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Estimation and analysis of emissions from on-road vehicles in Mainland China for the period 2011–2015

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ABSTRACT

With the enforcement of emissions standards and fuel-economy standards in Mainland China, it is both important and interesting to see how these recent emissions reduction strategies affected the spatiotemporal patterns of emissions over the period 2011–2015, which have rarely been examined in previous studies. This study aimed to fill this gap by estimating and analyzing vehicle emissions patterns to support the development of emissions reduction strategies. We established emissions inventories for Mainland China and individual provinces using statistical data from official yearbooks. The aggregated results showed that emissions of greenhouse gas increased slowly and emissions of pollutants decreased sharply. The individual results showed that there was an imbalance in the distribution of emissions, with high total emissions and emissions per inhabitant in developed provinces and high emissions per unit GDP in developing provinces. Specifically, light passenger cars and heavy-duty trucks contributed more than 50% of emissions, and their emissions were statistically spatially auto-correlated, which might hint that there were inherent spatial clustering patterns among emissions. Thereafter, a self-organizing map was used to cluster individual provinces, and indicated that a few provinces can be clustered together according to the similarity of their emissions patterns. Finally, we found that the influences of socioeconomic factors on emissions varied across space, where emissions in northeastern provinces were more likely to be affected by population and those in southwestern provinces tended to be influenced by GDP. These findings are believed to be useful for the development of emissions reduction strategies for sustainable development.

1. Introduction

With the rapid progress of urbanization, increasing numbers of people are resettling from dispersed rural settlements to concentrated urban areas. According to UN statistics (United Nations, 2015), it is reported that the urban population constitutes approximately 49% of the population of Mainland China. The trend in urbanization has had a positive impact on economic development, but at the same time it has led to formidable challenges to environmental sustainability, not just for China, but for the entire world (Zhang, 2015). One urgent problem is the huge volume of emissions contributed by the large number of on-road vehicles, which are very important sources of global warming and air pollution. For instance, a previous study showed that emissions of CO, CO_2, non-methane volatile organic compounds (NMVOC), NO_x, PM_{10} and SO_2 at the national level in China increased at an average annual rate of 15%, 15%, 15%, 14%, 16% and 15%, respectively, from 1980 to 2005 (Cai and Xie, 2007). In recent years, new emissions standards (referred to as China I to China V) and emissions reduction strategies have been gradually enforced in Mainland China, which has helped to reduce the increases in emissions due to the rapid growth in the vehicle population at the regional level (Lang et al., 2012; Lu et al., 2013; Song et al., 2016; Liu et al., 2017) or the prefectural level (Chan and Yao, 2008; Wang et al., 2010a; Zhang et al., 2013, 2014). However, with the enforcement of the emissions standards China IV in 2011 and China V in 2013, and the implementations of fuel-economy standards, it is still unclear how these recent emissions reduction strategies have affected the spatiotemporal patterns of emissions owing to the lack of relevant studies.

On-road vehicle emissions are mainly composed of air pollutants and greenhouse gases (Sun et al., 2016). The former includes CO, NO_x, NMVOC and PM_{10}, which will give adverse impacts on air quality and human health (Chen et al., 2017). It is estimated that more than 75% of urban dwellers might be exposed to the air that did not meet the national standard of ambient air quality (Shao et al., 2006). The latter

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mainly contains CO_2, which is known as greenhouse gas with the ability of atmospheric heat-trapping and consequently cause the effect of global warming. It is estimated that temperature of the Earth's surface might exceed historical value as early as 2047 if no reduction strategies were taken to control the growth rate of greenhouse gas emissions, which will result in an environmental catastrophe and affect the livelihoods of people worldwide (Mora, 2013). Therefore, to facilitate the development and assessment of vehicle emissions reduction strategies, it is of vital importance to estimate the vehicle emissions and examine their spatiotemporal patterns.

To estimate the emissions of on-road vehicles, studies in the literature have adopted the bench tests (Huai et al., 2004), the tunnel tests (Zanini et al., 2005), the remote sensing technique (Geng et al., 2013) and the model-based method. The last method can be either the micro-scale model or the macro-scale model. The micro-scale model is typically used to calculate the vehicle emissions with the real-time collected movement data in terms of location, time and velocity. For instance, Oguchi's model (Oguchi et al., 2002) was adopted to estimate the CO_2 emissions from volunteer's GPS trajectories in the city of Borlange, Sweden (Jia et al., 2013), and the IVE model was used in Chennai (Nesamani, 2010). The macro-scale model is widely used for deriving the emissions inventories with official yearbooks including the registered vehicle number and the vehicle miles travelled. For instance, the US EPA Mobile Model was developed to estimate emissions inventories of 49 US states (EPA, 2003). The EMFAC Model operates according to the Californian emissions standard and is specifically used in California (Reid et al., 2016). The European COPERT model is designed for member countries of the EU and derives emissions inventories with a detailed classification of vehicles (Achour and Olabi, 2016). Furthermore, there are other models, such as the LIISA model in Finland and the TREMOD model in Germany (Azzolini et al., 2014).

In the literature, on-road vehicle emissions inventories have been generated for various regions. For example, emissions inventories were derived for Spain for the period 1988–2010 (Buron et al., 2004), Denmark for the period 1990–2030 (Winther and Nielsen, 2011), Sardinia, Italy (Bellasio et al., 2006), Norwich, UK (Nejadkoorki et al., 2008), India (Nagpure and Gurjar, 2012) and the Federal District, Brazil (Réquia et al., 2015). In Mainland China, emissions inventories have been estimated and examined at different spatial levels. At the national level, Song and Xie (2006) established an emissions inventory for the single year 2002 using the COPERT III model. Cai and Xie (2007) used the same model to derive emissions inventories for the period 1980–2005 and reported an imbalance in the spatial distribution of emissions. Recently, Lang et al. (2014) derived emissions inventories for the period 1999–2011 using the COPERT IV model and found good linear relationships between vehicle emissions and GDP. At the regional or provincial level, emissions inventories have been developed and analyzed for metropolitan areas or developed provinces, such as the Beijing-Tianjin-Hebei region for the period 1999–2010 (Lang et al., 2012), the Pan-Yangtze River Delta for the period 1999–2013 (Song et al., 2016), Shandong province for the period 2000–2014 (Sun et al., 2016), Guangdong province for the period 1994–2014 (Liu et al., 2017). At the city level, vehicle emissions inventories have also been established for the three most developed cities (Chan and Yao, 2008), namely, Beijing for the period 1998–2020 (Zhang et al., 2014), Shanghai for 2004 (Wang et al., 2008) and Guangzhou for the period 2005–2009 (Zhang et al., 2013).

However, there are several limitations in previous studies. Firstly, considering the rapid socioeconomic development and, in particular, the enforcement of the emissions standards China IV in 2011 and China V in 2013, the implementation of fuel-economy standards in 2006, 2009, and 2011, an in-depth study of Mainland China for the period 2011–2015 is missing. Secondly, the patterns of spatiotemporal trends in vehicle emissions were examined well in previous studies, but how the emissions contributed by different types of vehicles were spatiotemporally auto-correlated and clustered was not well reported; such details might be useful for the development of local emissions reduction strategies. Thirdly, the influence of socioeconomic factors (such as GDP) on emissions was assumed to be spatially homogeneous in previous studies, but in fact this influence might vary spatially owing to imbalances in socioeconomic development. Therefore, this study aimed to conduct an in-depth investigation of the derivation of on-road vehicle emissions inventories for Mainland China for the period 2011–2015 and also to analyze the spatiotemporal patterns of emissions. Specifically, our study may help to answer the following questions: (1) what was the temporal trend in emissions in Mainland China or individual provinces from 2011 to 2015? (2) how were the emissions contributed by different types of vehicles in individual provinces spatiotemporally auto-correlated and clustered? and (3) how did the influences of socioeconomic factors on emissions vary across space? To address these questions, we established emissions inventories and used novel spatiotemporal data mining methods to reveal emissions patterns. Our results will be beneficial for understanding the mechanisms of vehicle emissions and developing new emissions reduction strategies.

After the introduction in this Section, we illustrate the procedure used to establish the emissions inventories in Section 2. The results of spatiotemporal analysis and socioeconomic analysis are elaborated and discussed in Section 3. Conclusions are drawn in Section 4.

