

Response to Reviews

Manuscript: An improved high-resolution passenger vehicle emission inventory for China using ride-hailing big data (egusphere-2025-5554)

We sincerely appreciate the constructive comments and valuable suggestions provided by the reviewers, which have greatly contributed to improving the quality of our study. The response to each comment is listed below. In the point-by-point response, reviewers' comments are marked in black, our responses are in blue, and the revised content in the manuscript is highlighted in red.

Response to Reviewer #1:

General Assessment

Passenger vehicle emissions constitute a significant source of urban air pollution, and accurate quantification of their emission characteristics is fundamental for formulating effective control measures. This study integrates ride-hailing big data with traffic flow modeling to get hourly vehicle speed data gridded at a 0.01° resolution across the nation, and constructs a high spatiotemporal resolution passenger vehicle emission inventory ($0.01^\circ \times 0.01^\circ$; hourly). The research quantifies the distribution characteristics of multiple pollutants across different time scales (from hourly to annual), with comparative analyses conducted against conventional algorithms. Furthermore, the WRF-Chem model was employed to validate the inventory through simulation. The methodology employed in this study offers a novel approach for compiling motor vehicle emission inventories and provides enhanced data precision for urban traffic pollution management and air quality modeling. The manuscript is well-organized. Several additional comments are provided for further improvement as follows:

Response: Thanks for your positive comments. We have carefully considered each of your comments and have made the necessary revisions accordingly.

Major Comments:

1. The core of this paper is to establish the relationship between vehicle speed and emission factors (EF). However, the existing figures and tables do not intuitively present the EF-Speed. It is recommended to add a new figure in Section 3.1 showing the EF-Speed curves for NO_x , CO, and VOCs, with some explanation.

Response: We highly appreciate the reviewer's insightful suggestion, which is crucial for highlighting the core contribution of our study. To address this comment, we have added Figure 2(d) in Section 3.1 of the revised manuscript, which intuitively depicts the EF-speed curves for NO_x , CO, and VOCs derived from the ride-hailing big data. Accordingly, we have supplemented detailed descriptions of this figure in the text as follows:

“The emission factor of CO, VOCs, and NO_x all exhibited a trend of sharp decrease followed by gradual increase in response to vehicle speed, which was consistent with the combustion kinetics of internal combustion engines (Fig. 2d). Among them, the EFs of incomplete combustion pollutants (CO and VOCs) showed more significant responses to speed variations, while the EFs of thermal-generated NO_x were mainly controlled by the temperature and oxygen concentration inside the cylinder and thus showed relatively moderate responses to speed changes (Chen et al.,

2022).”

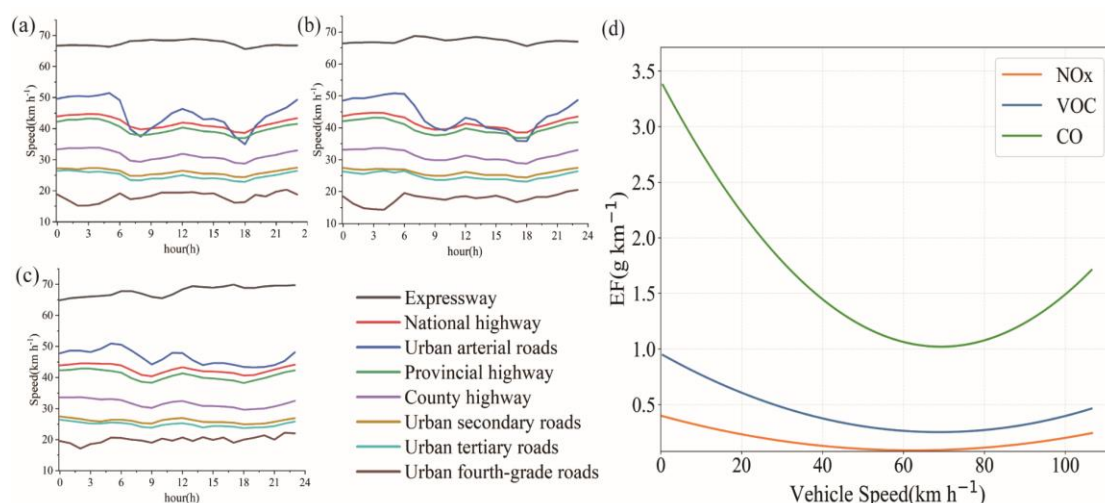


Figure 2. Temporal variations in vehicle speed on different road classes and corresponding EF-Vehicle Speed curves. Diurnal speed profiles of different road classes on (a) workday; (b) weekend; (c) holiday; (d) responses of CO, VOCs, and NO_x EF to vehicle speed.

2.207: Figures 1a and 1b present the national gridded vehicle speeds at 08:00 and 22:00. In my opinion, additional information should be included in this section, such as the differences in vehicle speeds across different road types (National Highways, Provincial Highways, and County Roads), and explain them properly in the text.

Response: We fully agree with your comment and have supplemented the analysis of vehicle speed differences across all involved road types in Section 3.1.

“Specific to the road type, the average driving speeds were higher on expressways (workday: 8:00: 67.12 km h⁻¹; 22:00: 68.59 km h⁻¹), urban arterial roads (workday: 8:00: 51.43 km h⁻¹; 22:00: 45.33 km h⁻¹) and national highways (workday: 8:00: 40.05 km h⁻¹; 22:00: 42.92 km h⁻¹) compared to other types of roads (Figs. 2a, 2b, 2c). Notably, urban arterial roads speeds fluctuated sharply during workdays and weekends, with fluctuation magnitudes of 25.3 km h⁻¹ and 12.8 km h⁻¹ respectively; this was attributable to the heavy intercity and interregional commuting traffic they carry, which caused a rapid surge in road saturation and thus a sharp speed drop, followed by a swift rebound (by 63.2% and 41.2% respectively) during midday off-peak hours as commuting demand wanes (Wang et al., 2016). By contrast, holiday travel was dominated by interregional family visits and tourism, with highly dispersed travel timings, leading to mitigated speed fluctuations across all road types.”

