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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