Characterization of Road Freight Transportation and Its Impact on the National Emission Inventory in China

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Abstract

Diesel trucks are major contributors of nitrogen oxides (NO_x) and primary particulate matter smaller than 2.5 μm ($PM_{2.5}$) in transportation sector. However, there are more obstacles to existing estimation of diesel truck emissions compared with those of cars. The obstacles include both inappropriate methodology and missing basic data in China. According to our research, a large number of trucks are conducting long-distance inter-city or inter province transportation. Thus, the method, used by most existing inventories, based on local registration number is inappropriate. A road emission intensity-based (REIB) approach is introduced in this research instead of registration population based approach. To provide efficient data for the REIB approach, 1,060 questionnaire responses and approximately 1.7 million valid seconds of onboard GPS monitoring data were collected in China.

The estimated NO_X and $PM_{2.5}$ emissions from diesel freight trucks in China were 5.0 (4.8 – 7.2) million tons and 0.20 (0.17 – 0.22) million tons, respectively in 2011. The provinces based emission inventory is also established using the REIB approach. It was found that the driving conditions on different types of road have significant impacts on the emission levels of freight trucks. The largest differences among the emission factors (in g/km) on different roads exceed 70% and 50% for NO_X and $PM_{2.5}$, respectively. A region with more inter-city freeways or national roads tends to have more NO_X emissions, while urban streets play a more important role in primary $PM_{2.5}$ emissions from freight trucks. Compared with inventory of Ministry of Environment, which allocate emissions according to local truck registration number and neglect inter-region long distance transport trips, the differences for NO_x and $PM_{2.5}$ are +28% and -57%

differences respectively. The REIB approach matches better with traffic statistical data on province level. Furthermore, the different driving conditions on the different roads types are no longer overlooked with this approach.

1 Introduction

China has been facing severe air quality challenges in the past several years. Air pollution in China not only endangers the health of billions of people but also creates a substantial burden on the economy (Matus et al., 2012). The 2005 marginal welfare impact to China, considering only ozone and particulate matter, was US$112 billion (1997 US$) (Hammitt and Zhou, 2006). Vehicular emissions form one of the greatest contributors to the air pollution in China, especially for NO_x and $PM_{2.5}$. According to the Ministry of Environmental Protection (MEP), vehicular emissions contributed 27.4% of the total NO_x emissions in 2012 (MEP, 2012a). Vehicle emissions also contribute more than 30% of $PM_{2.5}$ in Beijing, as announced by the Beijing government.

Preparing inventories is essential to the assessment and management of current atmospheric problems (Ohara et al., 2007;Streets et al., 2003;Beaton et al., 1995). Among all the sources, the mobile source is one with the greatest uncertainty and ambiguity (Cai and Xie, 2007;Wang et al., 2008a). Among all the vehicles, diesel freight trucks contributed to a large portion of vehicular emissions. According to the MEP, diesel vehicles, mainly consisting of freight trucks, contributed 70% of NO_X and 90% of PM in the total vehicular emissions in 2012 (MEP, 2013). Therefore, improving current emission inventory and reducing the uncertainty is of great necessities.

Another major impediment to developing a new approach to estimate freight truck emissions is that most inventories were based on the local registration numbers, which means there is an assumption that trucks are running within the province or city where they registered (Zheng et al., 2013). However, according to this research, many trucks are conducting long-distance inter-city or inter-province transportation trips. Therefore, a road-based estimate approach was introduced in this research instead of the former local registration number based approach. This simulation addresses more on the freight transportation system as a whole rather than a local emissions scale.

In summary, we attempt to identify and reduce the impact of the factors mentioned above by adopting a road-based approach with collected activity level data including both questionnaire answers and GPS records. In particular, this research serves to (i) provide more accurate activity level data for freight trucks including mileage traveled versus age, activity regions and driving conditions, (ii) identify the different emission rates caused by different driving conditions on each type of road and (iii) provide a national emissions inventory that considers the road freight system as whole instead of separating it into different pieces according to the province divisions.

2 Data and Methodology

2.1 Data Source

The data source of this research primarily consists of two major parts: 1. Questionnaires that investigated the driving behavior of professional truck drivers, along with experiential data that related to their driving pattern. 2. Driving condition tests of trucks driving on different types of roads. Information about the questionnaires and GPS data, such as the sample numbers and location range, is shown in Table 1.

A series of questions related to driving pattern, fuel consumption, route selection, transport range, etc. were included in the questionnaires. All the investigated drivers are professional freight truck drivers. Because most of the freight truck drivers are not highly educated, all the questionnaires were conducted by college students, and a detailed explanation was required to make sure that the drivers understood the question correctly. To ensure the quality of the answers, related questions that validate each other are designed to identify careless or wrong answers. A total of 1,060 samples from 16 provinces were investigated. Therefore, it is a large sample study according to the theory of statistics (Box et al., 2005). Previous studies on driver behavior in China also conducted questionnaire investigations. For example, 520 samples, which were targeted all at automobile drivers and not limited to trucks, were studied in 2002 to understand the behavior of drivers (Xie and Parker, 2002). Another 87 completed samples were used to make comparisons between China and Hong Kong in 2009 (Chan et al., 2009). Questionnaires are also used on truck drivers in Australia (N=433), Germany (N=10,101), Brazil (N=4,878) and New Zealand (1,065) for different purposes (Sullman et al., 2002;Lajunen et al., 2004;Moreno et al., 2006;Moreno et al., 2004). Compared with other sample sizes of domestic and foreign studies on truck drivers, the number of samples in this study is adequate to describe the average level of freight truck activities.

Trucks are classified into four types according to weight in this research, following the rule made by National Statistics Bureau (CATARC, 2012): Mini Trucks (MiniT) with weights less than 1.8 t, light duty trucks (LDT) with weights of 1.8–6 t, middle duty trucks (MDT) with weights of 6–14 t and heavy duty trucks (HDT) with weights greater than 14 ton. The classification is used to get vehicle stock from national statistic, questionnaires investigation and data analysis in this study. Because the MiniT population only consists of a very small proportion of the total truck fleet, approximately 0.98% of the total freight truck stock in 2011, and the differences between MiniT and LDT are not significant, MiniTs and LDTs are grouped together in the calculation of emission factors.

Because the normal method of testing driving patterns focuses on driving in cities, this method is less relevant to freight trucks; a freight truck has significant operation differences with that of a private passenger car (Holguin-Veras et al., 2006;Kamakaté and Schipper, 2009). Freight trucks in China generally travel between cities and do not stop for extended time periods, except for a small portion that run inside cities for short distance freight transit or other special public service (like garbage collection or road sprinkler) (Hine et al., 1995). To obtain the real time driving patterns of freight trucks, a Global Positioning System (GPS) receiver and speed sensor were used. For many years, GPS has been used to monitor the driving conditions of vehicles in many emission related studies (Ochieng et al., 2003;Rakha et al., 2004;Canagaratna et al., 2004). A multifunction Columbus GPS data logger V-990 produced by GPSWebShop (Canada) Incorporation was used in this research. The GPS data logger is set to automatically turn on or off when the engine of the investigated truck is turned on or off. Therefore, the data was collected every second when the engine of the truck under investigation is running. We were allowed to do this because a sensor was put into the GPS to capture the voltage change in the cigarette-lighter.

The investigated trucks were all driven by professional truck drivers during the tested time period. The GPS data logger was required to be used for at least one week to record the full driving pattern of the freight trucks. All drivers maintained their business as usual during the test time period. In total, 1,728,622 valid seconds from 16 trucks with different load capacities and functions were tested. All of the tested data were classified into five different types according to the road type they were on. The road type is identified by Google Map. The roads are divided into 5 classifications: urban roads, rural/town road, provincial roads, national roads and inter-city freeways. Typical speed tracks and routes of each type of the tested roads are shown in Figure 1. To present the speed distribution in identical scales, only the first 4,000 seconds of speed are shown in Figure 1. For urban road, there are only 3,989 seconds of data, and it represents the longest single trip in urban area that was monitored in this research.

2.2 Emission Rates and Emission Factors

Vehicle-specific power (VSP) is a concept that is designed to describe the working conditions, such as aerodynamic drag, acceleration, rolling resistance and hill climbing, of a vehicle and is used in the evaluation of vehicle emissions (Jimenez-Palacios, 1998). VSP is now widely used in emission factor modeling, such as in the IVE and MOVES models. For the VSP calculation, the equation for heavy duty diesel trucks (HDDTs) from the MOVES model was applied in this study (Eq. 1).

$$\mathrm{VSP}=\frac{A}{m}\cdot v+\frac{B}{m}\cdot v^2+\frac{C}{m}\cdot v^3+a\cdot v+gv\cdot\sin\theta \qquad \text{Eq.1}$$

where m is the vehicle weight, tons; v is the instantaneous vehicle speed, $\mathrm{m\cdot s^{-1}}$; a is the instantaneous vehicle acceleration, $\mathrm{m\cdot s^{-2}}$; θ is the road grade, radians; A is the rolling resistance coefficient, $\mathrm{kW\cdot s\cdot m^{-1}}$; B is the rotational resistance coefficient, $\mathrm{kW\cdot s^2\cdot m^{-2}}$; and C is the aerodynamic drag coefficient, $\mathrm{kW\cdot s^3\cdot m^{-3}}$. The road-load coefficients (i.e., A, B and C) by each major category are shown in Table 2. The coefficients were estimated according to the typical weight type used in Motor Vehicle Emission Simulator (MOVES) model (Koupal et al., 2004).