2. Estimation of on-road vehicle emissions

2.1. Dataset collection

The main datasets used in this study were obtained directly from the China Statistical Yearbooks for the period 2000–2016 and comprised a vehicle-related dataset and a socioeconomic dataset. The first dataset was used to estimate the vehicle population in each year, whereas the second dataset was used to reveal the spatial variations of socioeconomic factors for vehicle emissions. Besides, we used meteorological data obtained from the Chinese Meteorological Data Sharing Service System, which contained information on temperature and humidity for each province for the period 2011–2016.

However, it should be noted that motorcycles were excluded from our vehicle data for several reasons. Firstly, the motorcycle population is relatively small in comparison with those of other types of vehicles; hence, motorcycle emissions (Lang et al., 2012, 2014) accounted for only 0.01% of total emissions in 2015. Secondly, the registered number of motorcycles cannot closely reflect the real situation, because a significant number of motorcycles are not registered in the system, which is mainly due to loose regulation. Thirdly, the number of motorcycles has decreased dramatically in recent years owing to the emergence and popularity of electric motorcycle in Mainland China.

2.2. Estimation of emissions inventories

The respective emissions inventories were estimated using the following equations:

$$E_{i,y,j,k} = \sum_s VP_{i,y,j,s} * VKT_{i,y,j} * EF_{i,y,j,k,s} \;\; (k \neq CO_2, \;\; s = es) \tag{1}$$

$$E_{i,y,j,k} = \sum_s VP_{i,y,j,s} * VKT_{i,y,j} * FCR_{y,j,s} * r \;\; (k = CO_2, \;\; s = fs) \tag{2}$$

$$E_{i,y,k} = \sum_j E_{i,y,j,k} \tag{3}$$

$$E_{y,j,k} = \sum_i E_{i,y,j,k} \tag{4}$$

$$E_{y,k} = \sum_i E_{i,y,k} \tag{5}$$

where i denotes the province, y denotes the year, j denotes the vehicle type including gasoline-powered light passenger car (LPC) and light-duty truck (LDT), diesel-powered heavy passenger car (HPC) and heavy-duty truck (HDT), k denotes the emission type, and s denotes the

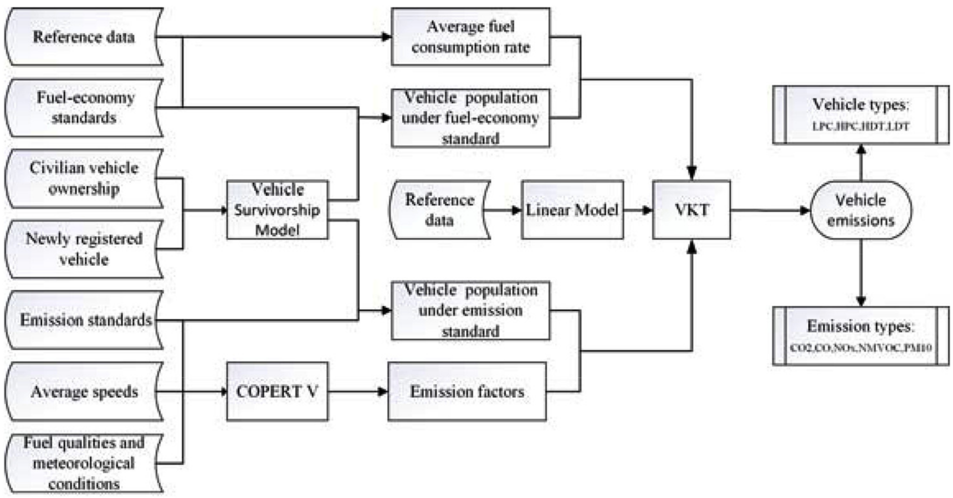

Fig. 1. A flow chart to show the derivation of vehicle emissions inventories.

emissions standard (*es*) or fuel-economy standard (*fs*). $VP_{i,y,j,s}$ is the population of vehicles of type *j* complying with standard *s* in province *i* in year *y*; $VKT_{i,y,j}$ is the average annual vehicle kilometers travelled (*VKT*) by vehicles of type *j* in province *i* in year *y*; $EF_{i,y,j,k,s}$ is the emission factor of emission type *k* for vehicles of type *j* complying with emissions standard *s* in province *i* in year *y*; $FCR_{y,j,s}$ is the fuel consumption rate for vehicles of type *j* complying with fuel-economy standard *s* in year *y*; *r* is the CO_2 emission factor of 2360 g/L (Wang et al., 2010b); $E_{i,y,j,k}$ is the amount of emissions of type *k* in province *i* in year *y* from vehicles of type *j*; $E_{i,y,k}$ is the amount of emissions of type *k* in province *i* in year *y* from all types of vehicles; $E_{y,j,k}$ is the amount of emissions of type *k* in Mainland China in year *y* from vehicles of type *j*; and $E_{y,k}$ is the amount of emissions of type *k* in Mainland China in year *y* from all types of vehicles. On this basis, the above emissions inventories were estimated at both national and provincial levels (see Fig. 1), and they were hot running emissions from tailpipe.

2.2.1. Estimation of vehicle population complying with emissions standards and fuel-economy standards

Firstly, according to the timetable for the implementation of the emissions standards given in Table 1, the vehicle population complying with different emissions standards in the period 2011–2015 were calculated using the following Equation (6). Here, *ys* is the year of implementation of emissions standard *s*, $N_{i,t,j,s}$ is the number of newly registered vehicles of type *j* complying with emissions standard *s* in province *i* in year *t*, $T_{i,y,j,}$ is the total number of vehicles of type *j* in province *i* in year *y* and *SF(i, j, y-t)* is the vehicle survival function for vehicles of type *j* in province *i*. The survival function has a Weibull distribution owing to the effect of scrapping older vehicles, and the detailed technique used to determine it can be found in the study by Hao et al. (2011). It can be clearly seen that the estimation of vehicle population was composed of two steps. The first step comprised calculating the vehicle population complying with the emissions standards from China I to China V using the survival function, and the second step comprised determining the vehicle population complying with the emissions standard China 0 by subtracting the population complying with the other emissions standards from the total population. Besides, this study assumed that once a new emissions standard was implemented, newly registered vehicles would thereafter comply with the same standard (Lang et al., 2012).

Secondly, we refer to the mandatory fuel-economy standards released by the Chinese government in 2004 (GB, 19578–2004) and 2007 (GB, 19578–2007). The first standard was implemented in 2006 for Phase 1 and in 2009 for Phase 2, whereas the second standard took effect in 2009 for Phase 1 and in 2011 for Phase 2. According to the timetable in Table 2, the vehicle population complying with the two fuel-economy standards in the period 2011–2015 were calculated using Equation (6). However, it is used under the two fuel-economy standards, and *s* denotes the fuel-economy standard. Besides, we assumed again that once a new fuel-economy standard was implemented, newly registered vehicles would thereafter comply with the standard.

$$VP_{i,y,j,s} = \begin{cases} \sum_{t=ys}^{y} N_{i,t,j,s} * SF(i,j,y-t), & s \neq China\ 0\ \ or\ \ s \neq Phase\ 0 \\ T_{i,y,j} - \sum_{s \neq China0} VP_{i,y,j,s}, & s = China\ 0\ \ or\ \ s = Phase0 \end{cases} \tag{6}$$

By applying Equation (6) to the total number of vehicles and the number of newly registered vehicles, the vehicle population distributions under the emissions standard and the fuel-economy standard for the period 2011–2015 were estimated, respectively. For the purpose of illustration, we display the vehicle population distributions for seven selected provinces. In Fig. 2a, it is clearly seen that the number of LPC constituted a significant proportion of the total vehicle population. In particular, during the implementation of an emissions standard, the number of vehicles complying with this emissions standard increased, whereas the number of vehicles complying with earlier emissions standards decreased over time. The similar finding can be also observed in Fig. 2b, but the population of HPC and HDT do not comply with any fuel-economy standard.

2.2.2. Calculation of average annual VKT

The average annual *VKT* is an important parameter that indicates

Table 1
Timetable (year) for the implementation of emissions standards (Note: China 0 means no emissions standard is implemented).

	Vehicle types	China 0	China I	China II	China III	China IV	China V
Beijing	LPC, LDT	Before 1999	1999	2003	2006	2008	2013
	HPC, HDT	Before 2000	2000	2003	2006	2008	2013
Other provinces	LPC, LDT	Before 2000	2000	2005	2008	2011	
	HPC, HDT	Before 2001	2001	2004	2008	2013	

Table 2
Timetable (year) for the implementation of fuel-economy standards (Note: Phase 0 means no fuel-economy standard is implemented).

