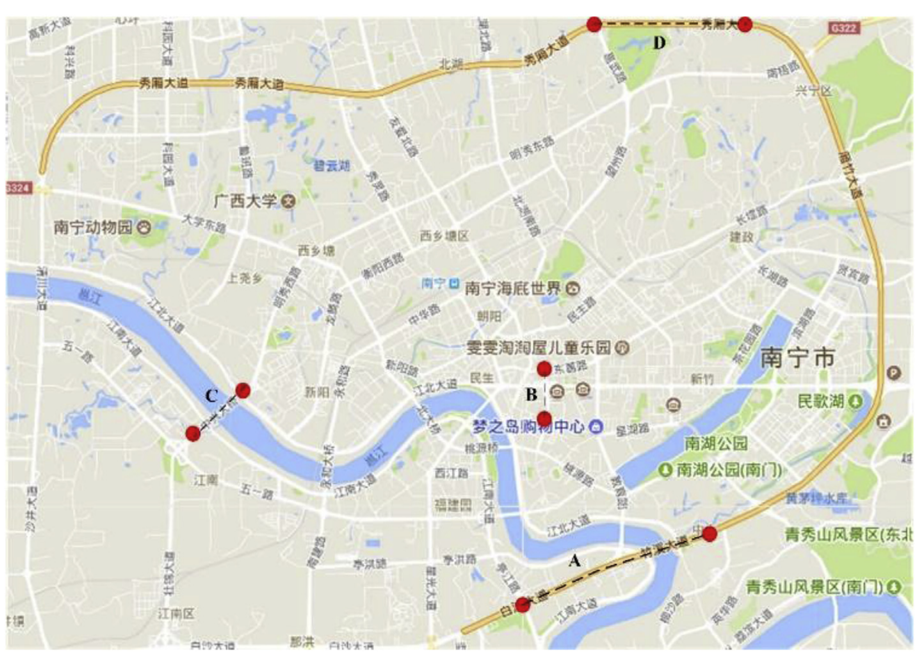

Fig. 8. Four typical road segments.

Table 3
Changes in traffic volume during the taxi strike.

Road segment	7:00 a.m.–8:00 a.m.	8:00 a.m.–9:00 a.m.	9:00 a.m.–10:00 a.m.	10:00 a.m.–11:00 a.m.	11:00 a.m.–12:00 p.m.	12:00 p.m.–1:00 p.m.
A	−32.36%	−24.73%	−29.31%	−29.10%	−23.37%	−28.36%
B	−40.36%	−17.72%	−3.68%	−2.82%	11.10%	2.83%
C	−4.87%	0.46%	−0.80%	−9.27%	2.45%	4.71%
D	−24.60%	−12.50%	−22.06%	−11.96%	−4.28%	−9.68%