Engine stress (ES), which includes 25-second historical VSP data, was introduced by emission models such as International Vehicle Emission (IVE) model to represent how early running conditions impact current emissions. ES is calculated in following equation (Eq.2) from the IVE model (CE-CERT et al., 2008):

$$\mathrm{ES}=\mathrm{RPMIndex}+(0.08\ \mathrm{ton}\cdot\mathrm{kW}^{-1})\times \mathrm{Pr}\,eaveragePower \qquad \text{Eq.2}$$

where PreaveragePower is the average VSP during -5 s to -25 s, $\mathrm{kW}\cdot\mathrm{ton}^{-1}$; RPMIndex is the $\mathrm{Velocity}_{\mathrm{t=0}}\ /\ SpeedDivider$, unitless; and the minimum RPMIndex is 0.9. The detailed SpeedDivider is shown in Supplementary Information Table S1.

Operating mode bins are identified according to the VSP and ES. Data from multiple researches was used to obtain the representative emission rates in this research since no study provides sufficient data of emission rates for all types of trucks. Emission rates of each bin from Liu's study (Liu et al. 2009) were used to generate curves of emission versus bins, what we called bin-emission curves. Emission factors of different vehicle classes from Wang et al. (2012) and Zhang et al. (2013) were used to amend the bin-emission curves, moving the curves up or down without changing the relative relationship among bins. The outcome representative emission rates of each bin are shown in Supplementary Information, Figure S1. With GPS monitoring data from tested trucks in this research, distance-specific emission factors can be calculated with the following equation (Eq.3):

$$\mathrm{EF}_{i,j}=\frac{1000\cdot\sum_{t}ER_{i,j,t}}{\sum_{t}v_{i,j,t}} \qquad \text{Eq.3}$$

where EF is the distance-specific emission factor, $g \cdot km^{-1}$; ER is the second-by-second emission rate, $g \cdot s^{-1}$; and v is the velocity. The subscripts i, j and t represent road type, type of tested truck and time, respectively.

2.3 Setting up the Regional Emission Inventory

Top-down approaches are widely used in estimating anthropogenic emissions for a relatively large geographic range. According to the annual vehicle population numbers from the China's Automotive Industrial Statistics Yearbook (CATARC, 2012) and the survival curve from a former study (Hao et al., 2011), details about the existing vehicle population, such as the portion of trucks at different ages and weight, can be calculated. Following the Yearbook, the trucks were divided into 4 types according to their GVW (shown in Table 2). In addition, the annual VKT (vehicle kilometer traveled) of trucks at different ages is acquired from the investigation. Combining the fleet information and the VKT data together yields the total activity level number.

In this research, a new road emission intensity based (REIB) approach was introduced to calculate the regional emission inventory of diesel trucks. Instead of relying on local registration numbers, the road emission intensity served as the base of the REIB approach. The basic assumption for REIB is that for freight trucks, the driving conditions and truck flow were similar on the same type of road in different regions. The emission intensity of different types of road was calculated according to the activity distribution obtained from this research. Then, the emissions in each grid cell or province could be calculated according to the length of different types of road. Unlike former approaches that assumed that truck operation was limited to the region where they are registered, the REIB approach examines the road freight transportation as a nationwide system. The REIB approach is a better fit, given the fact that a large portion of trucks run across provinces. In the GPS monitoring conducted in this research, the longest single trip traveled across 8 provinces. The local registration based approach introduces great inaccuracy by overlooking the cross region trips of freight trucks.

Different types of trucks were investigated to determine their traveling information. The drivers were asked to estimate the distance portion that they drive on different types of roads. In this study, the roads are classified into freeway, national roads, provincial roads, rural roads, urban roads and other special roads such as those within factories and ports. Then, the emission density of different types of roads was calculated according to following equation (Eq.4):

$$\rho_{\mathrm{i}} = \frac{\sum_{\mathrm{j,k}} \overline{VKT}_{\mathrm{j,k}} \cdot NV_{current\_year-\mathrm{k},j} \cdot SR_{j,k} \cdot EF_{i,j,k} \cdot \mathrm{DP}_{\mathrm{i},j}}{L_{\mathrm{i}}} \qquad \text{Eq.4}$$

where ρ_{i} is the emission density of i type road, $\mathrm{g \cdot km^{-1} \cdot year^{-1}}$; $\overline{VKT}_{\mathrm{j,k}}$ is the average VKT per vehicle, $\mathrm{km \cdot year^{-1}}$; $NV_{current\_year-\mathrm{k},j}$ is the new vehicle population of type j k years ago; $SR_{j,k}$ is the survival rate of a k-year-old type j vehicle, The data came from a nationwide vehicle survival pattern research conducted by Hao el al. (2011). And the survival curves are shown in SI, Figure S2; $\mathrm{DP}_{\mathrm{i},j}$ is the distance portion for type j truck running on type i road; and L_{i} is the total length of type i road in China, km. The subscript k refers to the age of a vehicle. The remaining variables are the same as described above.

With the emission density number, the national emissions inventory can be calculated according to the spatial distribution of different types of road. In this research, multi-dimensions of inventories have been created to present the spatial distribution of freight truck emissions.

3 Results and Discussion

3.1 Activity Level of Freight Trucks

Freight trucks with different ages were investigated in this research. According to a former study, the total distance that a passenger car traveled has a quadratic relationship versus its age (Liu et al., 2008). This relationship means that as the passenger car ages, the mileage traveled per year decreases. According to the investigated samples in this study, the average total kilometers that a truck traveled also follow the similar pattern (shown in Figure 2). With an R-squared value of 0.9651, the empirical quadratic equation is adequate to describe the average activity level. The standard error in this research is relatively high compared with passenger car, revealing large variation among the trucks of the same age. This significant variation is caused by the diversity of functions of different trucks, which makes the investigation of truck activity a difficult task. However, the investigation result is the only data available to understand the characteristics of trucks at different ages. Moreover, unlike former research that used average mileage traveled for the entire fleet (Huo et al., 2012b;Fu et al., 2001), these results represent the aging effect of trucks, namely that the annual mileage decreases as the truck grows older. By neglecting the annual mileage reduction as trucks age, the impact of old trucks may be exaggerated because they do not actually run as much as newer trucks. Therefore, this investigation will help to identify the contribution of trucks under different ages more accurately.

Moreover, mileage correction factors by vehicle type were introduced to identify the differences between each type of truck, as shown in Table 2. The correction factors were the ratio of the average kilometers travelled of a certain type of truck versus the entire truck fleet. From the value of correction factors we can see that as GVW grows, the average kilometers travelled increase.

Both the mileage traveled and emission rates for trucks of different ages are different. Therefore, it is required to have the detailed age composition of truck fleet in the target year. The fleet composition and the total mileage traveled in 2011 by vehicle age are shown in Figure 3 (a) and (b). The total diesel truck population in 2011 reached 193.3 million, of which 53% came online during 2009-2011 and therefore meet the China 3 tailpipe emissions standard. Chinese government adopted vehicle emission standards following emission standards in Europe since 1999. The emission level 1 to 3 in China are equivalent to Euro 1 to 3 standard respectively, while China 0 means no emission control was applied. The limits of NO_x and PM based on China vehicle emission standards are shown in SI, Table S2. Truck population in China experienced a tremendously growth during 2009-2011, according to the data from National Statistical Bureau of China. In 2009, there was 0.98 million more new trucks came into the market compared with 2008, which was equivalent to 8.7% of the total truck stock in 2008. And most of the 2009-2011 trucks survived in the 2011 market. Therefore, there was an obvious excess of trucks from 2009-2011 in the 2011 market compared with previous years. Different from the vehicle population, the total mileage contributed by the China 3 trucks reaches 60% because new trucks are more frequently used. A total of 1.47 trillion kilometers were conducted by diesel freight trucks in 2011. The large portion of new vehicles in both population number and mileage traveled indicates that the application of stricter emissions standards has great significance because China is experiencing a boom in its truck population. However, the application of the China 4 emissions standard on diesel vehicles has been delayed because oil companies in China were unable to supply diesel that met the standard (Zhang et al., 2012). Considering the booming increase of new diesel trucks and the large share of them in the total mileage traveled, the impact of the delay of upgrading the emissions standard would be highly significant.