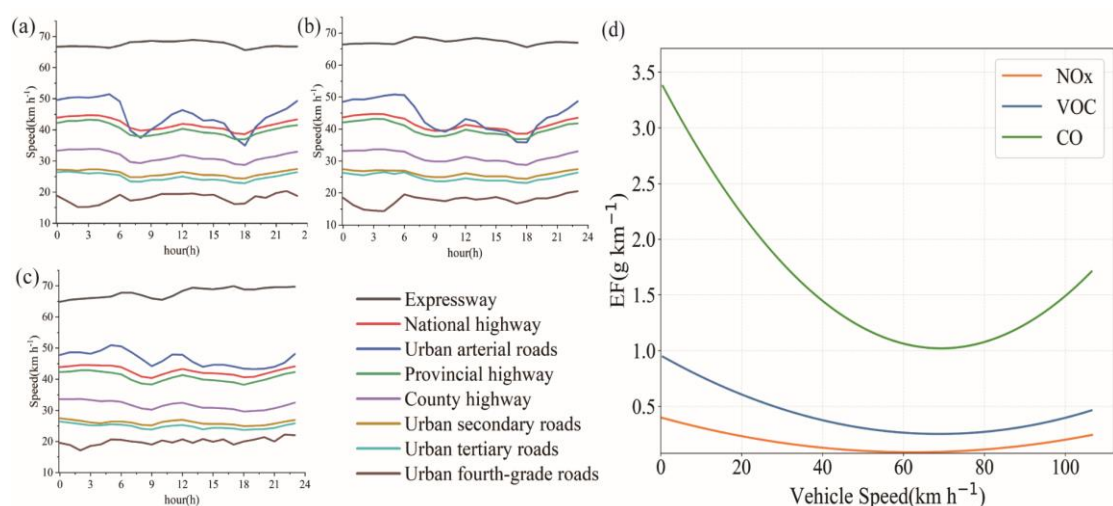


Figure 2. Temporal variations in vehicle speed on different road classes and corresponding EF-Vehicle Speed curves. Diurnal speed profiles of different road classes on (a) workdays; (b) weekends; (c) holidays; (d) responses of CO, VOCs, and NO_x EF to vehicle speed.

3.231: In Section 3.2, the manuscript states that “Urban areas, despite occupying only 0.8% of the country’s total land area, accounted for a high 35.3% of total vehicle emissions.” What is the definition criterion for “urban and rural areas”? It is necessary to clarify the criteria for defining urban boundaries, so as to avoid potential interpretation bias caused by ambiguous definitions.

Response: We appreciate the valuable comment regarding the definition criteria for urban and rural areas. The definition of urban and rural areas is based on the research of Li et al.(2020). We adopted the urban boundaries defined in this study as our judgment criterion. This demarcation method can effectively avoid interpretation biases caused by ambiguous criteria for urban-rural division. Corresponding clarification has also been added after the caption of Fig. 3.

“Furthermore, the definition of urban and rural areas involved in this study was based on the research of Li et al.(2020)”

4.Among different urban agglomerations, the emission density difference between urban and rural areas is pretty noticeable. What are the primary reasons for such differences?

Response: Thank you for raising this important point. Compared with rural areas, urban areas have a higher ownership of passenger vehicles and lower driving speeds, resulting in significantly higher emission density. This also accounts for the divergent urban-rural emission density gaps across different urban agglomerations (Zhao et al., 2019). Among these, the Beijing-Tianjin-Hebei (BTH) urban agglomeration exhibits the largest urban-rural emission density ratio of 16.4, which is 13.5 higher than the national average. This gap stems from its higher per capita vehicle ownership (0.23) than the national average (0.16), and smaller urban built-up areas than other agglomerations (Duan et al., 2024).We have added relevant content in Section 3.2.

“However, variations in urban-rural vehicle ownership and land area across different urban agglomerations led to different urban-rural emission density gaps (Zhao et al., 2019). Notably, the Beijing-Tianjin-Hebei (BTH) urban agglomeration exhibited the largest urban-rural emission density ratio of 16.4, which was 13.5 higher than the national average. This gap stemmed from its higher per capita vehicle ownership than the national average, and smaller urban built-up areas

than other agglomerations (Duan et al., 2024).”

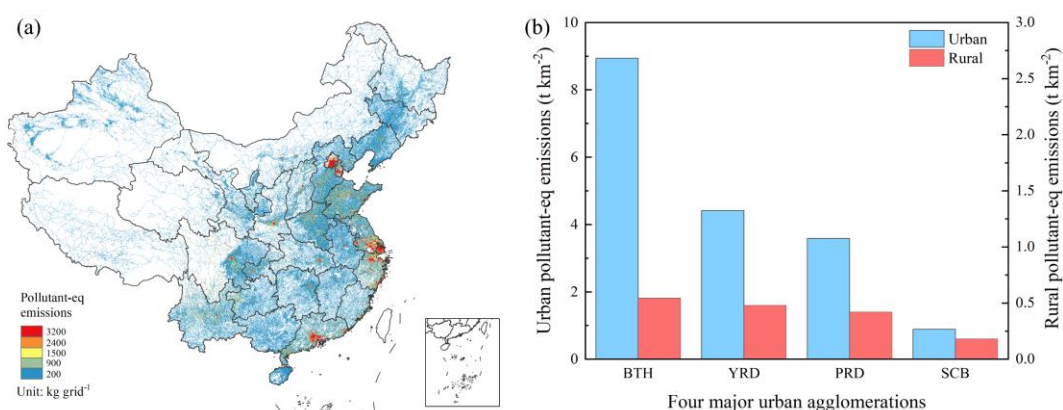


Figure 4. Geospatial distribution of passenger vehicle emissions and the disparities between urban and rural areas: (a) total pollution-eq emissions (TPEs) at $0.01^\circ \times 0.01^\circ$ resolution and (b) urban-rural differences in vehicle emission densities in four major urban agglomerations (BTH: the Beijing-Tianjin-Hebei region; YRD: the Yangtze River Delta region; PRD: the Pearl River Delta region; SCB: the Sichuan Basin) in 2019.

5. The authors obtained national vehicle speeds using ride-hailing big data, but could this data introduce spatial bias into the results? Can it cover all roads? The authors need to conduct further discussions on these aspects to make sure the national-scale emission estimates are reliable.

Response: Thanks for your comment on the potential spatial bias in the big data of ride-hailing. The ride-hailing dataset employed in this study covers all major road categories nationwide; however, constrained by the relatively low penetration rate of ride-hailing services in western China, the sample size of this region is relatively insufficient. To address this limitation, on the basis of constructing the initial gridded vehicle speed dataset, we adopted the nearest neighbor interpolation method to supplement data for road segments with missing values across each road type. This ensures that all roads nationwide are assigned vehicle speed information, thereby effectively reducing errors caused by insufficient data volume. Consequently, this dataset does not affect our main research findings. Relevant description on this content has been supplemented in Section 2.2.1:

“This dataset had covered all major road types nationwide. To address the insufficient sample size of ride-hailing services in western China, we adopted the nearest neighbor interpolation method to supplement the speed information of road segments with missing values across each road type.”

6.L.279: The manuscript notes: “During the morning peak, hourly average emissions on workday exceeded those on weekend and holiday by 8% and 5%, respectively, increasing to 12% and 18% during the evening peak.” Why does the phenomenon occur?