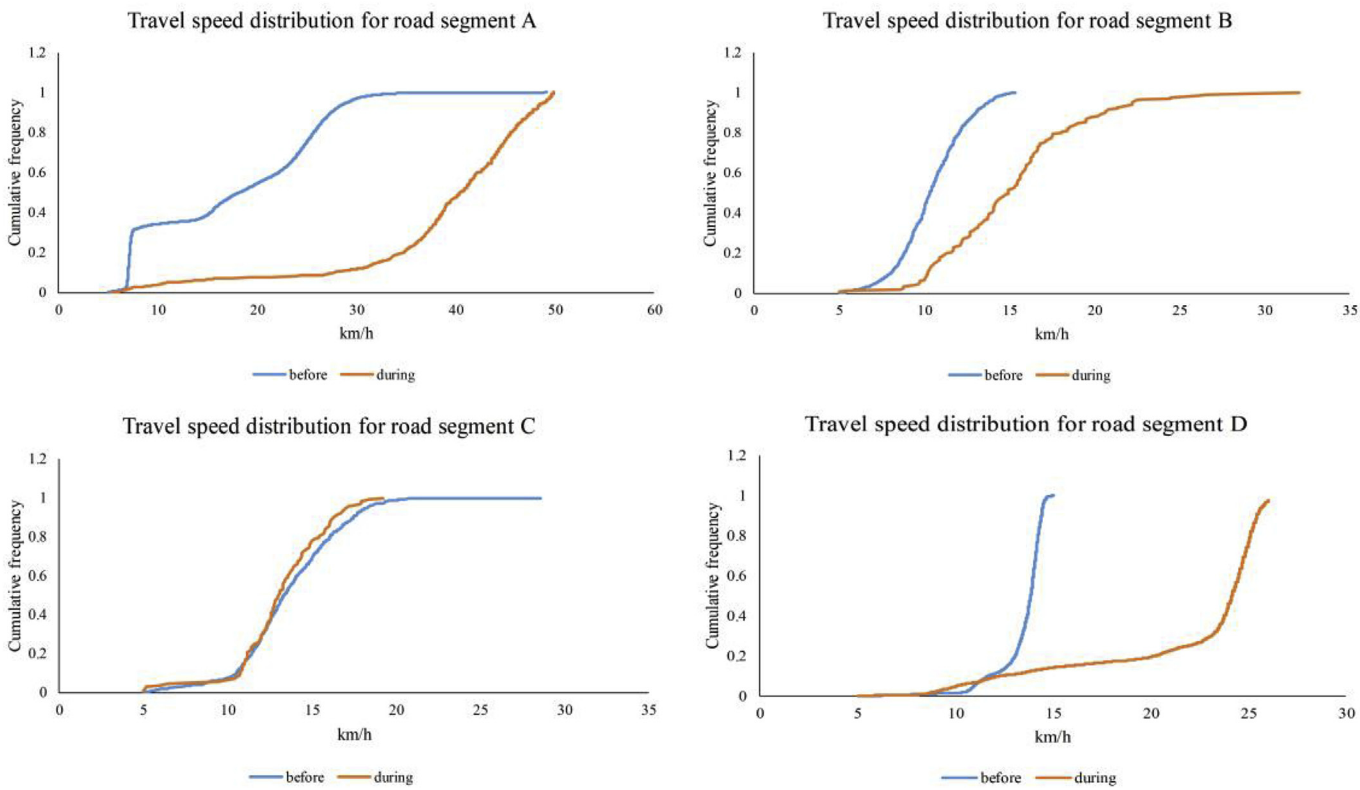

Fig. 9. Travel speed distributions on four typical road segments between 7 a.m. and 1 p.m.

segment D, the traffic volume decreases by 4.28%–24.60%, and significant changes in the travel speed are observed during the taxi strike.

Changes in the emissions and FC on the four road segments between 7 a.m. and 1 p.m. during the taxi strike are shown in Fig. 10. With the significant decrease in traffic volume and increase in travel speed during the taxi strike on road segment A, all of the emissions types and the FC on road segment A are reduced by more than 25% between 7 a.m. and 1 p.m. On road segment B, the emissions and FC between 7 a.m. and 11 a.m. exhibit a decreasing trend during the taxi strike, with a dramatic decrease in the HC and CO emissions. However, with the increasing traffic volume between 11 a.m. and 1 p.m. on road segment B, the emissions and FC also increase during the taxi strike for this period. On road segment C, the changes in emissions and FC during the taxi strike are within 10%, showing that the taxi strike has a minimal effect on road segment C. In general, the emissions and FC on road segment D all decrease during the taxi strike, with the largest decrease occurring between 9 a.m. and 10 a.m. However, the percentage of this decrease is smaller than that on road segment A.

Different road segments have unique functions and traffic condition characteristics in road networks; thus, the taxi strike exerts different effects on the traffic volume, travel speed, and emissions on each individual road segment. The road segment-level impact analysis indicates that the taxi strike not only affects direct emissions but also indirect emissions of the taxis. For example, the traffic volume on road segment A between 8 a.m. and 9 a.m. decreases by only 24.73%, but the HC emissions could decrease by more than 50% because the decreasing traffic volume changes the travel speed and emission factors of the other vehicles on the road. Hence, indirect emissions can be also be affected by a taxi strike.

4.4. Implications

Based on the results, it can be seen that although taxis usually constitute only a small fragment of urban transportation systems, their average travel distance per day is longer compared than that of a typical private car. Therefore, pollutant emissions from taxis account for a remarkable proportion of the total transportation emissions. On the other hand, taxis involved in high-frequency operations contribute to increased traffic volume and a reduced average travel speed in the road network, thereby influencing traffic conditions and causing additional indirect emissions. To reduce the total pollutant emissions caused by taxis in a city, several potential taxi management counter-measures can be implemented. These include limiting the total travel distance of taxis, enhancing the efficiency of taxi trips, and improving the fuel quality used in taxis. These strategies are described below.