One of the challenges in mapping the emissions of freight trucks is that it is hard to identify where the trucks are running. The problem is more challenging with trucks than with other types of automotives because trucks are not limited to their registration region as cars are nor do they have fixed routes as buses do. In the questionnaires conducted in this research, the professional truck drivers estimated the length proportions they drive on different types of road. The length proportions of roads that trucks run on is summarized into different groups according to their GVW, as in Figure 4. As Figure 4 shows, we determined that different types of trucks tend to have different running patterns. It is obvious that heavier trucks are more likely to run on the high speed freeways; heavy duty trucks are generally employed for long distance transportation because they are more economical than lighter carriers. For long distance transportation, high speed freeways are the primary options for the drivers. On the contrary, inside an urban area, mini trucks and light duty trucks are more common given their flexibility and also possible constrictions on heavy duty trucks. This result is used to estimate the truck flow and fleet composition and to assign total kilometers traveled for each type of truck. The mileage and fleet information on each type of road are inputs for the calculation of emission intensity. The differences of fleet compositions between the different types of road have long been overlooked in past inventory work.

3.2 Different Driving Characters on Different Types of Roads

Trucks with different weights usually serve different purposes. This consequently leads to different driving patterns of the different types of trucks. According to the research results, the annual mileage traveled and average speed have significant differences among the different types of trucks.

Generally, heavier trucks ran at higher speeds and traveled greater mileage than lighter trucks. This behavior is due to the varying main function of trucks with different load capacities. Heavier trucks are usually used for long-distance transportation to reduce average cost, which means heavier trucks operate more on high-speed roads. Lighter trucks run more on urban roads because of their flexibility. The differences in the time portions from running on each type of road by the different levels of trucks are shown in Figure 4. These differences lead to different driving patterns for the different types of trucks. As shown in Figure 1, the speed records on selected routes for each type of road were quite different. For the tested route on the G93 Freeway, the average speed was maintained at approximately 70 km/h, and the stop times (when the speed reaches zero) were rare. It indicated that the traffic flow on the G93 Freeway during the tested time was very fluid. For the tested routes on the G309 National Road and S343 Provincial Road, the speed rarely exceeded 70 km/h, and the stops and sudden drops in speed were more frequent than on the G93 Freeway. Although the speed distributions on the G309 and S434 looked similar, the speed on the S434 obviously fluctuated more frequently than that on the G309. This revealed that the driving conditions on these two roads were similar, while traffic flow on the G309 was more fluent. For the urban road in Changsha City, Hunan, it was difficult for the truck to reach 40 km/h during the tested time. Stops were much more frequent than on former roads potentially due to traffic lights and traffic jams within the city. As for the country road between two villages in Shandong, the driving conditions were the worst among all the roads. The maximum speed during the tested time period was 40 km/h, and 85.5% of time the speed stayed below 20 km/h. In summary, the selected examples roads show that the driving conditions were distinctly different.

To demonstrate that the differences were not special cases, a statistical summary was made to see whether significant differences could be found in the large amount of data that we collected. The velocity and acceleration distributions for the total monitored data on urban roads (226,290 valid seconds) and freeways (583,922 valid seconds) are shown in Figure 5 as selected examples to illustrate the differences between the running conditions on these two types of roads. (Monitoring data on other roads are shown in Supplementary Information Figure S3-5.)Velocity and acceleration are divided into several bins, and the frequency of each bin is calculated. Velocity is divided into 30 bins from 0 – 30 m/s, and acceleration is divided into 7 bins from -1.5 to 2 m/s^2.

The results show two obvious different running conditions on the urban roads and inter-city freeway. The average speed and the maximum speed on the urban road are much lower than that on the inter-city freeways. Additionally, the urban road has much greater low-speed-running and idling time. If the high peak of the low-speed zone is removed, the speed distribution on the urban road is relatively flat with the range from 5 m/s to 20 m/s. On the other hand, the situation on the inter-city freeway is quite different. There are two peaks on the inter-city freeway: a smaller peak in the lower speed zone and a larger peak in the high speed zone. The percentage of the middle speed is very low. From the results, it shows that the difference is still significant considering all the collected data from different roads and trucks. Because both velocity and acceleration affect the vehicle specific power and engine stress, different velocity and acceleration distributions lead to different emission results. Without considering the differences in emission factors caused by the different driving conditions, uncertainties and inaccuracy were introduced to former vehicular emissions inventory. In the upcoming section, the differences in emission factors on the different roads will be discussed.

3.3 Emission Differences Caused by Different Driving Cycles on Each Type of Road

As discussed in the previous section, different driving cycles on the different types of road lead to different emission factors. The IVE model is a widely accepted tool to estimate vehicle emissions, and previous research in China has already localized the IVE model so that it applies to the Chinese vehicles. The IVE model uses velocity and VSP as two inputs and classifies the driving conditions into different bins. For each bin, a measured typical emission factor is used to represent the average emission level. The distribution of bins on each type of road is shown in Figure S6, and the emission factors that are derived for each type of the road using the IVE model are shown in Table 2. As introduced in section 2.2, on-board measurement data in China was used to calculate the average emission factor on the different types of road with real time monitoring GPS data. The results are shown in Figure 6.

From the results, it can be concluded that running conditions on different types of road lead to significant differences in the emission factors. Generally, rural or town areas tend to have the worst conditions for diesel freight trucks. In almost all the cases, the emission factors for both NO_x and $PM_{2.5}$ on rural or town roads are the largest among the 5 types of roads. This is mainly due to the long idling time without shutting down the engine on the rural or town roads while loading or unloading. Generally, the highest emission factor is 73.5% and 51.2% higher than the lowest one for NO_x and $PM_{2.5}$, respectively. These differences will lead to equivalent scaling errors in the total emissions of freight trucks. Generally, the emission factors tested on urban roads where the driving conditions are relatively worse, leading to a higher emission factor.. However, inter-city national, provincial road and freeway are also important places where many freight trucks run, especially those with heavier gross vehicle weights. This means previous studies have over-estimated emissions from freight trucks, because when running on inter-city roads or freeways, trucks have a lower emission factor due to better running conditions.

3.4 Emission Inventory of Freight Trucks

According to this research, the total NO_X from freight trucks in 2011 was 5,000,000 ton. The primary $PM_{2.5}$ emissions from diesel trucks in 2011 were 200,000 tons.

Figure 7 shows the NO_x and $PM_{2.5}$ emissions from trucks of different ages in the 2011 fleet. For both NO_x and $PM_{2.5}$, heavy duty trucks accounted for over 70% of the total emissions despite only counting for 26% of the total population. Hence, focus should be placed on controlling the emissions from heavy duty trucks. If the age of trucks is considered, the trucks that went into the market during 2009-2011 accounted for 40% of the total population and 60% of the total mileage traveled due to the mushrooming sales and the greater activity of new vehicles. This means the tightening of the emissions standard for new vehicles plays a critical role in the vehicular emissions control section. Moreover, the Yellow Label Vehicle, which means the pre-China 3 emissions standard diesel vehicles, has a more significant contribution to primary $PM_{2.5}$ emissions than NO_x.

Figure 8 shows the emissions distribution calculated according to the emission intensity of the different types of roads in the eastern part of China, where the major emissions occurred, with a resolution of 0.5×0.5 degrees per cell. Unlike approaches that are based on the local registration numbers of trucks, the approach applied in this research relies on the assumption that the traffic volume of freight trucks on each type of road remains similar. This approach views the freight transport in the nation as a whole system. From the emissions map and the emission intensity comparison, the freeways and national roads, where most of the freight transportation in China is conducted, have large emission intensities and emission impacts on their surroundings.

From Figure 8, freight transportation has the strongest impact in locations where the economy is well developed and the population has high density. The Beijing-Tianjin-Hebei (Jing-Jin-Ji) district, Yangzi River Delta and Pearl River Delta, the three biggest economic circles in China, are also the regions with highest emission density. From another perspective, 12 out of the 13 key control regions listed in the 12^{th} Five Year Plan (FYP) of Air Pollution Control in China have relatively high emission densities, as shown in Figure 8 (MEP et al., 2012). (The remaining key region, Urumqi and its surroundings in the Xinjiang province, which is not shown in the East China map, is also a hot spot of freight emission.) Therefore, the significance of controlling emission from diesel freight trucks is greater considering the high impact on the air quality and human health in the key regions.