Response: We appreciate the reviewer for pointing out the issue regarding the widened emission gap during the evening peak period. Morning peak travel is dominated by work trips, while evening peak traffic flow also includes passenger vehicle flows from daily activities such as shopping and dining (Azari et al., 2025). This directly increases the vehicle density and prolongs the duration of congestion in the urban road network during the evening peak. As a result, vehicles in low-speed and start-stop conditions produce much higher emission intensities, which ultimately

enlarges the emission difference between workdays and non-workdays at night (Choudhary et al., 2016). We have added one sentence to explain this phenomenon.

“This expanding difference was attributed to the more diverse types of nighttime travel activities, which included both work trips and daily consumption trips such as dining and shopping. This led to higher vehicle density and prolonged traffic congestion, thereby substantially increasing emission intensity (Azari et al., 2025; Choudhary et al., 2025).”

7. When comparing with the traditional algorithm, what vehicle speed is adopted in the traditional method? And what are the differences between it and the inventory developed in this study?

Response: We sincerely thank the reviewer for the comments. The traditional method adopted in this study is strictly based on the recommended datasets specified in the current technical guidelines for compiling on-road vehicle emission inventories (MEE, 2014). Specifically, this method categorizes vehicle speeds into several discrete intervals (e.g., 0–20 km·h⁻¹, 20–30 km·h⁻¹, 30–40 km·h⁻¹, 40–80 km·h⁻¹, >80 km·h⁻¹), with a single averaged emission factor assigned to each interval, regardless of the speed fluctuation within each interval. Compared with traditional algorithms, this paper mainly has two improvements. First, this study innovatively adopts continuous real-world vehicle speed data derived from ride-hailing big data. Second, we integrate the congestion index with the traffic flow model to disaggregate the monthly-scale vehicle activity level of the traditional method down to the hourly scale, thereby improving the accuracy of emission estimation.

We have added the differences between the traditional algorithm and the inventory developed in this study in the main text’s Section 2.1 and supplemented Table S2 in the supporting materials.

In the Section 2.1: “The core difference between the traditional algorithm and the improved algorithm in this study was that the former assigned a fixed speed correction factor for each of the five speed intervals with monthly-scale activity levels, while the latter obtained continuous speed correction factors and further refined the activity levels by combining the congestion index with the traffic flow model. The detailed correction values could be found in Table S2.”

In the supporting materials:

Table S2. Average speed correction factor for passenger vehicles under the traditional algorithm.

Pollutants	Speed Range (km h ⁻¹)				
	<20	20-30	30-40	40-80	>80
CO	1.69	1.26	0.79	0.39	0.62
VOCs	1.68	1.25	0.78	0.32	0.59
NO _x	1.38	1.13	0.90	0.86	0.96
PM	1.68	1.25	0.78	0.32	0.59

8.L.295: Section 3.4 only provides an overall emission comparison with the traditional method. It doesn’t show the differences in underestimation rates across different time periods—like seasons or holidays.

Response: Thank you for your valuable comments. To address this concern, we have supplemented Section 3.4 of the revised manuscript with comparative diagrams illustrating the differences in underestimation rates across distinct temporal scenarios, including seasonal emissions as well as emissions during weekdays, weekends and holidays. This revision further highlights the advantage of the emission inventory developed in this study in capturing dynamic

emission characteristics. We have added the relevant descriptions in the main text.

“The traditional method exhibited a significant underestimation of passenger vehicle emissions across distinct seasons and day types (Fig. 7c). From a seasonal perspective, this method underestimated the average daily passenger vehicle emissions by 31.6%, 31.0%, 32.7% and 31.8% in spring, summer, autumn and winter, respectively, with a relatively small overall fluctuation range. In contrast, the discrepancy in underestimation across different day types was more pronounced, and the method’s underestimation of passenger vehicle emissions on weekends (33.4%) was significantly higher than that on weekdays (27.7%). The formation of this characteristic difference was not only associated with refined vehicle speed correction, but also stemmed from the quantitative analysis of vehicle activity levels across different day types based on congestion indices in this study.”