Vehicle types	Phase 0	Phase 1	Phase 2	Vehicle types	Phase 0	Phase 1	Phase 2
LPC	Before 2006	2006	2009	**LDT**	Before 2009	2009	2011
HPC	null	null	null	**HDT**	null	null	null

the extent of vehicle activity and hence plays a substantial role in the estimation of vehicle emissions. However, there is a lack of *VKT* data in the China Statistical Yearbooks. *VKT* information was therefore obtained by summarizing the results of previous research (He et al., 2005; Wang et al., 2010a; Huo et al., 2012b; Lang et al., 2012). Specifically, previous studies reported a significant linear relationship between *VKT* and economic indicators (Huo et al., 2012b; Liu et al., 2017). On the basis of the *VKT* values for representative provinces obtained from the literature, we constructed linear relationships of these values with the economic indicator GDPI (i.e., GDP index, which denotes the ratio of the GDP in the current year to the previous year) for each type of vehicle. Using this linear model, we estimated the average annual *VKT* for each province for the period 2011–2015. Fig. 3 shows the average annual *VKT* values for selected provinces, which show that heavy-duty trucks (HDT) and heavy passenger cars (HPC) travelled much further than light passenger cars (LPC) and that their *VKT* values gradually increased from 2011 to 2015 for all provinces. This indicates that public passenger transport is flourishing and freight transport might give rise to high levels of emissions.

2.2.3. Calculation of emission factors for vehicles complying with emissions standards

In this study, we chose the COPERT V model (EEA, 2016) to calculate the pollutant emission factors. The reasons for our choice can be attributed to the following three factors. Firstly, the COPERT V model is a collection of algorithms and models that can be specifically used to estimate emission factors at the European level for road transport. Secondly, most vehicles in Mainland China were manufactured using European vehicle technologies and hence are comparable to European vehicles from a technological perspective (Xie et al., 2006; Cai and Xie, 2013). Thirdly, the vehicle emissions standards implemented in Mainland China are comparable to those used in Europe, which is due to the similarity in vehicle technologies.

Using the COPERT V model, we estimated the emission factor of each emission type for each vehicle type complying with a certain emissions standard in each province for the period 2011–2015. The inputs into this model were relatively simple and included the average speed, fuel quality, meteorological data (temperature and humidity), the types of vehicles (LPC, HPC, LDT and HDT), and the emissions standards. Specifically, the average speed of each province was directly obtained from the literature (Tang et al., 2011); the fuel quality mainly referred to the sulfur content according to the Chinese national and local fuel standards. As can be seen in Fig. 4, the implementation of stringent emissions standards (from China I to China V) did in fact reduce the emission factors of pollutants emissions, which is in good agreement with the findings of many previous studies (Huo et al., 2012b; Lang et al., 2012).

2.2.4. Derivation of average fuel consumption rates for vehicles under fuel-economy standards

In this study, CO_2 emissions were calculated using average fuel consumption rates, which were derived from the two fuel-economy standards and the literature. The first standard includes Phase 1 and 2 fuel consumption limits for the vehicles containing LPC, whereas the second standard also includes Phase 1 and 2 fuel consumption limits for the vehicles covering LDT. However, they are weight-based fuel-

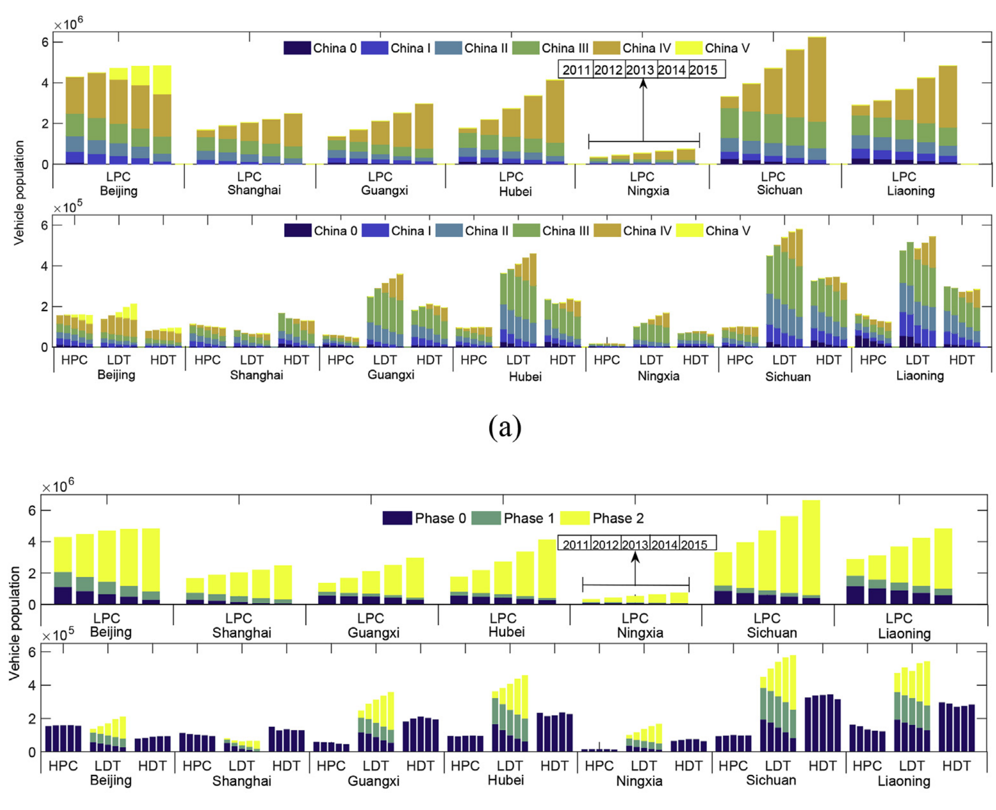

Fig. 2. The distributions of vehicle population complying with different (a) emissions standards and (b) fuel-economy standards for selected provinces.

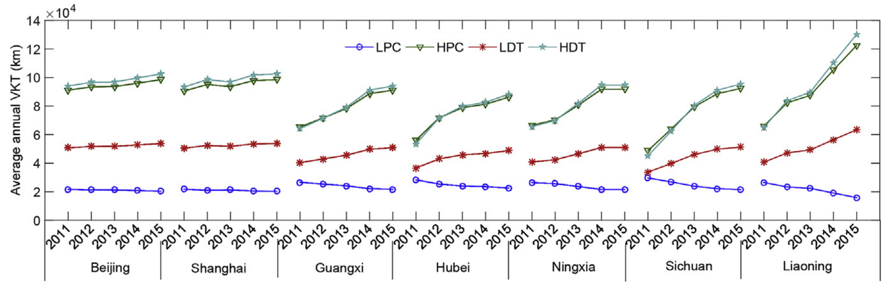

Fig. 3. Average annual *VKT* values for selected provinces.

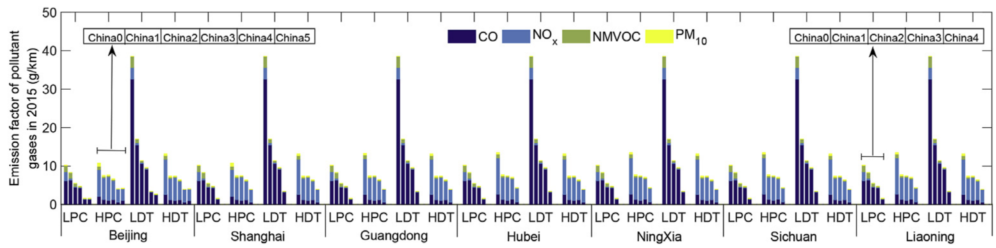

Fig. 4. Emission factors of pollutant gases for selected provinces in 2015.

Table 3
Average fuel consumption rates (L/100 km) for the four types of vehicles in China.

Vehicle types	Phase 0	Phase 1	Phase 2	Vehicle types	Phase 0	Phase 1	Phase 2
LPC	11.5	10.9	9.8	**LDT**	12.1	11.3	10.3
HPC	22.0	22.0	22.0	**HDT**	24.9	24.9	24.9

economy standards, which means a fuel consumption rate limit is specified for a group of vehicles within a certain range of weights. Considering the absence of the vehicle weight information, we assumed that the number of vehicles is the same for each group, and thus the arithmetic mean value of the fuel consumption rate limits were calculated for LPC and LDT at Phase 1 and 2. Besides, the average fuel consumption rates at Phase 0 for LPC and LDT were roughly estimated as the corresponding values at Phase 2 dividing by 85%, because previous studies suggested that fuel efficiency could be improved roughly by 15% by the implementations of the two-phase standard (Huo et al., 2012a). As for HPC and HDT, the national mandatory fuel-economy standard took effect in July 2015, and hence, we ignored its affect and used the fuel consumption rates reported in the literature for the vehicles of HPC and HDT (Wang et al., 2010b). The average fuel consumption rates for vehicles under fuel-economy standards are shown in Table 3.