Figure 9 shows more detailed emissions inventories of diesel freight trucks in the three biggest economic circles, Jing-Jin-Ji, Yangzi River Delta and Pearl River Delta, with a resolution of 0.1×0.1 degrees per cell. The emission map indicated that cities with developed road networks and their surroundings suffered the most from the emissions of freight trucks. The distributions in the three districts were not the same. Pearl River Delta had the highest density of emissions. The high emissions area is close to Guangzhou and Shenzhen, the core cities in PRD. Meanwhile in Yangzi River Delta, the emissions are much more dispersed due to the large numbers of cities with high economic growth and well developed road networks. From the differences in the emission distribution, we can conclude that emissions from freight trucks in PRD are more aggregate.

3.5 Comparisons with Other Studies

NO_X emission from this research is 28% higher than the MEP's estimation of 3,900,000 ton NO_x emissions from trucks in 2011 (MEP, 2012b). And according to the MEP, the total $PM_{2.5}$ emissions from the truck fleet were 460,000 ton in 2011 (MEP, 2012a), which is 130% higher than estimation in this research. The differences come from method, basic data and major assumptions.

Briefly, MEP estimated vehicle emission on the basis of local vehicle stock, activity level and emission factors. The truck classification is the same with our study, according to gross vehicle weight and the national emission standards. For each group, the emission equals the product of local registration number, kilometer travelled per vehicle and emission factor. Adding up emissions of each group is the total emission. The emission factor that MEP used is based on the national emission standard. Detailed information of emission standards in China is shown in SI, Table S2. However, no further input data related to vehicle kilometer travelled was provided in this inventory.

The difference in NO_x emissions was mainly caused by emission factors used in these two studies. In our study, the emission factor of China 3 trucks was not improved compared with China 2 (Wu et al., 2012; Liu et al., 2009). Thus, compared with MEP inventory and other inventory based on low NOx emission rate, our NO_x emission is much higher.

Compared with MEP results, the $PM_{2.5}$ emissions calculated in this research are significantly lower. A major reason for this lower result is that we included the decreasing trend of mileage traveled by trucks per year in this calculation. In China, overloading was common for commercial trucks. This accelerated the deterioration of trucks, which means older trucks had to run less due to deteriorated performance and more frequent repair and maintenance. The decrease of VKT was proved by our questionnaire investigation. If the mileages variation with age were omitted, the calculated $PM_{2.5}$ emissions would increase 50%, exceeding 300,000 ton. However, the VKT variation is not such a large problem for NO_x because the NO_x emission factor did not improve from old trucks to new trucks.

The provincial level NO_x and $PM_{2.5}$ emissions from road freight transportation are shown in Figure 10 (a) and (b), respectively, ranking from the highest to the lowest. For both NO_x and $PM_{2.5}$, Shandong and Guangdong, where most of the freight transportation in China is conducted, take the leading positions in freight truck emissions. The NO_x and $PM_{2.5}$ emissions in these two provinces exceeded 600,000 ton and 25,000 ton, respectively. Provincial emissions from MEP inventory are also shown in Figure 10. The provincial differences between the outcome of REIB approach and MEP inventories are obvious. The greatest differences are 220% and -72% for NOx and PM2.5 respectively (REIB compared with MEP inventory). Not only the emission scales different, discrepancies also exist in the rankings of provinces. The differences come from both different basic data and different methods. To avoid influence from input data, we re-calculated provincial VKT using our method and the traditional approach. Here traditional approach means calculating total VKT based on local registration data and average mileage travelled. The differences between the provincial proportions of VKT are shown in Figure 11. Taking Shanghai as an example, REIB method has 39.9% lower VKT compared with the traditional method. In the report published by MEP (2012a), the largest contributor of both NO_x and $PM_{2.5}$ in China during 2011 was Hebei province. However, Shandong contributed the most road freight emissions in 2011 according to this research. This difference was caused by the methodology on which the inventory was based. As discussed earlier, the registration number based approaches have a significant bias because trucks are not limited to the province where they are registered. Therefore, a province with the largest registration number of trucks might not have the most freight transportation. According to the China Statistics Bureau, Shandong has the greatest cargo volume and cargo turnover volume in the road transportation sector (Bureau, 2012). These data verified our assumption from a different perspective. Therefore, the former approach would be inaccurate without considering that the real range of truck activities might be different from the place where they are registered. There is an assumption of REIB approach that the same type of roads have equal congestion in different provinces. This is a limitation of our study mainly because of the limited data amount. This limitation could be avoided if future GPS data could be sufficient to characterize driving conditions in each province, which means that the REIB approach is still suitable for future massive data analysis. Now, we can still trust the results because the differences among the same types of roads are less significant than among different types.

3.6 Uncertainty Analysis

Monte Carlo simulation is used to quantify the uncertainty in both NO_x and primary $PM_{2.5}$ emissions from diesel freight trucks. Monte Carlo methods are widely used in identifying uncertainties in emission inventories (Hammersley and Handscomb, 1964;Sawyer et al., 2000;Wang et al., 2008b). The simulation is based on activity data and emission factors variety distribution. The statistical distributions of the annual kilometers travelled and stock are determined according to Zhang et al. (2013). And the uncertainty of mileage distribution was estimated according to our questionnaire results. For uncertainties of emission factors, we used the standard errors in the emission measurements to represent the uncertainties (Wang et al. 2012; Zhang et al, 2013). Considering that the activity level data are estimated based upon survey since it is not available through official channels, there is inevitable systematic bias in the estimation (Zheng et al., 2009).The uncertainties of the input parameters are listed in Table 3. The distribution of the inputs follows normal distribution. The trials of the simulation were set to 100,000 times.

The overall uncertainties in this inventory are estimated at -24.1% to 44.7% for NO_x emissions and -16.3% to 31.3% for primary $PM_{2.5}$ emissions. The uncertainty is significant compared with other types of anthropogenic emissions because the uncertainties in both activity level and emission factor of mobile sources are more significant than other types of sources. The greatest uncertainties in the simulation are the uncertainties of emission factors of freight trucks. The uncertainties were significant during the test procedure. The emission data from the on-board measurement of diesel freight truck emissions has significant variances, which even reached 100% in some cases (Huo et al., 2012a). In this research, comprehensive research into the activity levels of freight trucks was conducted to minimize the uncertainties in activity level. The new REIB approach also reduced the uncertainties in the distribution of freight truck activity. Further improvements can be achieved by more accurate measurements on emission factors.

4 Conclusions

We presented a REIB approach to estimate NO_x and $PM_{2.5}$ emissions in China, 2011. The estimated emissions inventory may be used to forecast and evaluate the impact of road freight transportation on air quality in China. Unlike approaches that are based on the local registration numbers of trucks, the REIB approach views the freight system as a whole nationwide system. The activity of freight trucks is distributed according to the development and infrastructure of the local road system. The REIB approach is feasible in the freight transportation sector, because in many cases, freight trucks conduct long-distance trips across several provinces, neglecting where they are registered. The distribution of emissions among the different provinces has significant differences compared with the former research that was based on local registration numbers. However, the REIB approach would be less beneficial when applied to the passenger car sector because private cars tend to have a more local range of activity.

According to the GPS monitoring results, the driving conditions on the different types of road are different for trucks. These differences would lead to significant variances in emission factors. According to the simulation results by the IVE model that were interpolated with local on-board test data in China, the differences between the emission factors from different types of trucks of same emissions standard could reach as high as 70% and 50% for NO_X and $PM_{2.5}$, respectively. Uncertainties in emission factors are the major drivers of the total uncertainty in the emissions inventory of diesel freight trucks. The improvements of emission factors on the different roads reduce the uncertainty and inaccuracy of diesel freight truck emissions.

In 2011, the diesel truck fleet emitted 5.0 (4.8 – 7.2) million ton NO_X and 0.20 (0.17 – 0.22) million ton primary $PM_{2.5}$ in China. According to our research, the failure of reducing NOx emission of the China 3 diesel trucks is the main reason of high NO_X emissions in total. The challenge of NOx reduction will last for many years until all the existed trucks were replaced by new trucks with after-treatment system. Moreover, locations with the highest diesel freight truck emission density are the regions with most severe air quality problem. In addition, 12 out of the 13 key air quality control areas listed in the 12th FYP of Air Pollution Control in Key Regions have high densities of truck emissions. Therefore, controlling diesel truck emissions plays a critical role in the air quality control plan in China. According to our emission distribution in 2011 of the fleet by vehicle age, promoting more stringent emission standard on new trucks is more efficient than eliminating the old Yellow Label Trucks. However, the fact is that the Chinese government postponed the application of the China 4 diesel truck emissions standard nationwide several times in the past few years.

Our research also indicates the uncertainties in freight truck emissions are approximately from -24.1% to + 44.7% for NO_x and from -16.3% to + 31.3% for $PM_{2.5}$. The uncertainties mainly come from the uncertainties in the emission factors from on-board measurements. Via improvements in specifying the emission factors to road type levels, this research reduced the uncertainties in freight truck inventories.