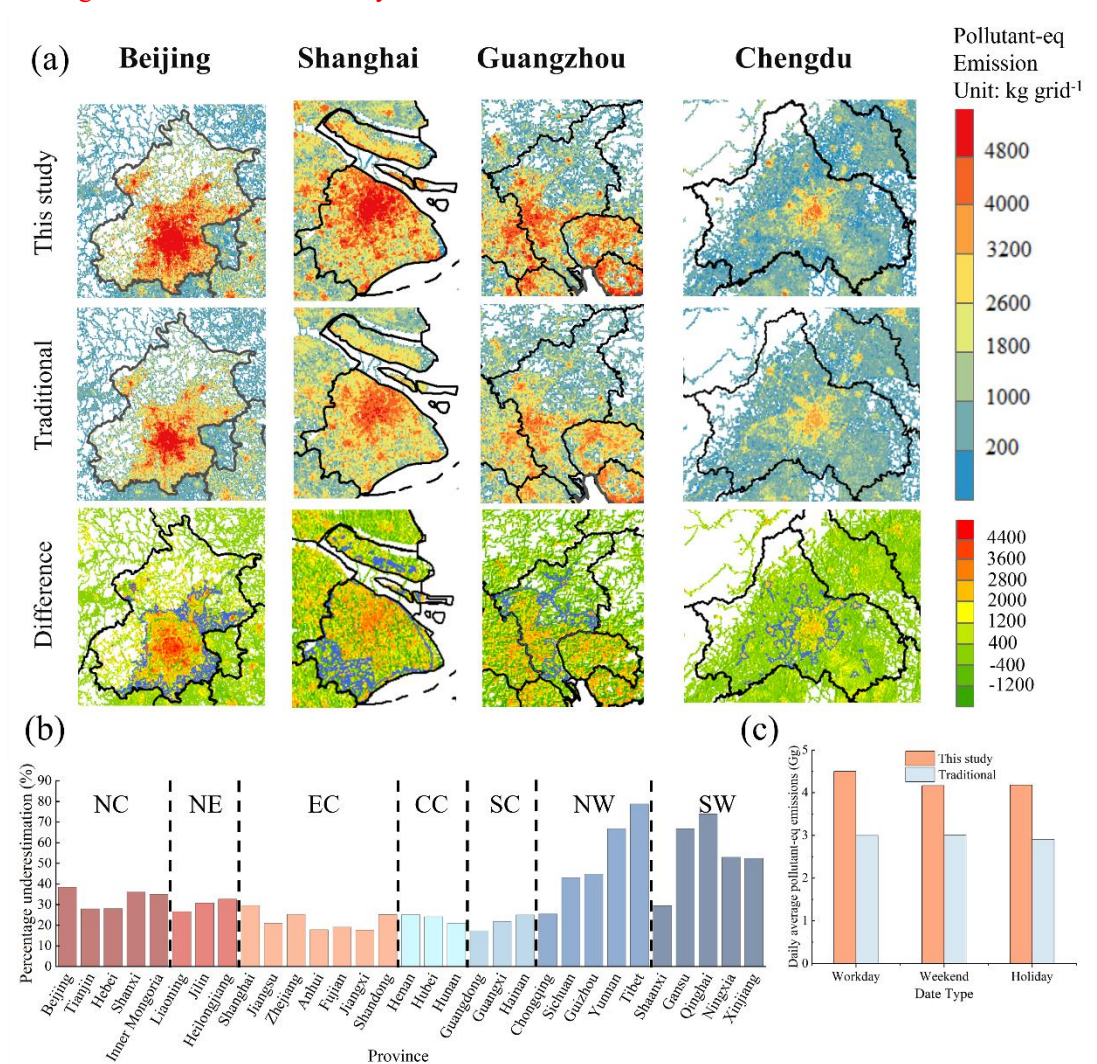


Figure 7. Comparison of this study with traditional algorithms: (a) Beijing, Shanghai, Guangzhou to compare it with the results of the present study (Difference = This Study – Traditional); (b) Comparison of daily average results across (c) four seasons and (d) three date type; The percentage of underestimation for each province calculated with the traditional method. The purple boundary in (a) is the Urban Growth Boundary (UGB).

There are some minor comments:

1. In Section 2.4, The authors should provide the total number of monitoring stations, as well as the

number of those located in regions with the top 20% road density.

Response: Thanks for your suggestion. To clarify the spatial distribution of monitoring stations, we have supplemented the relevant information in the Section 2.4:

“This study used observational data from 114 national monitoring stations within the simulated area to comprehensively evaluate the simulation results of the emission inventory developed in this study and the traditional inventory, as well as the improvement effects at the 15 stations located in the regions with the top 20% road density.”

2.L.208: It is recommended to revise the caption of Figure 1 from “Average speed in China” to “The average vehicle speed of passenger vehicles in China in 2019”.

Response: Thank you for your advice, we have revised the caption from “Average speed in China” to “The average vehicle speed of passenger vehicles in China in 2019” in the revised manuscript.

3.L.146 and L.158: Some symbols (such as K_j , v_f , $L_{p,i}$) lack complete unit annotations when they first appear.

Response: We have added unit annotations for all symbols at their first occurrence.

“Where, λ is the congestion delay index, dimensionless; T is the actual time spent travelling (h); T_f is the time spent travelling at the smooth speed (h); L is the length of the road section (km), v is the actual travelling speed (km h^{-1}), and v_f is the smooth speed of the vehicle (km h^{-1}), then:”

“Where Q is the flow rate (veh h^{-1}); λ is the congestion delay index; K_j is the congestion density (veh km^{-1}); v_f is the unimpeded vehicle speed, and K_j and v_f are constants.”

4.L.228: Section 3.2 states “ The annual amount of CO, VOCs, NO_x, PM and NH₃ emitted from national passenger vehicles in 2019 were 4087.8, 1069.4, 211.7, 1.9, 77.5 kt, respectively” while Table 1 shows “CO: 408.78 ten thousand tons...” The unit conversions should be consistent throughout to avoid data ambiguity.

Response: Thank you for the comments. We have unified all the units in the paper as kt.

5. Check the citation format of all references in the full text.

Response: We appreciate the reviewer's correction. We have checked and revised the formatting of the references accordingly.

Response to Reviewer #2:

General comments:

The article “An improved high-resolution passenger vehicle emission inventory for China using ride-hailing big data” by Li et al., provides information about emission inventory for pollutants emitted by passenger cars in China. The study highlights the importance of average vehicle speed on emission factors. These findings were established in comparison with traditional methods, both showing discrepancies between urban and rural vehicle emissions, weekend relative to workdays emissions and seasonal distribution of pollutants released from vehicular emissions.

Response: We sincerely appreciate the reviewer’s positive evaluation of the value of our research findings. Each comment and suggestion have been carefully addressed, as detailed below.

Major comments:

1. The authors should provide more detailed information regarding the vehicular fleet, type of motorization, percentual distribution over the entire country, type of fuel, etc. Also, there is a need to discuss about the type of industrial vehicles and those used for agriculture, passenger car legislation related to the restrictions on pollution and how this apply to other nations.

Response: We thank the reviewer for the constructive suggestions. We have revised this study accordingly in response to these advices. In the supplementary materials, Figure S1b presents the national passenger vehicle ownership in 2019, and Figure S2 is newly added to show the regional distribution of small and mini vehicles under different emission standards. Relevant descriptions of vehicle types and fuel types were also added in the methodology section. This study focuses on passenger vehicles and will expand to industrial and agricultural vehicles in future work. With the growing share of China V and China VI vehicles, the rising penetration of new energy vehicles (China’s new energy vehicle ownership reached 31.4 million by 2024, increased by 53.84% year on year; Liang et al., 2019; Wang et al., 2026), and the implementation of vehicle scrappage policies, the overall emission intensity of passenger vehicles in China will continue to decline (Liu et al., 2024; Zhu et al., 2022). These measures synergistically promote emission standard upgrading and energy structure transition, and provide important references for other countries to balance environmental governance, energy security, and transportation development.

In the Methods section: “This study focused on gasoline-fueled passenger vehicles. The vehicle kilometers traveled (VKT) of light-duty gasoline passenger vehicles (LDPVs) in 2019 were obtained from Ma et al. (2022). Based on the China Statistical Yearbook 2004–2019, we calculated the proportion of passenger vehicles by emission standard, the total number of passenger vehicles in each province in 2019 (Fig. S1), and the regional distribution of small and mini passenger vehicles by emission standard (Fig. S2).”

In the Conclusions section: “At present, this study focuses on passenger vehicles; to improve its accuracy and applicability, future research will be further extended to freight trucks, industrial vehicles, agricultural vehicles, and the entire transportation sector.”

“In the future, with the continuous increase in the proportion of China V and China VI vehicles, as well as the rising penetration rate of electric vehicles (EVs) (China’s stock of electric vehicles reached 31.4 million by 2024, a year-on-year increase of 53.84%) (MEE, 2025; Liang et al., 2019; Wang et al., 2026), coupled with the implementation of policies for the elimination and renewal of old vehicles, the overall “speed-emission” relationship in the passenger vehicle sector will be gradually weakened (Liu et al., 2024; Zhu et al., 2022).”

“These above-mentioned measures coordinate the upgrading of emission standards with the transformation of the energy structure, providing an important reference for other countries to balance environmental governance, energy security and transportation development.”