3. Results and discussions

3.1. Spatiotemporal patterns at the aggregated level

This Section starts by reporting the temporal trends in different types of emissions in Mainland China from 2011 to 2015 (see Fig. 5). Regarding the main greenhouse gas, we can see that CO_2 displayed a similar trend of growth in total emissions, emissions per inhabitant, and emissions per unit GDP from 2011 to 2014. In 2015, the total emissions and the emissions per inhabitant showed a declining trend in growth rate, whereas the emissions per unit GDP presented a decrease. This finding suggested that the implementation of fuel-economy standards had a limited impact on reducing CO_2 emissions, because it might be offset by the growth of vehicles. Specifically, from 2011 to 2015, CO_2 emissions increased by approximately 423 million tonnes (MT) with average annual growth rates of 9.9%. Regarding emissions produced per unit GDP (one hundred million Yuan), CO_2 emissions increased by approximately 94.9 tonnes with an average annual growth rate of 1.3%, although a clear reduction could be observed in 2015. With the implementation of more stringent fuel-economy standard, CO_2 emissions are expected to continue decreasing.

Regarding total pollutants emissions, CO, NO_x, and NMVOC experienced a continuous decrease from 2012 to 2015, whereas PM_{10} displayed a sharp decrease from 2014 to 2015 (see Fig. 5). This observation can mainly be attributed to the implementations of the emissions standard China IV in 2011 for LPC and LDT and the emissions standard China IV in 2013 for HPC and HDT. Besides, we can clearly see that emissions of PM_{10} underwent a fluctuating increase before 2014, which might indicate that the emissions reduction due to the implementation of the emissions standard China III in 2008 was offset by the growth in the vehicle population. By normalizing the total emissions, emissions of the four pollutants per inhabitant displayed a similar trend to the total pollutant emissions, but emissions of the four pollutants per unit GDP exhibited a decreasing trend over time. Specifically, from 2011 to 2015, the emissions of CO, NMVOC and NO_x decreased by approximately 1.2 MT, 0.49 MT and 1.1 MT with average annual rates of decline of 2.3%, 6.9% and 4.8%, respectively, but PM_{10} emissions increased by a small increment of 8.1 KT with an average annual growth rate of 1.1%. However, regarding the pollutant emissions produced per unit GDP, emissions of CO, NMVOC, NO_x and PM_{10} decreased by approximately 8.6, 1.7, 4.7 and 0.1 T with average annual rates of decline of 10.0%, 14.3%, 12.3% and 7.0%, respectively. Thus, we can see that the current implementation of emissions standards has effectively reduced pollutant emissions in Mainland China.

Then, we examined the temporal trends in emissions contributed by different types of vehicles in Mainland China for the period 2011–2015, as shown in Fig. 6. Regarding the greenhouse gas, LPC and HDT were the dominant vehicle types in terms of CO_2 emissions, but the percentage contribution from LPC gradually increased from 50.3% in 2011 to 52.8% in 2015 and that from HDT decreased from 29.9% to 28.6%. This finding further suggests that stringent management policy should be enforced to limit the growth of LPC population.

Regarding the air pollutants, LPC and LDT were the dominant vehicle types in terms of emissions of CO, and their percentage contributions fluctuated around 51.1% and 37.1%, respectively, over the study period. This is consistent with many studies in the literature

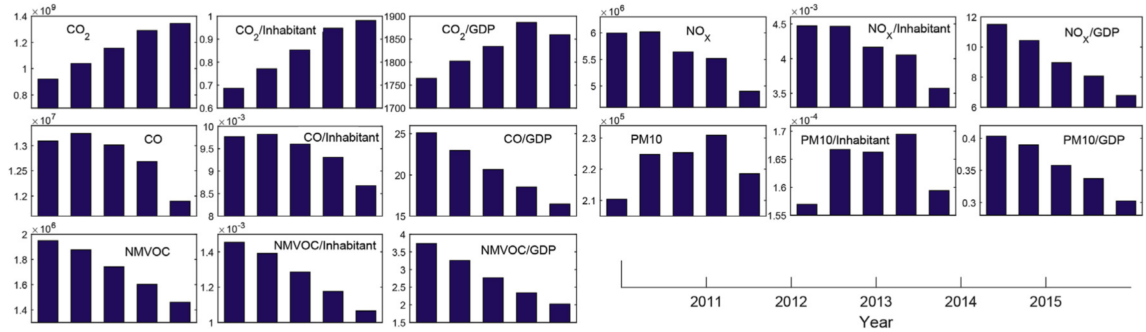

Fig. 5. Temporal trend of the total emissions, emissions per inhabitant and emissions per unit GDP for the period 2011–2015.

(Wang et al., 2010a; Lang et al., 2014; Song et al., 2016; Liu et al., 2017) and is partly due to their high emission factors of CO. LPC was also the dominant vehicle type in terms of the percentage contribution of NMVOC, which increased from 61.7% to 64.3%. This finding coincides with literature findings (Lang et al., 2012; Song et al., 2016; Liu et al., 2017) but represents a relatively large proportion in comparison with the previous studies, which mainly results from the large population of LPC and implies that the implementation of the emissions standard China IV had a limited influence on the emissions of NMVOC by LPC in comparison with other vehicle types. In addition, HDT was the sole dominant vehicle type in terms of emissions of NO_x and PM_{10}, of which its percentage contributions increased from 48.7% to 62.5% and decreased from 56.6% to 48.5%, respectively. This finding agrees well with literature findings (Lang et al., 2012, 2014; Ma et al., 2015; Song et al., 2016; Sun et al., 2016; Liu et al., 2017) and can be attributed to three reasons: firstly, HDT had a high emission factor of NO_x; secondly, it can be seen that a sharp growth in the HDT population occurred in 2014; and thirdly, the development of freight transport has increased the *VKT* of HDT. Thus, it suggests that the implementation of the emissions standard China IV had a greater influence on HDT in terms of emissions of PM_{10} than emissions of NO_x.

Next, we examined whether the emissions contributed by the dominant vehicle types were spatially auto-correlated, which would benefit the development of local emissions reduction strategies. Using the spatial auto-correlation technique, we computed the value of Moran's I (m) for each of the 35 categories of emissions contributed by the dominant vehicle types for the period 2011–2015. For instance, CO_2 emissions contributed by LPC in 2011 had the m value of 0.11 and p value of 0.04. As shown in Table 4, it seems that most (approximately 83%) of the categories of emissions contributed by the dominant vehicle types were spatially auto-correlated, which means that high (low) values of emissions tended to be spatially close to each other. This observation was further verified via a proportion test with the p value less than 0.001, which implies that there is sufficient evidence to conclude that the emissions contributed by the dominant vehicle types that were spatially auto-correlated were much more common than those that were not spatially auto-correlated. On the other hand, we found that most (approximately 68%) of the categories of emissions contributed by the non-dominant vehicle types displayed spatially random distributions. The above findings with respect to spatial auto-correlation hint that there were inherent spatial clustering patterns among emissions, which will hence be examined in the next Section.

3.2. Spatiotemporal patterns at the individual level

Considering the imbalance in development among provinces, we started by reporting the temporal trends in different types of emissions for individual provinces for the period 2011–2015, which may provide strategies for local policy-makers to control emissions. Regarding the CO_2 emissions, on average, Shandong ranked first among the provinces, and they were almost 27.8 times those in Xizang, which ranked last. The top five provinces accounted for approximately 37.8% of national CO_2 emissions. The findings indicate that there was an imbalance in the spatial distribution of emissions, with higher concentrations in the developed provinces, although the situation was better than that in 2005 (Cai and Xie, 2007). However, as for emissions contributed per inhabitant, Neimenggu ranked first and Hunan ranked last. In terms of the emissions contributed by per unit GDP, Xizang ranked first and Shanghai occupied the last position. These results are consistent with those of a previous study on CO_2 emissions (Guo et al., 2014).