Acknowledgments

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Table 1 Data Information

Data	Sample numbers	Region	Test Time
Questionnaires	1,060	16 provinces	2012.8-2013.8
GPS data	16 trucks/1,728,622 valid seconds	15 provinces	2013.6-2013.10

Table 2 Summary of Road-load Coefficient Values for Calculating VSP of Each Truck Category

	MiniT	LDT	MDT	HDT
Vehicle type	LIGHT	LIGHT	HEAVY	HEAVY
GVW (tonne)	<=1.6	(1.6, 6]	(6~14]	>14
Mileage Correction Factor	0.145	0.475	1.278	2.713
Typical GVW (tonne)	3.3		10.2	17.6
A/m	0.102		0.0875	0.0661
B/m	0.00131		0	0
C/m	0.000322		0.000248	0.000207

Note: With reference to the MOVES model, those vehicle types and coefficients are estimated according to the typical gross vehicle weight (GVW) (Koupal et al., 2004). The classification of truck type is explained in section 2.1.

Table 3 Uncertainties Scales of Inputs

Stock	Annual Kilometer Traveled	Emission Factor		Mileage Distribution
		NO_X	$PM_{2.5}$	
2%	15%	-41% to +79%	-31% to +58%	5%

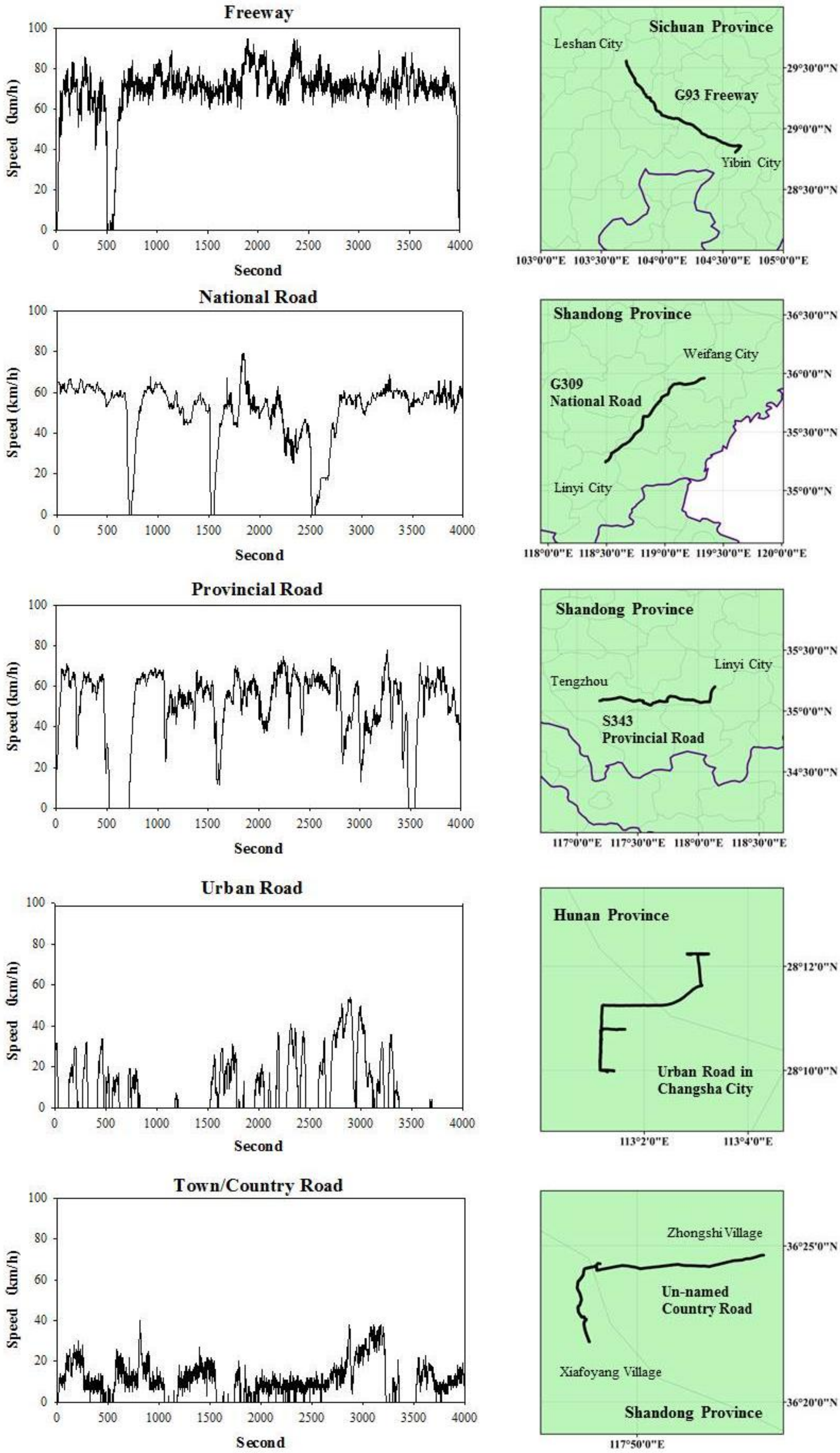
Freeway
Speed (km/h)
Second
Sichuan Province
Leshan City
G93 Freeway
Yibin City
National Road
Speed (km/h)
Second
Shandong Province
Weifang City
G309
National Road
Linyi City
Provincial Road
Speed (km/h)
Second
Shandong Province
Linyi City
Tengzhou
S343
Provincial Road
Urban Road
Speed (km/h)
Second
Hunan Province
Urban Road in
Changsha City
Town/Country Road
Speed (km/h)
Second
Zhongshi Village
Un-named
Country Road
Xiafoyang Village
Shandong Province

Figure 1 Speed and Route of Different Types of Tested Roads

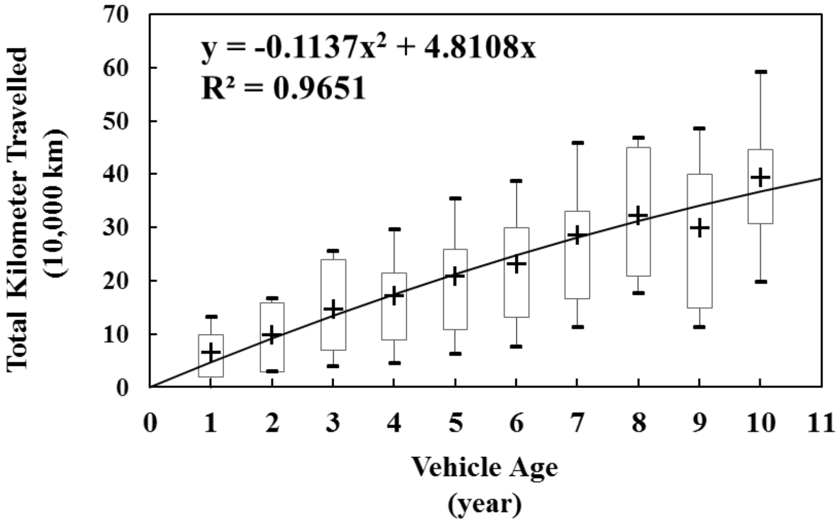

Figure 2 Accumulated Traveled Distance of Trucks under Different Ages (The boxes show the 1st and 3rd quartiles of the total investigated numbers and the bars show the standard errors.)