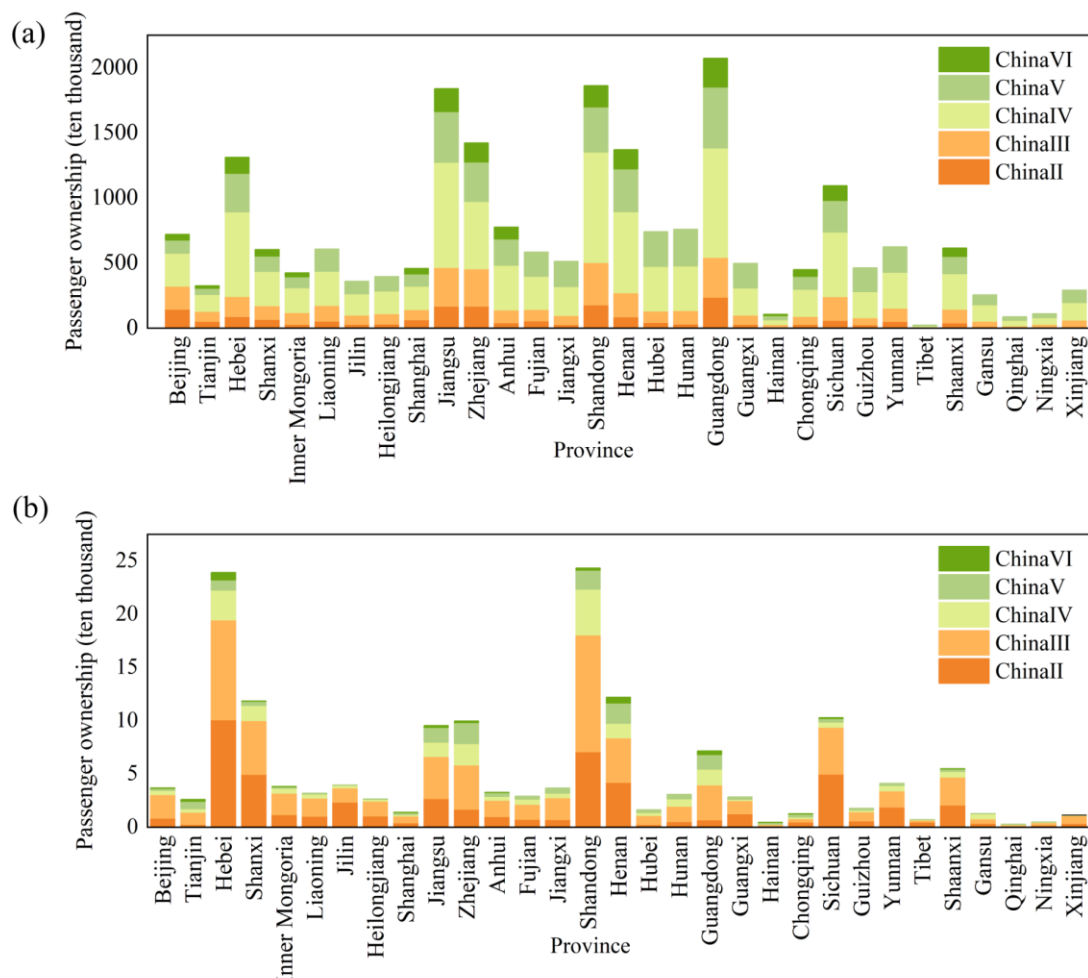


Figure S2. Distribution of passenger vehicles by emission standard in different regions: (a) small-sized vehicles and (b) mini-sized vehicles.

2. The authors should expand their consideration to the traffic worldwide and not over the few cities in China and India, even if those cities are very polluted. The emission inventories steady state data should be presented not over the cities in China and India. Even if the present study construct emission inventory of atmospheric pollutants in China the introduction should include a wider view.

Response: We appreciate the reviewer for raising this point. We have supplemented the Introduction section with studies on air pollutant emission inventory development in countries other than China and India.

“For example, Dey et al. (2019) estimated the emission levels of 8 types of pollutants from passenger cars in the Greater Dublin Area of Ireland based on the COPERT5 model.”

“The first category involves constructing high spatiotemporal resolution traffic emission inventories by using complex emission models, such as COPERT, MOVES, and IVE (Yang et al., 2018; Yu et al., 2021; Latini et al., 2005; Huo et al., 2009).”

3. The data collected from Amap Ride-hailing Platform are representative for the entire fleet? All the vehicles on the road send data to the platform? It is possible that, systematically, old vehicles emit constantly more pollutants but are not equipped with the tracking system?

Response: We appreciate the valuable comment from the reviewer. The data obtained from the Amap ride-hailing platform in this study is only used to reflect real-time road driving speeds. It should be emphasized that the platform data is derived from mobile terminal users with GPS positioning enabled; its uploading behavior is mainly related to the activation of the positioning function and has no direct connection with vehicle age. Given the sufficient sample size and wide spatiotemporal coverage of the data used in this study, it can reliably reflect the overall operating speed of the road network without significant bias caused by the exclusion of old vehicles, thus meeting the research requirements.

“The platform data originates from mobile terminal users who have activated GPS positioning. The data uploading behavior is primarily associated with the activation status of the positioning function and has no direct connection with vehicle age.”

4. The sections 2.1 and 2.2 include many equations which are not well described and their parameters are not always clearly explained in terms of units and meaning (e.g. congestion delay index, K_j , C_t , etc.).

Response: Thank you for the comments. We have clearly indicated the units and meaning of each parameter in Sections 2.1 and 2.2.

5. Please include in the papers the problems which usually national monitoring stations have in the terms of trustable data provided. Which parameters are usually provided with huge errors and how these uncertainties are affecting the model?

Response: Thank you for raising this important point. In practice, national environmental monitoring data may have certain limitations in spatial coverage, and can be affected by nearby local emissions, instrument conditions, and complex environmental factors (Ding et al., 2024; Zhao et al., 2025). Among these, the monitored concentrations of pollutants such as $PM_{2.5}$, PM_{10} , and CO may affect the accuracy of model validation to some extent and may introduce slight disturbances to model evaluation and concentration comparison (Wu et al., 2018). We have added the discussion of the issues related to national environmental monitoring station data and their impacts in the Discussion section of the manuscript.

“In addition, this may also be related to the insufficient spatial representativeness of national environmental monitoring data during actual acquisition and the influence of local pollution sources around monitoring sites, which slightly affect the validation results (Ding et al., 2024; Zhao et al., 2025; Wu et al., 2018).”

6. Please describe in the paper the possible effect on the overall model of the average speed of $(42.42 \pm 5) \text{ km h}^{-1}$ for example. This average speed should be considered with a range of uncertainties and to extend this uncertainty to the model output data.