In addition, as shown in Fig. 7, individual provinces experienced different average annual growth rates of CO_2 emissions from 2011 to

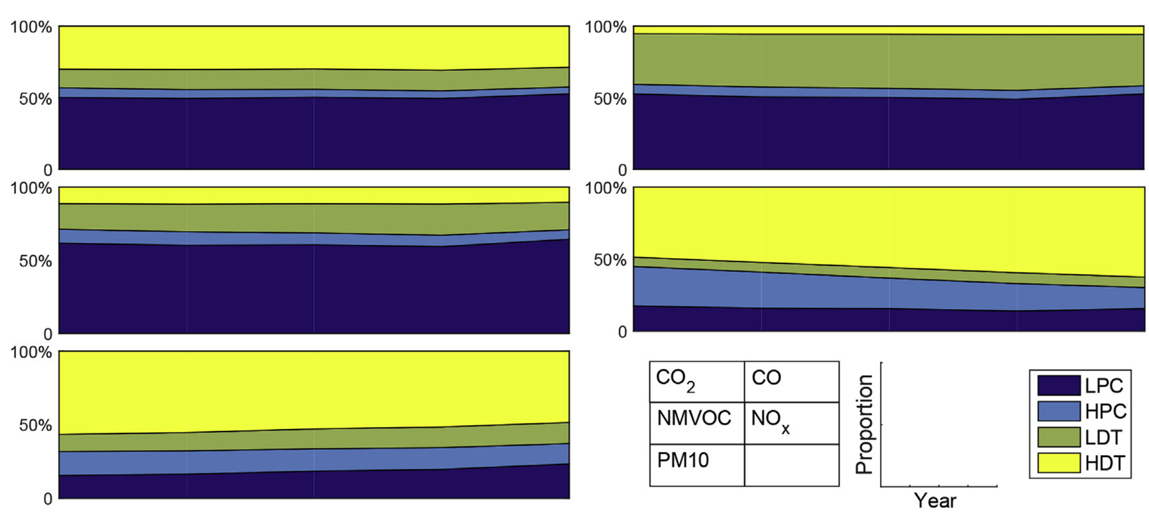

Fig. 6. Percentages of emissions contributed by different vehicle types for the period 2011–2015.

Table 4
The spatial auto-correlation test on the emissions contributed by the dominant vehicle types (Note: *m* is the value of Moran's I, and *p* is the significant level, which is calculated using a Monte Carlo simulation; in this study, the spatial pattern is auto-correlated if $m > 0.1$ and $p < 0.1$, and the green cells indicate the existences of significant spatial auto-correlation).

Emissions	Dominant Vehicle types	2011		2012		2013		2014		2015	
		m	p	m	p	M	p	m	p	m	p
CO_2	LPC	0.11	0.04	0.13	0.07	0.13	0.05	0.14	0.07	0.14	0.04
	HDT	0.363	0.01	0.24	0.01	0.24	0.02	0.26	0.02	0.28	0.01
CO	LPC	0.16	0.04	0.13	0.09	0.14	0.05	0.12	0.09	0.16	0.03
	LDT	-0.04	0.49	-0.05	0.66	-0.06	0.59	-0.07	0.61	-0.05	0.53
NO_x	HDT	0.36	0.01	0.23	0.01	0.22	0.01	0.24	0.01	0.29	0.01
NMVOC	LPC	0.18	0.01	0.12	0.07	0.12	0.05	0.07	0.18	0.15	0.07
PM_{10}	HDT	0.31	0.01	0.17	0.03	0.15	0.07	0.16	0.05	0.20	0.02

2015. Beijing had the lowest value of 1.8%, whereas Chongqing experienced the highest value of 18.8%. The finding coincides well with the stringent policies adopted in Beijing to control the vehicle population and manage the use of private vehicles. However, for the emissions produced per inhabitant, the average annual growth rate pattern was very similar to that reported for total emissions. For the emissions produced per unit GDP, the average annual growth rates in individual provinces dramatically decreased. For instance, Beijing had the lowest value of −6.7%, whereas Gansu had the highest value of 6.7%. Statistically, 25.8% of provinces exhibited a decreasing trend. The above findings are in accordance with the aggregated results of analysis, and they indicate that the implementation of fuel-economy standard had a limited effect on controlling the CO_2 emissions and worked differently on different provinces.

With respect to emissions of the air pollutants, on average, Guangdong ranked first in terms of emissions of CO, NO_x, and NMVOC, and Shandong ranked first in terms of PM_{10} emissions. Xizang ranked last in terms of emissions of CO and NMVOC and Hainan ranked last in terms of emissions of NO_x and PM_{10}. Specifically, the emissions of CO and NMVOC produced by Guangdong were 37.3 and 34.0 times those in Xizang, NO_x emissions in Guangdong were almost 21.9 times those in Hainan and PM_{10} emissions in Shandong were nearly 22.4 times those in Hainan. The top five provinces accounted for 38.4%, 38.8%, 38.7% and 38.3% of national emissions of CO, NO_x, NMVOC and PM_{10}, respectively. The distributions of pollutant emissions were similar to those of CO_2 emissions but were much more concentrated than those in 2007 (Cai and Xie, 2007). However, in terms of emissions per inhabitant, Neimenggu or Xizang ranked first, whereas Henan, Guizhou, or Chongqing ranked last, for the four pollutants. In terms of emissions per unit GDP, Xizang always ranked first, whereas either Shanghai, Beijing or Tianjin ranked last, for the four pollutants.

Furthermore, as shown in Fig. 8, Beijing had the lowest value of average annual growth rates in emissions of CO, NO_x and NMVOC, namely, −11.7%, −14.3% and −20.0%, respectively, whereas Shanghai experienced the lowest value in PM_{10} emissions, namely, −11.9%. Chongqing had the highest values in emissions of CO, NO_x and PM10, namely, 3.5%, 13.9% and 15.8%, respectively, whereas Fujian displayed the highest value in NMVOC emissions, namely, 1.8%. Statistically, 61.3%, 67.7% and 93.6% of provinces experienced decreasing trend in emissions of CO, NO_x and NMVOC, respectively, whereas only 22.6% of provinces displayed decreasing trend in PM_{10} emissions although 67.7% of provinces exhibited obvious reductions in 2015. Compared with the above patterns, the average annual growth rates in emissions per inhabitant slightly decreased, but the average annual growth rates in emissions per unit GDP declined significantly. For instance, in terms of CO emissions per unit GDP, Beijing displayed the lowest value of −19.1%, whereas Shanxi exhibited the highest value of −4.1%. Statistically, 100%, 96.8%, 100% and 80.7% of

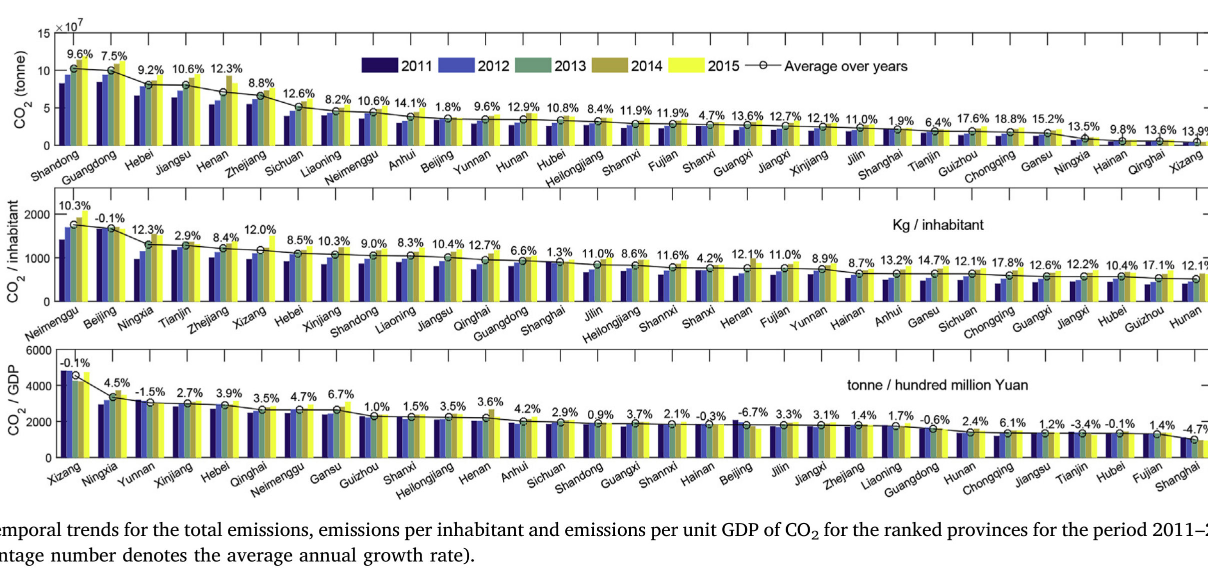

Fig. 7. Temporal trends for the total emissions, emissions per inhabitant and emissions per unit GDP of CO_2 for the ranked provinces for the period 2011–2015 (Note: the percentage number denotes the average annual growth rate).