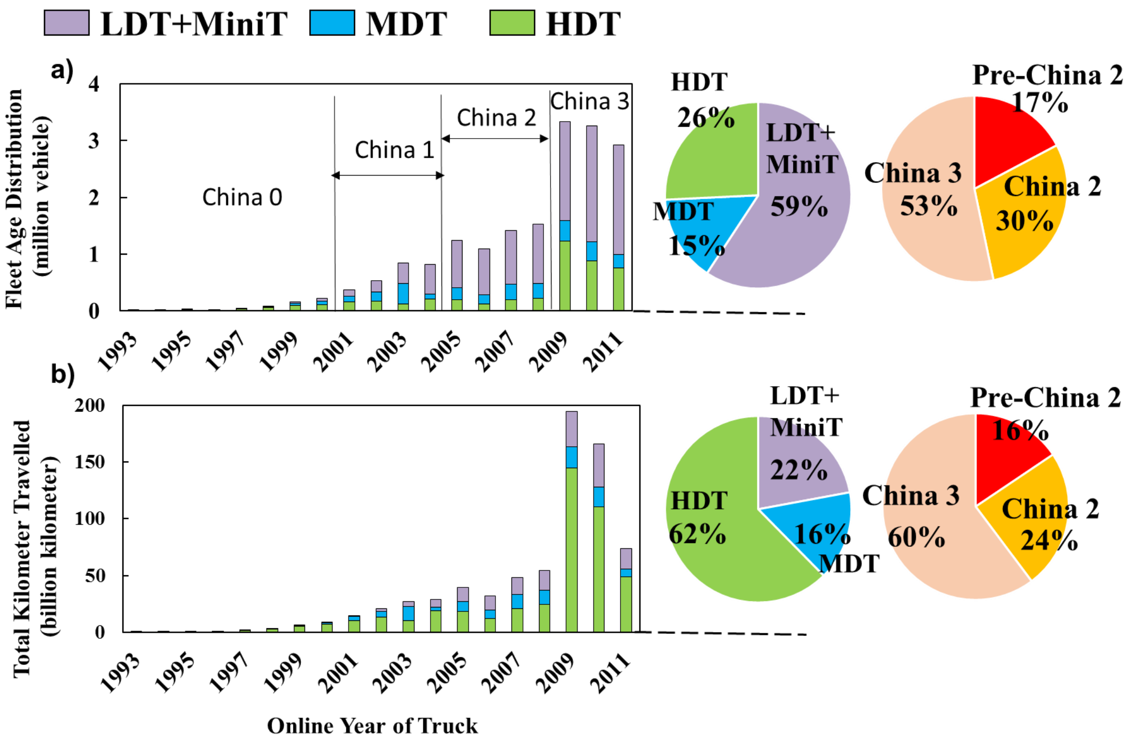

Figure 3 Age and Total Mileage Traveled Distribution of the Diesel Truck Fleet in 2011, China: a) Vehicle Population; b) Total Mileage

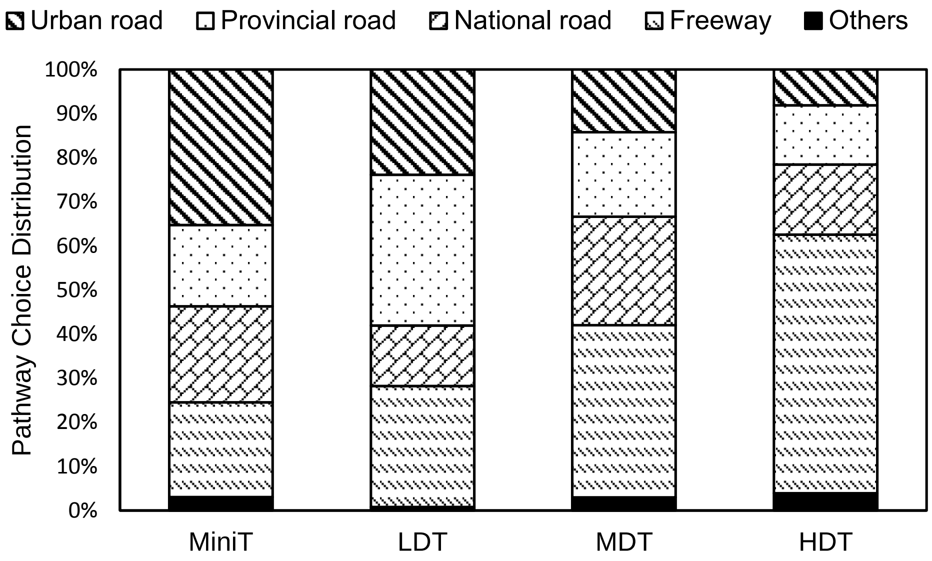

Figure 4 Proportion of Running time on Different Types of Roads

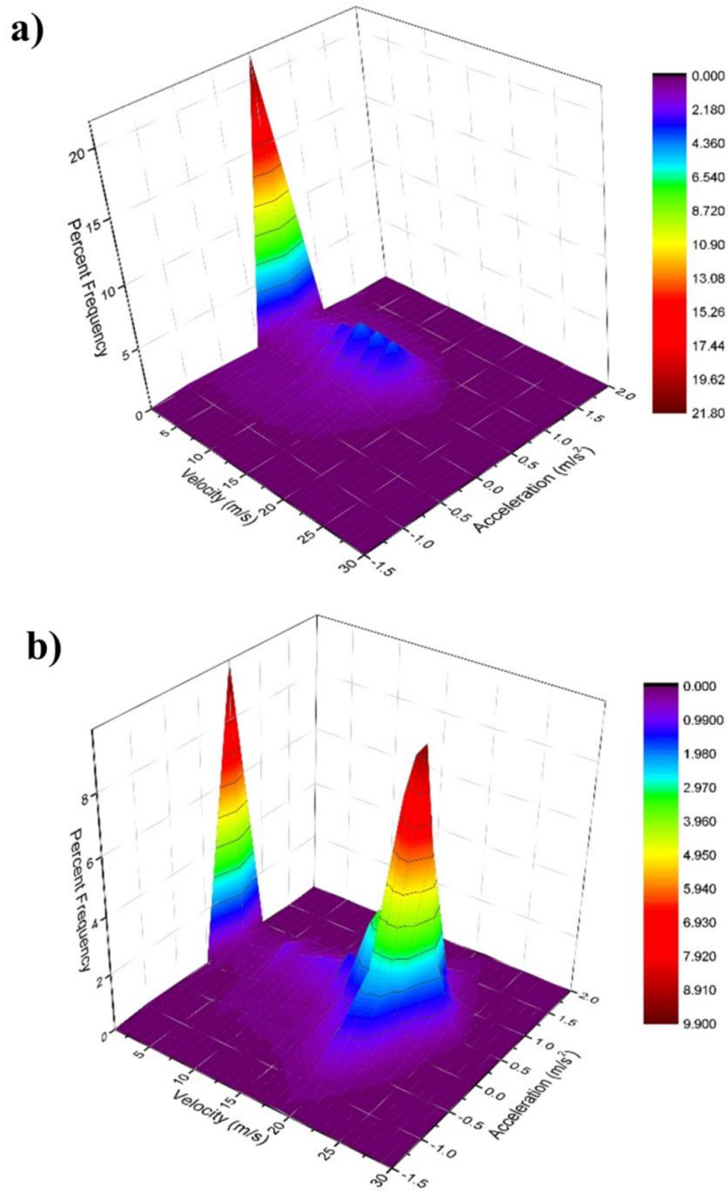

Figure 5 Velocity and Acceleration Distribution on Each Type of Roads: a) Urban Roads b) Inter-city Freeway

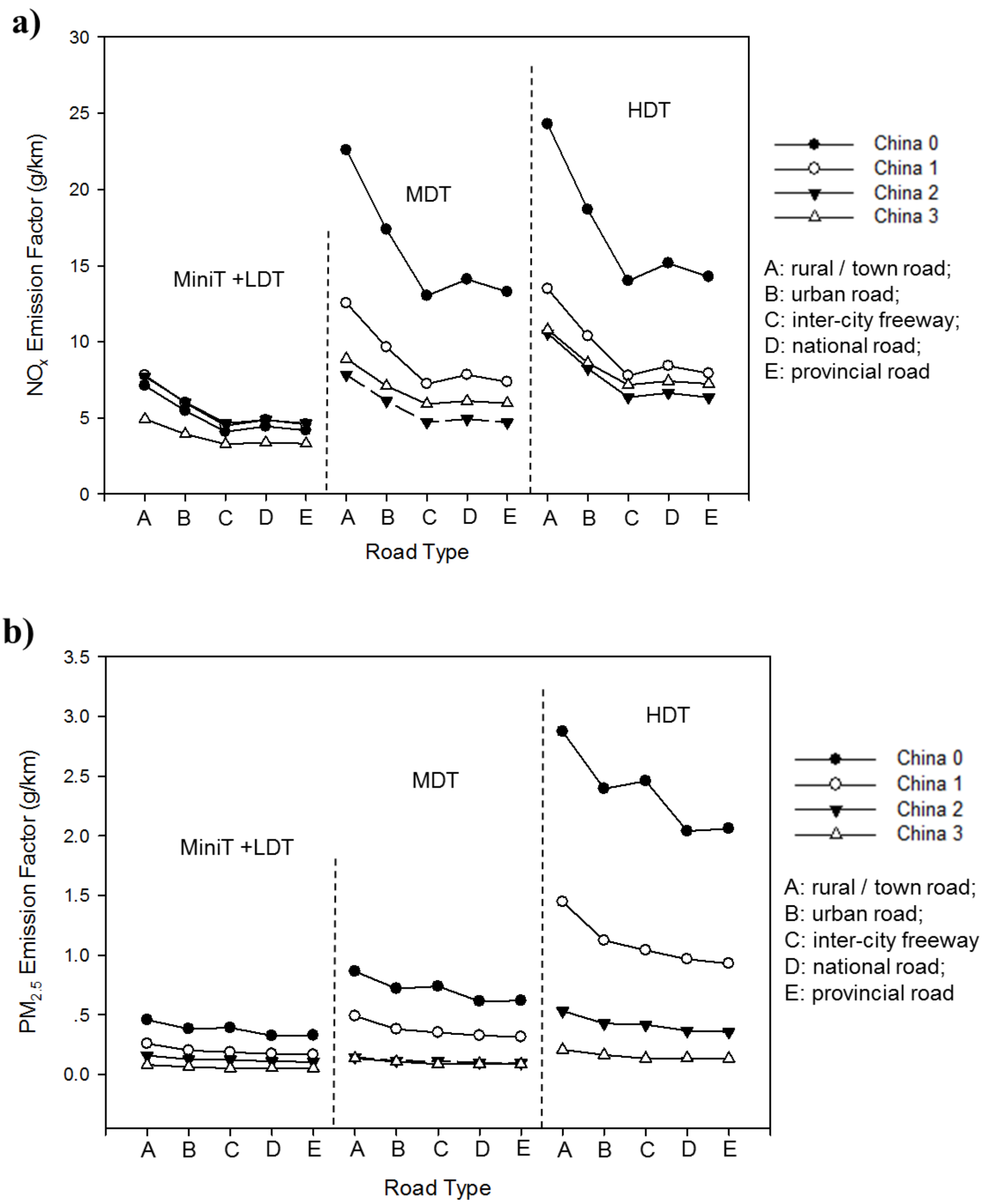

Figure 6 Emission Factors on Different Roads a) NOx Emission Factors; b) PM2.5 Emission Factors