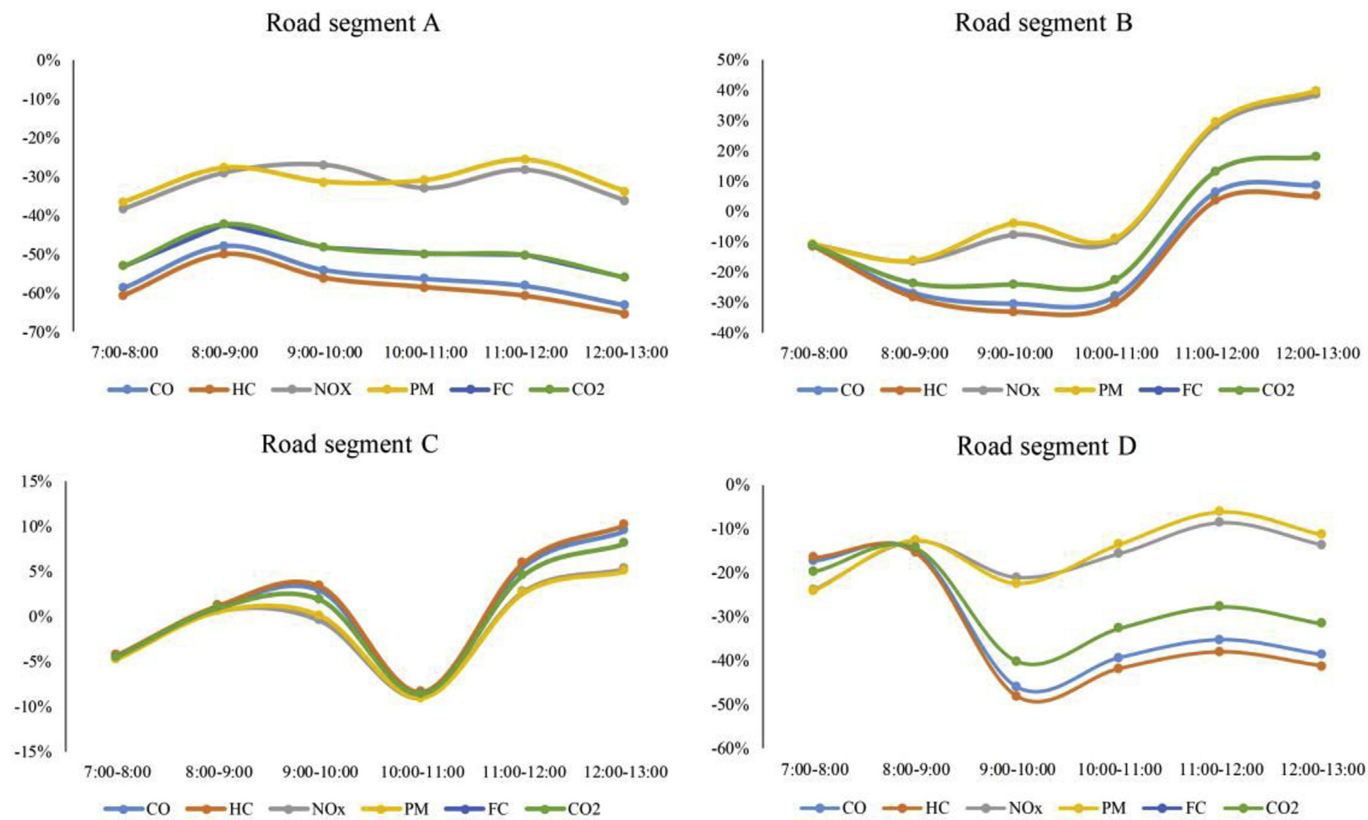

Fig. 10. Changes in emissions and fuel consumption on the four road segments during the taxi strike.