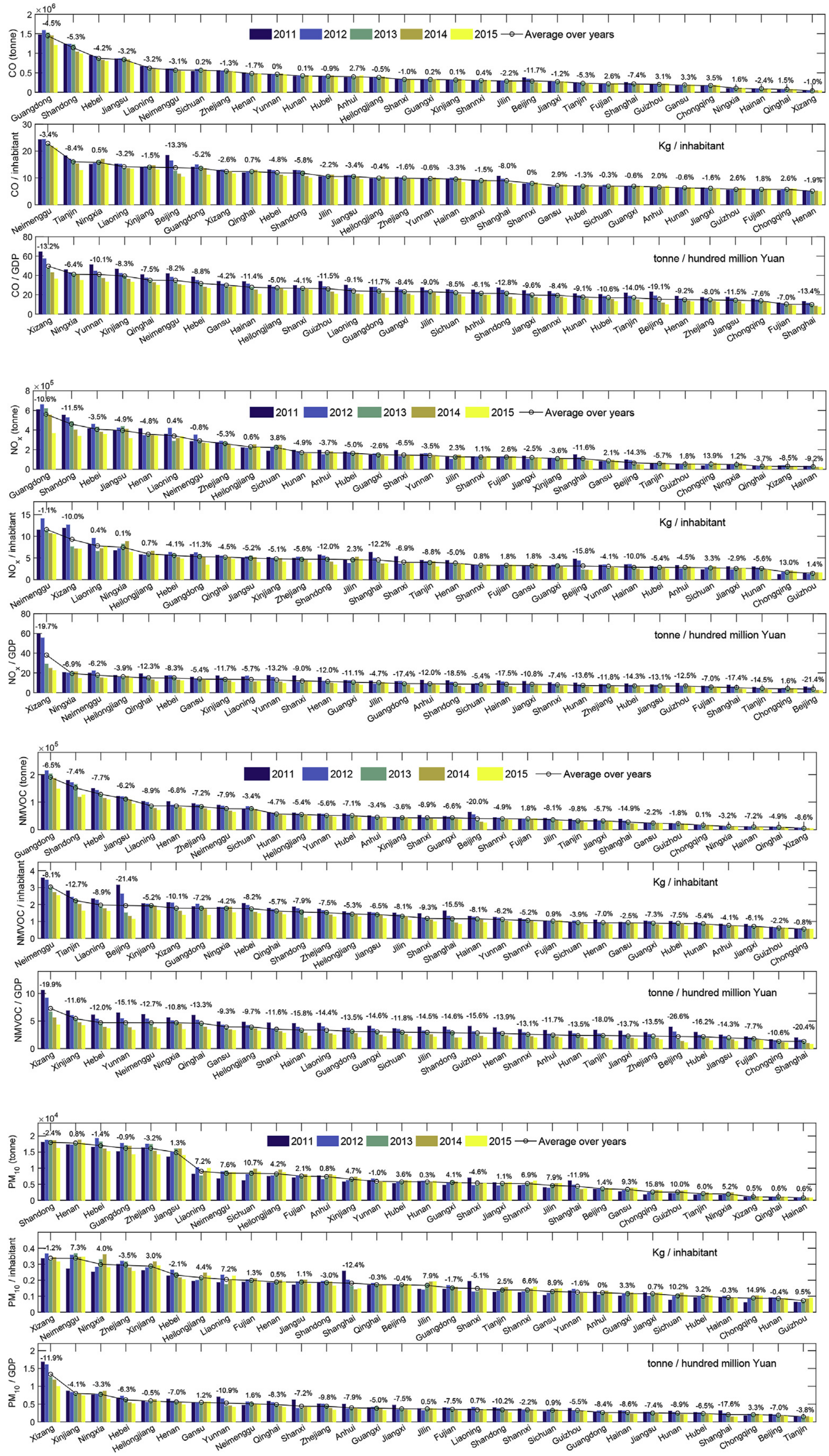

Fig. 8. Temporal trends for the total emissions, emissions per inhabitant and emissions per unit GDP of pollutants for the ranked provinces for the period 2011–2015 (Note: the percentage number denotes the average annual growth rate).

provinces exhibited decreasing trends in pollutant emissions per unit GDP.

These findings are also in line with the aggregated results of analysis, and they imply (1) that the implementation of China IV and China V had significantly reduced emissions of CO, NO_x and NMVOC and the reduction on PM_{10} became much more obvious in 2015 for most provinces, and (2) that variations in average annual growth rates among individual provinces require the development of local reduction strategies.

To facilitate the development of local emissions reduction strategies, we investigated the clustering of individual provinces in terms of the emissions contributed by different types of vehicles. The total emissions in each province are composed of 20 different types of emissions, namely, emissions of each of the five types of gases by each of the four types of vehicles. To cluster the provinces, we adopted the technique of self-organizing map (SOM; Kohonen, 1982), which is a type of artificial neural network trained with input samples using unsupervised learning. In the training process, each sample with multiple dimensions is matched to the most similar neuron to update its weight vector as well as the weight vectors of its neighbors. This process is repeated until a two-dimensional map in a hexagonal or rectangular grid is produced.

Using the SOM technique, individual provinces were clustered in two scenarios. Firstly, provinces were clustered by their emissions in 2015. Fig. 9a shows the resulting SOM grid with each neuron containing matching provinces and Fig. 9b displays the spatial distribution of the clusters. It can be observed that 41.9% of provinces form clusters in their own right, and the remaining provinces are grouped into seven clusters. For instance, Beijing and Shanghai are located in the same cluster because of the similarity of their emissions patterns, as shown in Fig. 9c. Secondly, provinces were clustered by their average annual growth rate of emissions from 2011 to 2015. Fig. 9d shows the resulting SOM grid and Fig. 9e presents the spatial distribution of the clusters. Specifically, in terms of this scenario, approximately 51.6% of provinces form clusters in their own right, and the remaining provinces are grouped into six clusters. For example, the north provinces including Jilin, Liaoning and Neimenggu are classified in one cluster, whereas Xizang, Beijing and Shanghai form clusters by themselves. As shown in Fig. 9f, we can see the differences between Beijing and Xizang, in that a majority of emissions declined in Beijing, but only a minority of emissions decreased in Xizang.

Apart from the implementations of emission standard and fuel-economy standard, these findings might be useful for the development of local emissions reduction strategies. In other words, different emissions reduction policies should be given to provinces in different clusters. For instance, stringent policies on vehicle population management should be enforced in the clustered developed provinces, such as Guangdong and Jiangsu, considering their high emissions and the large number of vehicles per inhabitant. However, relaxed policies on vehicle population management should be implemented in the clustered developing provinces, such as Xizang, Qinghai, Ningxia, and Hainan, considering their low emissions and the small number of vehicles per inhabitant. Besides, energy efficient technologies are urgently needed to be introduced to the clustered provinces to maintain their sustainable developments.

3.3. Socioeconomic analysis of vehicle emissions

Vehicle emissions in this study can be affected by vehicle population and VKT, and thus we firstly examined their relationships with the socioeconomic factors in terms of GDP and population (POP). The results suggest that vehicle population were indeed affected by GDP and POP irrespective of years. For instance, remarkable multivariate linear relationships with R square values of 0.91 and 0.94 could be observed for the socioeconomic factors with the total vehicle population and the newly registered vehicle population, respectively, in 2015. However, our results indicate that no relationship could be observed for the socioeconomic factors and VKT, although VKT were derived from GDPI as elaborated in Section 2.