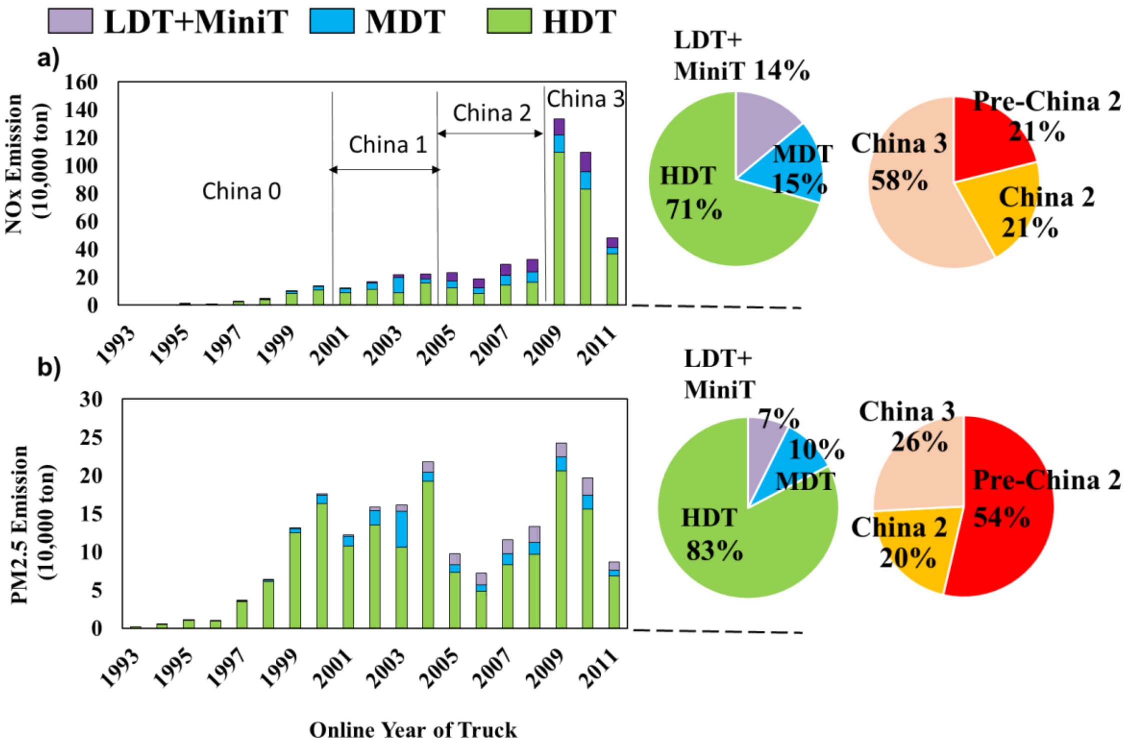

Figure 7 Emissions from Diesel Truck Fleet in 2011, China a) NOx Emission; b) PM2.5 Emission

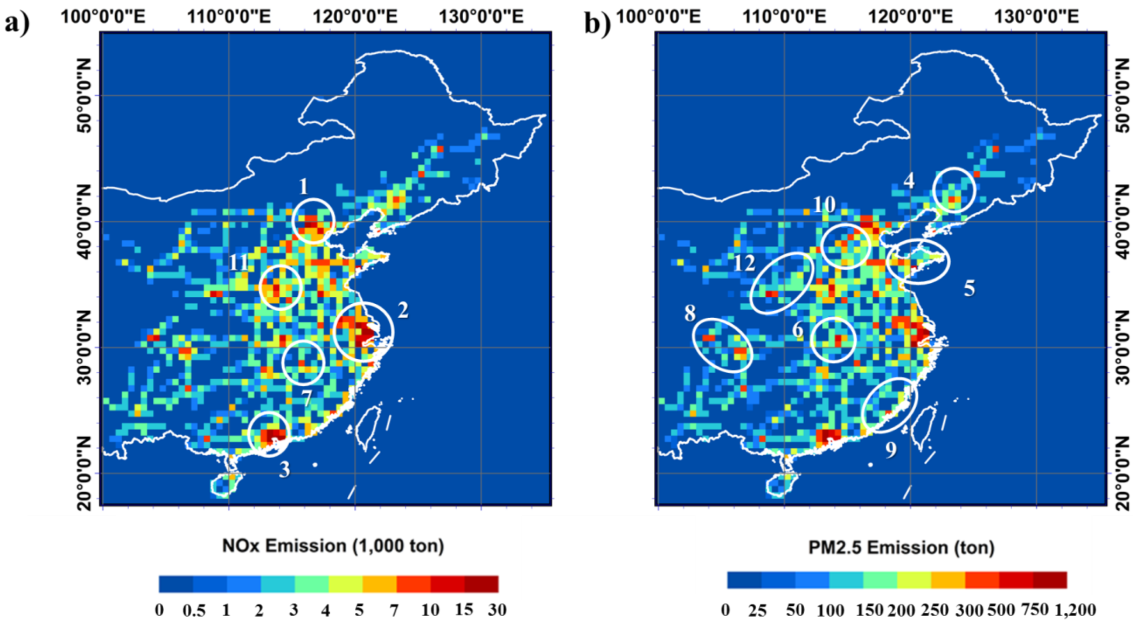

Figure 8 Maps of NO_x and $PM_{2.5}$ Emissions from Freight Trucks in the Eastern Part of China 2011: a) NO_X Emission; b) $PM_{2.5}$ Emission. （Key Control Areas in 12th Five Year Plan of Air Pollution Control: 1. Jing-Jin-Ji; 2. Yangzi River Delta; 3. Pearl River Delta; 4. central part of Liaoning Province; 5. Shangdong Province; 6. Wuhan City and its surroundings; 7. Changsha-Zhuzhou-Changde; 8. Chengdu and Chongqing; 9. west side of the Taiwan Strait; 10. central and north part of Shanxi Province; 11. Guanzhong region in Shaanxi; 12 Gan-Ning region is Gansu and Ningxia）