1) Reduce the taxi vacancy rate: In general, direct emissions from taxis can be categorized into two parts: service emissions when the taxis are serving customers, and non-service emissions when they are vacant. To reduce taxi emissions, non-service emissions should first be reduced. If the vacancy rate of taxis can be reduced significantly, it will provide two potential benefits for the reduction of pollutant emissions. First, direct emissions from taxis will be reduced because the mileage of vacant taxis is reduced. Second, when the number of vacant taxis on a road is reduced, the level of service on the road will be improved, thereby reducing the emissions of other vehicles. One solution is to establish an effective taxi booking system. At present, with the development of mobile internet, taxi-hailing apps are gaining prominence in China. As such apps increase in ubiquity, taxis should be encouraged to stop in a certain area to wait for their next customer instead of cruising while vacant. Taxi operation modes should be changed with the development of technology and demand for emissions reduction.

2) Improve the taxi occupancy rate: As mentioned above, taxi pollutant emissions are typically higher than those of other vehicle types in a city based on the emissions per passenger-km. Thus, the taxi occupancy rate can be improved. One possible solution is a taxi-sharing system, particularly in the newly emerging "sharing economy." At present, with the widespread use of smartphones and real-time applications, designing and deploying smart taxi-sharing systems is possible, and could reduce the total vehicle kilometers while retaining the same total number of delivered passengers. Santi et al. (2014) studied the potential benefits of taxi-sharing systems based on GPS taxi trip data; the results indicated that the cumulative trip length could be decreased by at least 40%. In the future, the promotion of taxi sharing in Chinese cities is a potential approach for improving the efficiency of taxi systems and reducing their negative effects on traffic operations and pollutant emissions.

3) Promote clean energy: Taxis have a significant impact on emissions; thus, the fuel quality or engine quality of taxis should be improved. For example, to promote the development of electric vehicles and reduce pollutant emissions from taxis, several cities in China, such as Taiyuan, recently began replacing old taxis with electric vehicles. If the environmental issues associated with electricity production are disregarded, electric vehicles can be considered to be zero-emission. However, replacing the current taxis with purely electric vehicles cannot reduce the effect of vacant taxis on other vehicles.

5. Conclusions

The taxi strike in Nanning provides an opportunity for researchers to investigate the overall effect of taxis on emissions in the transportation sector of the city both at the macro-level and micro-level based on LPR data. First, a taxi strike serves to reduce the direct emissions from taxis. Second, it reduces the traffic flow volume on most road segments, thereby contributing to an improvement in the average vehicle speed on the road (although not on all road segments). This study revealed that with the increase in average travel speed, most of the average emission factors over the entire road network decreased, thereby resulting in a reduction in indirect emissions.

The following several conclusions could be drawn from this study. (1) In the event of a taxi strike, the cumulative traffic volume and travel distance were observed to decrease by 10.17% and 7.78%, respectively, between 7 a.m. and 1 p.m. Correspondingly, reductions in the total amounts of CO, HC, NOx, PM, FC, and CO_2 emissions were observed to be on the order of 12.54%, 12.98%, 8.01%, 7.80%, 11.33%, and 11.33%, respectively. The observed decrease in emissions and FC was greater than the decrease in travel distance, indicating a reduction in the indirect emissions caused by taxis. (2) The absence of taxis (accounting for only 0.84% of private individual vehicles on the road) resulted in an approximately 8.77%–14.60% reduction in the total emissions of the different pollutants and FC. This confirms that taxis account for higher than average pollutant emissions compared to typical private cars. (3) The average travel speed in the entire road network between 7 a.m. and 1 p.m. was improved by 13.74% in the event of a taxi strike, indicating overall improved average traffic conditions. (4) The taxi strike did not change the spatiotemporal features of the emissions and FC. Similar temporal variations and spatial distributions of the emissions and FC were observed during the taxi strike. (5) Different road segments exhibited varying functions and traffic demands; hence, the effects on each individual road segment differed.

Owing to the coverage of detectors, this study covered only the road segments with valid LPR data in the center of Nanning, rather than all of the road segments. The limitations of this investigation include the obtained LPR data covering only three mornings. However, the data for these morning period could fully represent the impacts of the taxi strike. The effects were expected to be reduced with time because abundant time would be available for the original taxi passengers to find alternative modes of travel. With the development of high-resolution and high-accuracy real-time detection data, in the future, we can conduct in-depth studies and develop real-time emissions and FC estimation and prediction systems to support traffic and city management.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2019.01.123.

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