Response: We thank the reviewers for the constructive suggestions. As requested, we employed Monte Carlo simulation to quantify the uncertainty of emission factors. Across all speed intervals, the emission factors and their corresponding uncertainties for CO, VOC, and NO_x were $1.4866 \pm 21.42\% \text{ g}\cdot\text{km}^{-1}$, $0.4042 \pm 22.56\% \text{ g}\cdot\text{km}^{-1}$, and $0.1507 \pm 28.30\% \text{ g}\cdot\text{km}^{-1}$, respectively. Furthermore,

uncertainty analysis was conducted for each speed interval. The results indicate that although the 40–80 km·h⁻¹ interval exhibited the lowest emission factors, it contributed the largest share of pollutant emissions. In contrast, the uncertainty of emission factors reached its maximum when vehicle speeds exceeded 80 km·h⁻¹ (Fig. S3).

“To further quantify the impact of average vehicle speed on the model results, this study conducted a quantitative assessment of model uncertainty using Monte Carlo simulation. Across all speed intervals, the emission factors and their corresponding uncertainties for CO, VOC, and NO_x were $1.4866 \pm 21.42\%$ g·km⁻¹, $0.4042 \pm 22.56\%$ g·km⁻¹, and $0.1507 \pm 28.30\%$ g·km⁻¹, respectively. Furthermore, uncertainty analysis was performed for each speed interval. Although the 40–80 km·h⁻¹ interval exhibited the lowest emission factors, it represented the dominant driving range for passenger vehicles, with the highest probability density. In contrast, the uncertainty of emission factors reached its maximum when vehicle speeds exceeded 80 km·h⁻¹ (Fig. S3).”

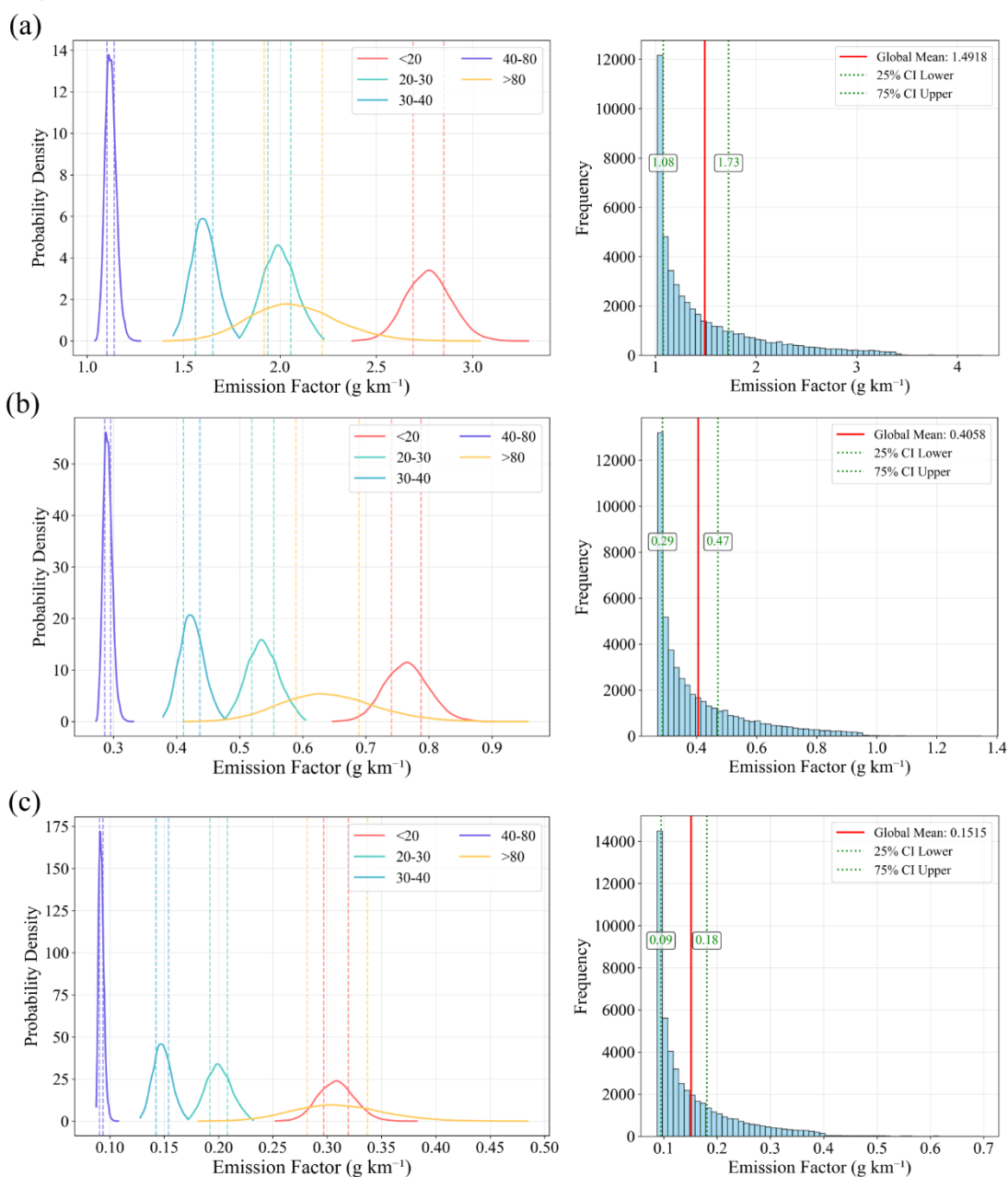


Figure S3. Probability density distributions of passenger vehicle emission factors across speed intervals and overall frequency statistics: (a)CO; (b)VOC; (c)NO_x.

7.Please include the uncertainty bars in the figure 2 for frequency on speed range. Three different days could have different frequency for the same speed range but there is an absolute number as average speed.

Response: We appreciate the reviewer’s valuable suggestions. Regarding the frequency distribution across different speed intervals, vehicle speed frequency better follows a log-normal distribution. Therefore, we used the log-normal distribution to more accurately characterize the dispersion of the data and reflect the frequency fluctuations within the same speed interval on weekday, weekend, and holiday. We have added error bars to Figure 4 and provided the average speed values for each speed interval. The relevant results and discussions have been supplemented in the main text.

“Compared with weekday, there were no morning and evening rush hours on holiday, resulting in a higher proportion in high-speed intervals (Yang et al., 2016).”