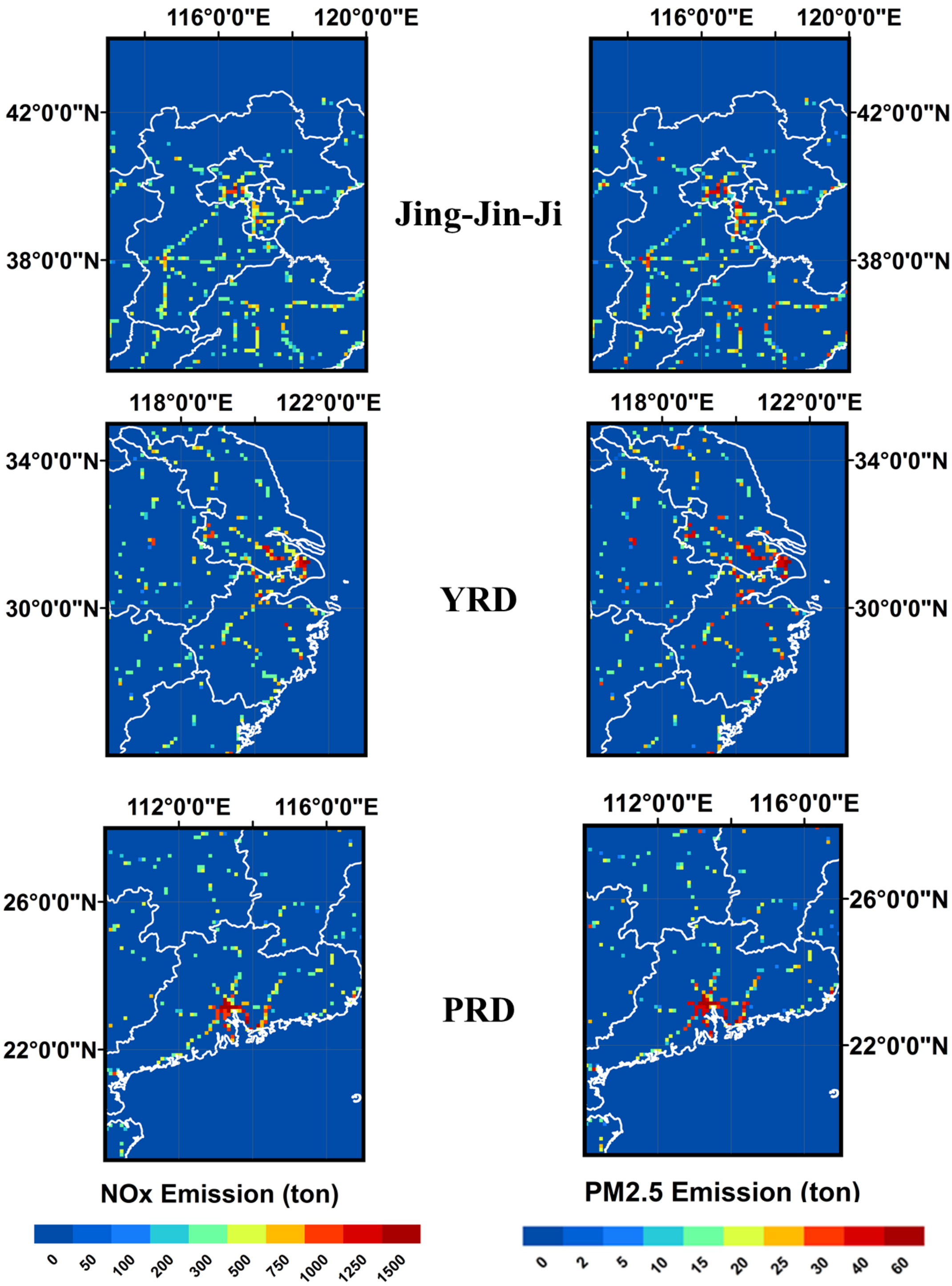

Figure 9 Maps of NO_x and $PM_{2.5}$ Emissions from Freight Trucks in East Part of China 2011

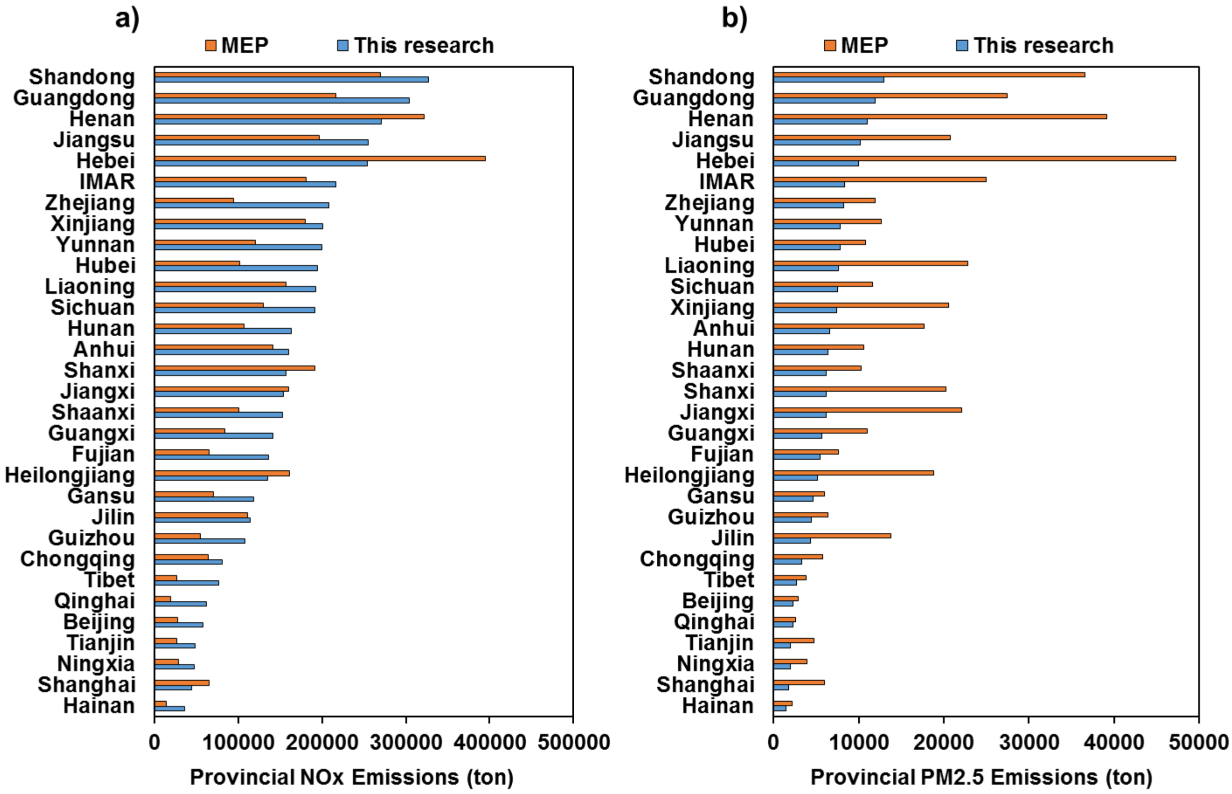

Figure 10 Provincial Diesel Truck Emissions from This and MEP Inventories: a) NO_x Emissions Ranks; b) $PM_{2.5}$ Emissions Ranks. (*Ranking according to emission scales in this research).

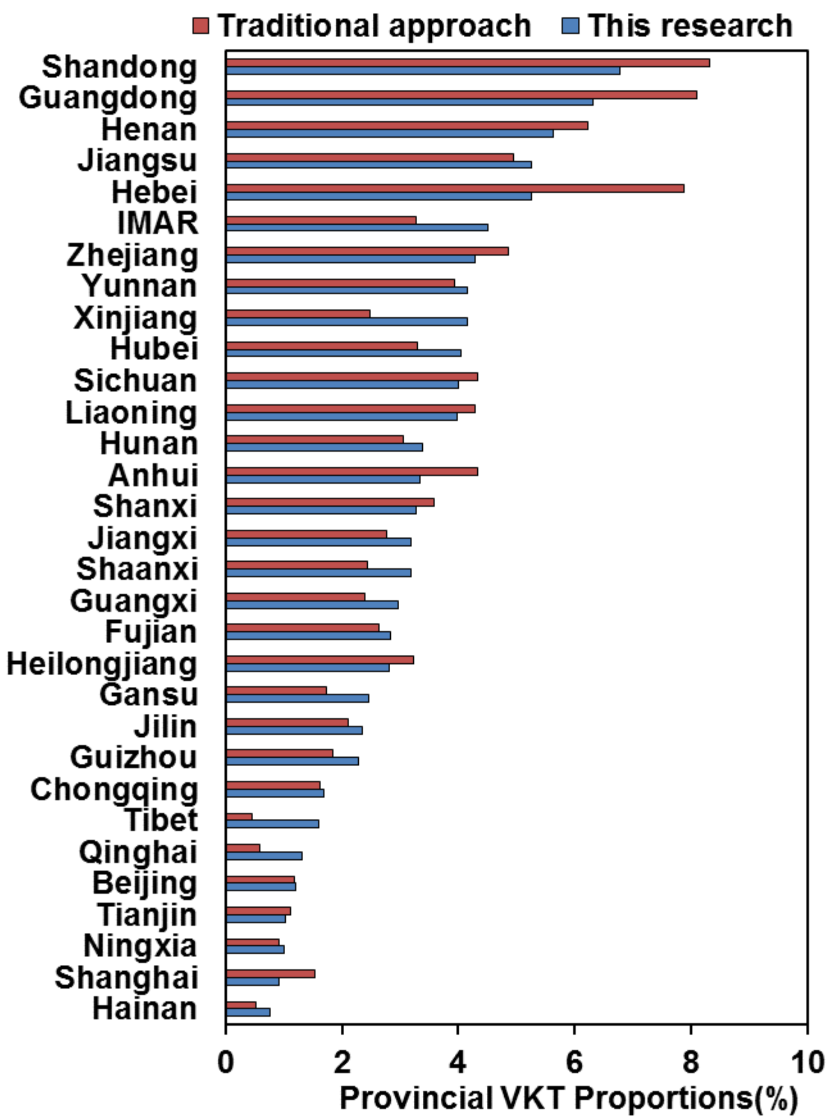

Figure 11. Provincial VKT Proportions in REIB Approach and Traditional Approach.