Nonetheless, we found that the socioeconomic factors were linearly correlated with the emissions of CO_2, CO, NO_x, NMVOC, and PM_{10} with R square values of 0.89, 0.82, 0.70, 0.83, and 0.76, respectively. This finding coincides well with the previous studies (Guo et al., 2014; Lang et al., 2014; Song et al., 2016; Liu et al., 2017), but the relationships were assumed to be spatially homogeneous. In fact, such relationships might vary across space, considering the imbalance in socioeconomic development among provinces. Therefore, we presented the results of spatial variations of socioeconomic factors in terms of their influences. Using the technique of geographically weighted regression (GWR; Fotheringham et al., 2015), we can see vividly how the impacts of the socioeconomic factors on emissions varied across space.

Fig. 10 illustrates the spatial variations in local parameter estimates of the socioeconomic factors for 2015. It can be clearly observed that the spatial variations in the relationships between the socioeconomic factors and different types of emissions displayed remarkable regularity. For example, CO_2 emissions were significantly correlated with GDP and POP, although emissions in northeastern provinces were much less affected by variations in GDP than those in southwestern provinces, and emissions in southwestern provinces were much less affected by variations in POP than those in northeastern provinces. This spatial variation pattern remained stable for other types of emissions. This observation has two implications. Firstly, economic growth in southwestern provinces might be accompanied with a significant amount of vehicle emissions, and hence government policies should be given to these provinces to encourage the development of clean service sector and energy efficient technologies to achieve a sustainable economic development. Secondly, people in northeastern provinces are on average own a larger number of vehicles than people in southwestern provinces, and hence they generate a high emission per inhabitant. In this respect, policies on controlling vehicle license plate or managing vehicle usage should be strictly implemented in northeastern provinces, as the cases in Beijing and Shanghai. However, in the case of marginal provinces, for example, Heilongjiang and Guangdong, the model might be over-fitted.

3.4. Comparison with previous studies

Very few previous studies have been conducted to establish vehicle emissions inventories for Mainland China at both national and provincial levels for the period 2011–2015. Most previous studies focused on deriving emissions inventories at either the national or regional level for earlier years (Cai and Xie, 2007, 2013) or the provincial or city level (Guo et al., 2014; Sun et al., 2016; Liu et al., 2017). To confirm the reliability of our work, the results of previous studies were summarized and compared with the emissions estimated in this study at three levels for a few selected types of emissions. As shown in Fig. 11, the results suggest that: (1) the CO_2 emissions calculated in our study displayed a very similar trend to those in previous studies from 2005 to 2012 at the national level, with an average difference of approximately 8.6%; (2) the NO_x emissions calculated in our study agreed roughly with those in previous studies at the regional level, with an average difference of 23.7%; (3) the CO_2 emissions in our study were also consistent with those in previous studies at the provincial or city level, with an average difference of 10.9%; and (4) the CO emissions in our study exhibited an average difference of 9.2% from those in previous studies of the respective provinces and cities.

The comparisons suggest that our emissions inventories are reliable. The differences can be attributed to the following aspects. Firstly, this study used the latest COPERT V model. For instance, one previous study (Cai and Xie, 2007) used the COPERT III model in which only the emissions standards China I and China II were considered, and several previous studies (Guo et al., 2014; Song et al., 2016) used the COPERT

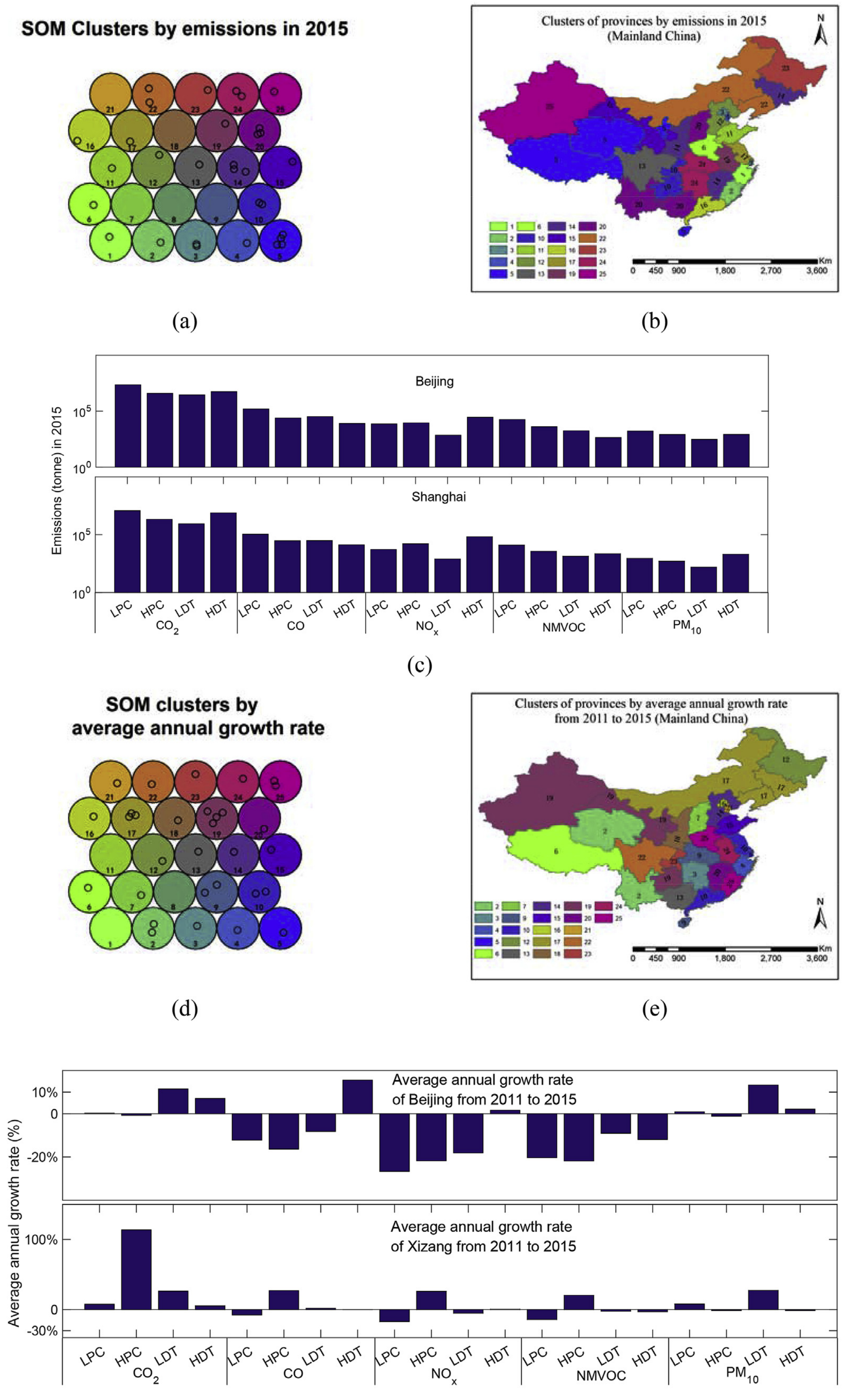

Fig. 9. Clusters of provinces according to their emissions patterns using SOM in two scenarios: (a) SOM clusters by emissions in 2015 and (b) its map; (c) emissions patterns of Beijing and Shanghai; (d) SOM clusters by average annual growth rate of emissions from 2011 to 2015 and (e) its map; (f) average annual growth rates of Beijing and Xizang.