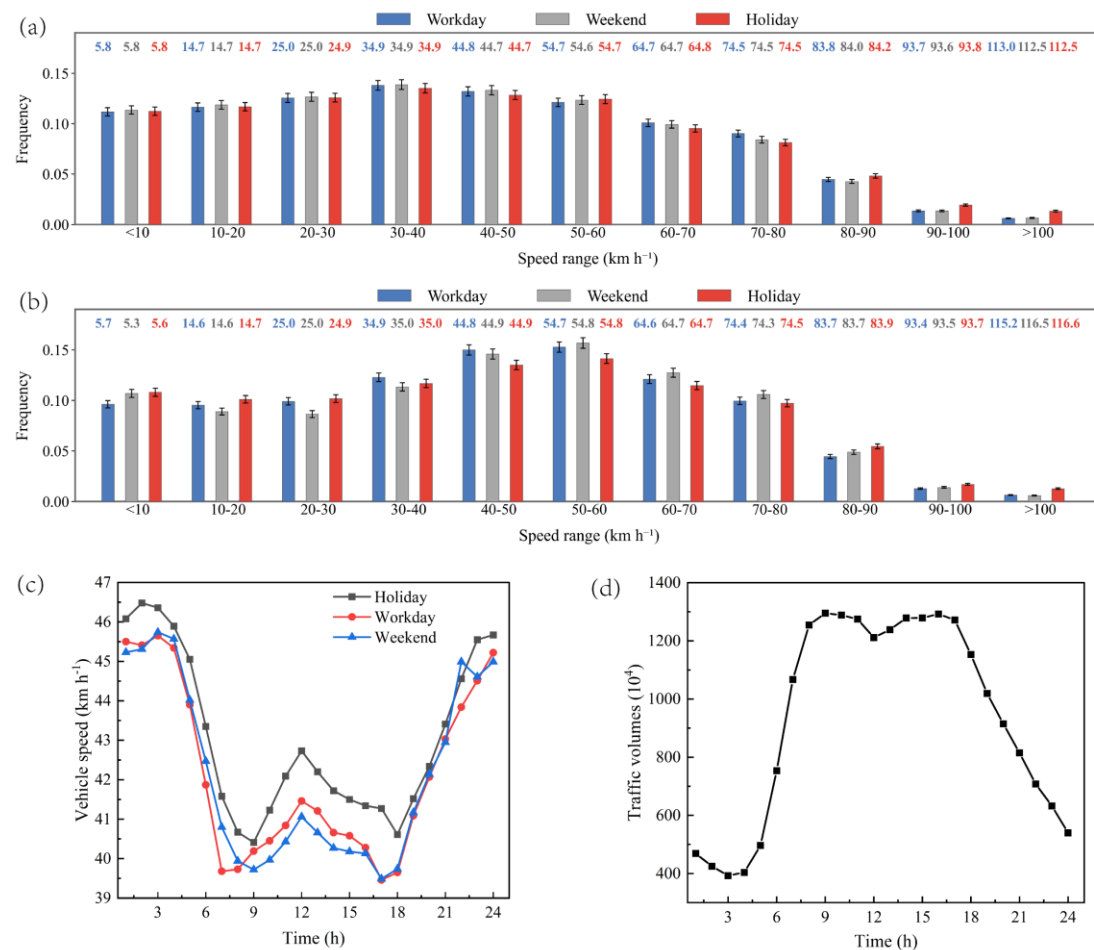


Figure 3. Characteristics of speed and traffic volume changes: speed distribution at (a) 8:00 and (b) 22:00 on workday, weekend and holiday. The values labeled in the figure represent the average speed of each interval; (c) Hourly speed variation on weekend, workday and holiday and (d) hourly traffic volume variation.

8. There is not convincingly that new model simulations with a better attribution of average speed

parameter are the only responsible for the difference between the results in the model validation. The inventory optimization are actually not an important improvements since 0.36% in NMB and 0.02 for R2 are insignificant changes. Please discuss more in detail about the other advantages of the speed average model improvement.

Response: We appreciate the valuable suggestions from the reviewer. Passenger vehicles accounted for relatively low emission shares of total emissions (approximately 3.2% for CO, 4.7% for VOCs, and 1.2% for NO_x, Li et al., 2023a), which resulted in insignificant improvements in NMB and R values. If this method could be extended to other vehicle categories in future work, it might lead to more substantial enhancements. In this study, the optimization of the average speed model was reflected not only in total emissions but also in the improved accuracy of emission estimates across different date types. Average speeds on weekends were generally higher than those on weekdays. The traditional method underestimated emissions more significantly on weekends (33.4%) than on weekdays (27.7%) because it did not consider differences in speed. However, the speed-corrected model in this study clearly showed these day-to-day changes. Spatially, the improved method avoided the limitation of using fixed speeds in traditional approaches. It can accurately identify higher emissions on crowded urban roads caused by frequent acceleration and deceleration, and properly show lower emissions on outside roads. This could support the precise implementation of traffic emission reduction measures at the road level. The above content has been elaborated in detail in Section 3.4 of the main text.

“Spatially, the improved method avoided the limitation of using fixed speeds in traditional approaches. It can accurately identify higher emissions on crowded urban roads caused by frequent acceleration and deceleration, and properly show lower emissions on outside roads (Fig. 7a) (Zhang et al., 2023a; Wen et al., 2020; Choudhary et al., 2016).”

“The traditional method exhibited a significant underestimation of passenger vehicle emissions across distinct seasons and day types (Fig. 7c). From a seasonal perspective, this method underestimated the average daily passenger vehicle emissions by 31.6%, 31.0%, 32.7% and 31.8% in spring, summer, autumn and winter, respectively, with a relatively small overall fluctuation range. In contrast, the discrepancy in underestimation across different day types was more pronounced, and the method’s underestimation of passenger vehicle emissions on weekends (33.4%) was significantly higher than that on weekdays (27.7%). The formation of this characteristic difference was not only associated with refined vehicle speed correction, but also stemmed from the quantitative analysis of vehicle activity levels across different day types based on congestion indices in this study.”

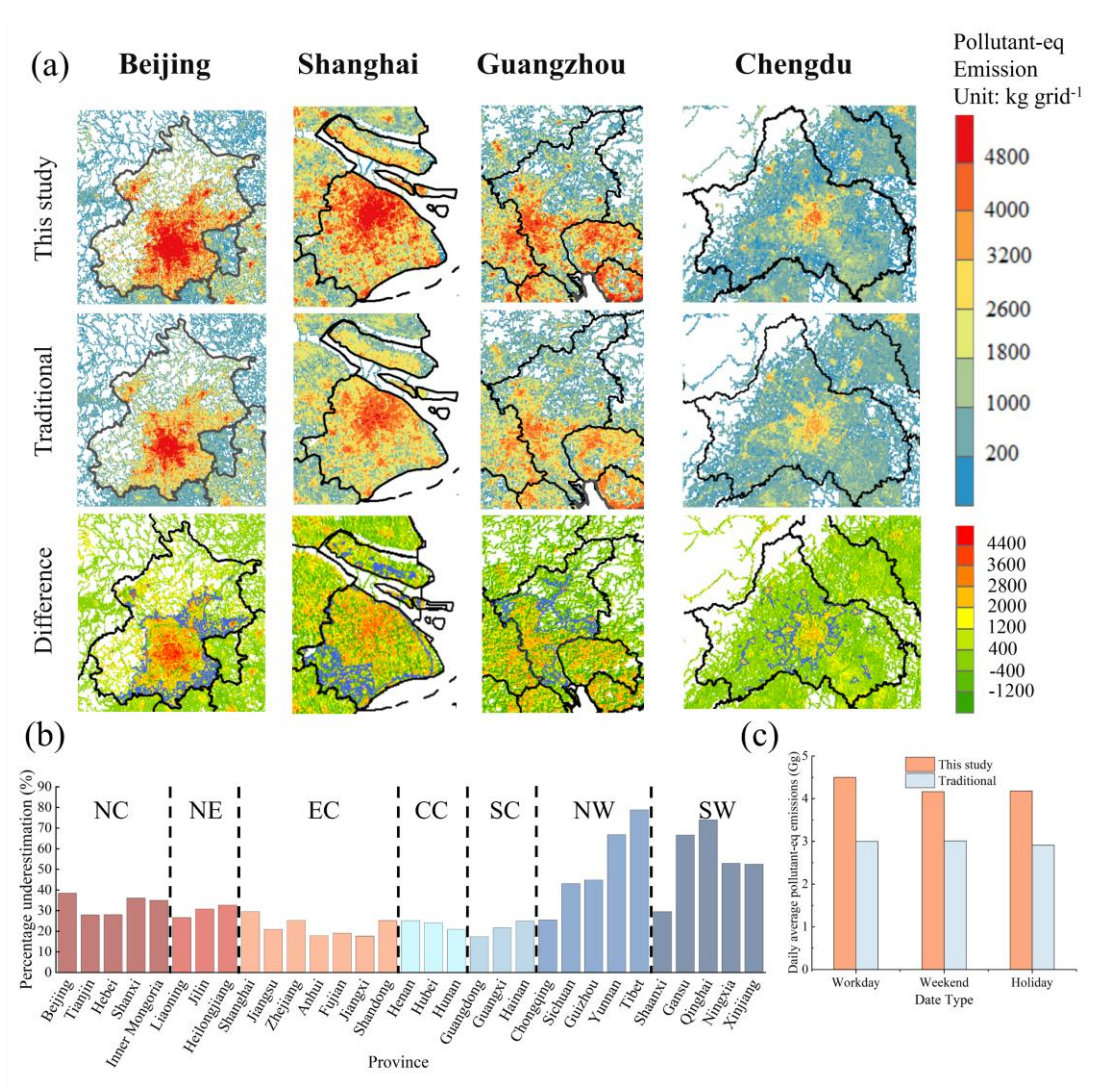


Figure 7. Comparison of this study with traditional algorithms: (a) Beijing, Shanghai, Guangzhou to compare it with the results of the present study (Difference = This Study - Traditional); (b) Comparison of daily average results across (c) four seasons and (d) three date type; The percentage of underestimation for each province calculated with the traditional method. The purple boundary in (a) is the Urban Growth Boundary (UGB).

Minor:

Line 95: please use consistent representation of the units, km per year, and g km⁻¹”

Response: Corrected.

Line 110: please include the year.

Response: Corrected.

Line 135: congestion delay index (λ)

Response: Corrected.

Response to Community #1:

This paper presents a significant advancement in the field of atmospheric science and transportation emissions modeling. By leveraging a massive dataset of 23.6 billion ride-hailing trajectories, the authors have successfully transitioned from traditional, often static, emission estimation methods to a dynamic, big-data-driven approach. The novelty of this study lies in its spatial and temporal granularity at a national scale. While previous high-resolution inventories have focused on specific urban agglomerations (like the Pearl River Delta or Beijing-Tianjin-Hebei), this work provides a $0.01^\circ \times 0.01^\circ$ hourly grid for the entirety of China.

Response: We sincerely appreciate the reviewer's recognition of our research on the development of high-resolution emission inventories for China. We have addressed each of your comments carefully as listed below.

Technical Comments for Improvement

1. As the study uses 2019 data, a brief discussion on how the rapid rise of Electric Vehicles (EVs) in China (post-2020) might alter these “speed-emission” curves would add valuable foresight.

Response: We sincerely appreciate the reviewer for highlighting this critical perspective. Your comment is insightful. With the continuous increase in the proportion of electric vehicles (EVs) in passenger vehicle ownership and the gradual tightening of emission standards for gasoline-powered vehicles, the overall “emission-speed” relationship in the passenger vehicle sector will be gradually weakened in the future. However, the core focus of this study is on passenger vehicles predominantly powered by gasoline, aiming to establish the Speed-EF relationship. Therefore, the impacts arising from the pollution-free nature of EVs have not been incorporated in the current research.

“In the future, with the continuous increase in the proportion of electric vehicles (EVs), China V and China VI vehicles in passenger vehicle ownership, the gradual tightening of emission standards for gasoline-powered vehicles, the rising penetration rate of new energy vehicles (China’s stock of new energy vehicles reached 31.4 million by 2024, a year-on-year increase of 53.84%) (MEE, 2025; Liang et al., 2019; Wang et al., 2026), as well as the implementation of policies for the elimination and renewal of old vehicles, the overall “speed-emission” relationship in the passenger vehicle sector will be gradually weakened (Liu et al., 2024; Zhu et al., 2022).”

2. While 23.6 billion data points are extensive, ride-hailing vehicles often have different driving patterns compared to private vehicles (e.g., more idling or cruising for passengers). Further clarification on how these patterns were normalized for the general passenger vehicle population would be beneficial.

Response: We thank the reviewers for the constructive suggestions. The 23.6 billion ride-hailing trajectory data used in this study is only to extract the actual on-road driving speeds, and construct refined grid speed correction factors. Ride-hailing vehicles belong to the category of passenger vehicles, and their driving speed characteristics can effectively reflect the actual driving states of passenger cars in the study area (Kan et al., 2019; Liang et al., 2022). Based on this, this study assumes that passenger vehicles have consistent on-road driving speeds. We have added a paragraph in Section 2.2.1 to explain this point.

“Moreover, we assumed that the vehicle speeds on other dates did not vary significantly compared

to these representative days, and that passenger vehicles had consistent on-road driving speeds.”

3. To further strengthen the discussion on the spatiotemporal characteristics of urban traffic pollutants and to provide a comparative perspective on localized monitoring versus nationwide modeling, I strongly suggest citing the following paper: Comprehensive spatiotemporal analysis of long-term mobile monitoring for traffic-related particles in a complex urban environment Atmospheric Pollution Research, 2025. <https://doi.org/10.1016/j.apr.2025.102870>

Response: We have added relevant description in *Introduction* Section of the revised manuscript.

“Yeganeh et al. (2025) quantified the high-resolution spatiotemporal characteristics of traffic-related PM_{2.5} and black carbon (BC) using long-term mobile monitoring data collected along five representative routes in Tehran, Iran.”

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