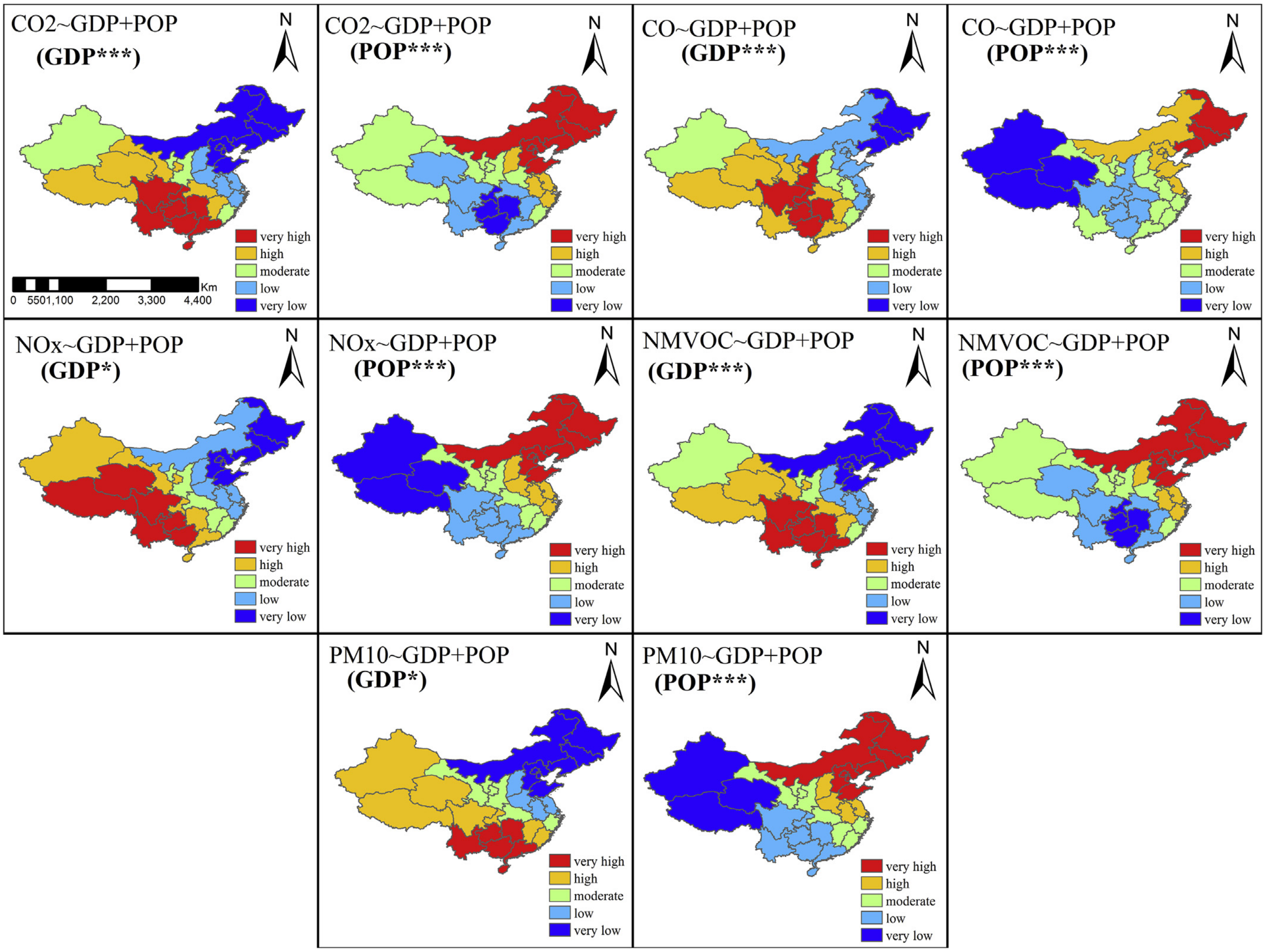

Fig. 10. Spatial variations of the influences of socioeconomic factors on the emissions using the GWR analysis. (Note: *, ** and *** indicate the significant levels of 0.05, 0.01 and 0.005, respectively).

IV model. Secondly, average fuel consumption rates were used to calculate the CO_2 emissions of LPC and LDT owing to the absence of vehicle population distribution under the weight. Thirdly, this study used an interpolation technique to calculate the *VKT* value in each year for each type of vehicle. Fourthly, most previous studies did not consider the removal of vehicles, which might affect the vehicle population distribution in each year. However, this study used a survival function with a Weibull distribution to scrape older vehicles in each year.

4. Conclusions

This study established the vehicle emissions inventories in Mainland China for the period 2011–2015 and presented an in-depth analysis on their spatiotemporal patterns. Firstly, the results of analysis on Mainland China suggested that CO_2 emissions displayed slow growth with 920.1 MT in 2011 to 1.3 billion tonnes (BT) in 2015. Emissions of CO, NO_x, and NMVOC showed continuous decrease with 13.2 MT, 6.0 MT, 1.9 MT in 2012 to 11.9 MT, 4.9 MT, and 1.5 MT in 2015, whereas emissions of PM_{10} exhibited a clear decrease with 230.9 KT in 2014 to 218.5 KT in 2015. These findings implied that the enforcement of fuel-economy standard had a limited impact on controlling the growth of CO_2 emissions and that current implementation of emissions standard had effectively controlled the growth of pollutant emissions. Besides, LPC was the dominant vehicle type in terms of contributing around 50% of the emissions of CO_2, CO and NMVOC, whereas HDT was the dominant vehicle type in terms of contributing around 50% of the emissions of NO_x and PM_{10}. Interestingly, the emissions contributed by the dominant vehicle types were spatially auto-correlated.

Secondly, the results of analysis on individual provinces revealed that developed provinces tended to produce more emissions than developing provinces, but the emissions produced per unit GDP in developing provinces were much higher than those in developed provinces. For instance, on average, the total emissions of CO_2 produced by Shandong were 27.8 times those in Xizang, and the emissions produced per unit GDP in Xizang were much higher than those in other provinces. In addition, there was a large variation among the provinces in terms of the average annual growth rates of emissions. These findings implied that current emissions reduction strategies worked differently for different provinces, and a SOM technique was used to cluster individual provinces according to the similarity of emissions patterns for developing local emissions reduction strategies. Thirdly, our finding reported a remarkable regularity for the spatial variations in the relationships between the socioeconomic factors and different types of emissions. For instance, emissions in northeastern provinces were less affected by variations in GDP than those in southwestern provinces.

Therefore, we suggest that emissions reduction strategies should be targeted at the cluster level. Stringent vehicle population management policies (via taxation, license plate or usage control) should be enforced in the clustered developed provinces with a specification on the population of LPC and HDT. However, relaxed vehicle population

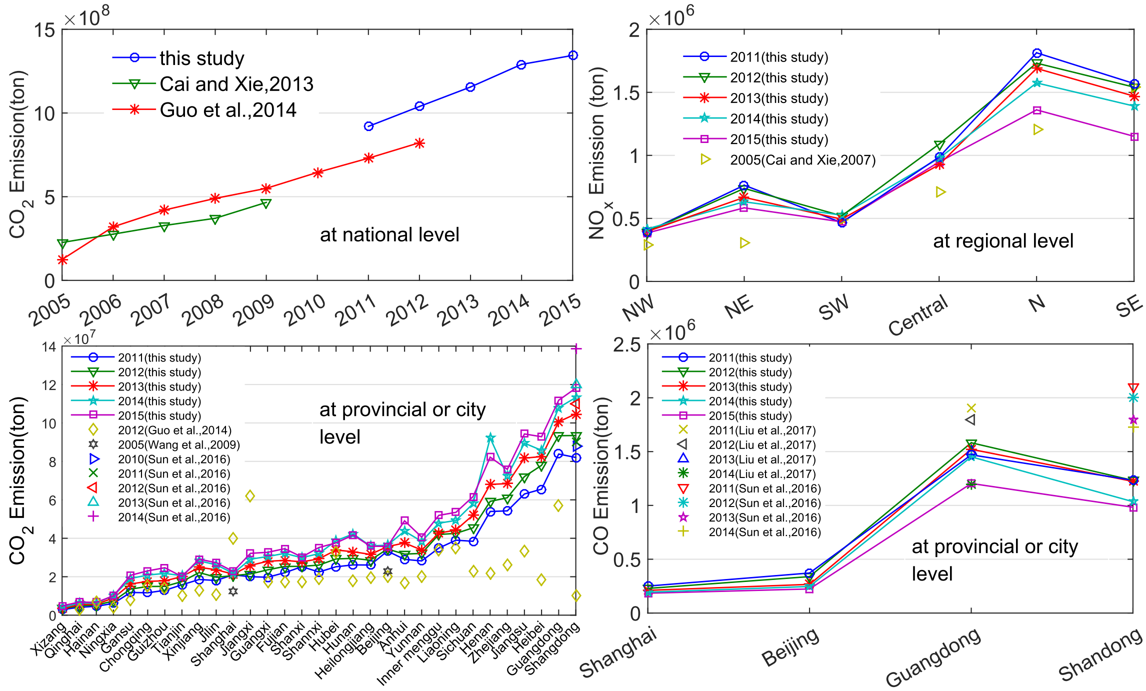

Fig. 11. Comparisons of our emissions with those reported in previous studies.

management policies should be implemented in the clustered developing provinces. Importantly, clean service sector or energy efficient technologies should be introduced to these provinces to reduce the heavy reliance of emissions on the variation in GDP. Nonetheless, future work should be concentrated on developing spatial allocation method to derive high accuracy emissions map at fine grid, which will allow to examine the spatiotemporal emissions patterns among small cities.

Declaration of interest

The authors declare no conflict of interest.

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