

1 **An improved high-resolution passenger vehicle emission** 2 **inventory for China using ride-hailing big data**

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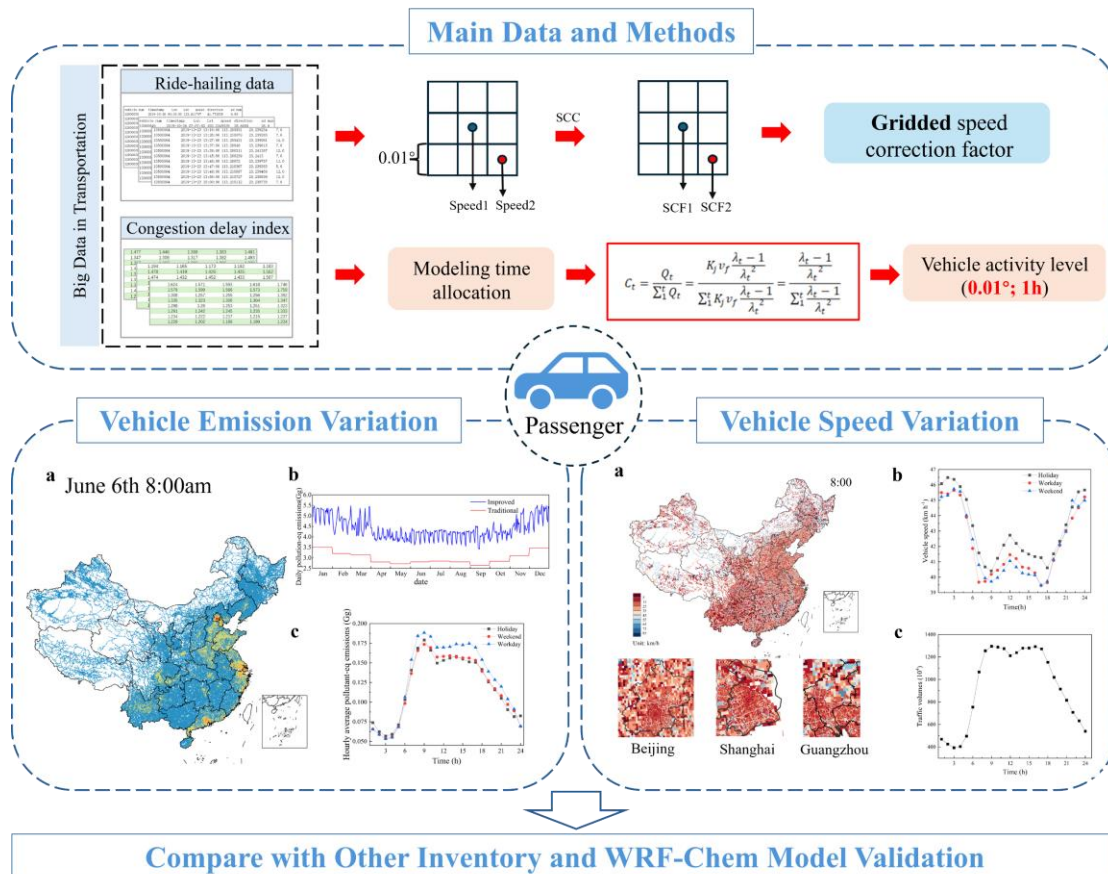
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15 **ABSTRACT:** As the global automotive industry continues to grow rapidly, the increasing number of
16 passenger vehicles has contributed to worsening air pollution. However, previous studies have
17 insufficiently addressed nationwide hourly vehicle emissions. This study firstly utilized big data of ride-
18 hailing services and traffic flow model to obtain nationwide hourly gridded speed and traffic volume.
19 Then we established a high spatiotemporal resolution ($0.01^\circ \times 0.01^\circ$; 1h) emission inventory by using
20 multiple correction factors. The annual amount of CO, VOCs, NO_x, PM and NH₃ emitted from national
21 passenger vehicles in 2019 were 4087.8, 1069.4, 211.7, 1.9, 77.5 kt, respectively. Despite occupying
22 merely 0.8% of the national territory, urban areas generated 35.3% of the country's total vehicle
23 emissions, due to high local traffic volumes and relatively low vehicle speeds. From a temporal
24 perspective, passenger vehicle emissions exhibit significant holiday effect and weekend effect. In
25 addition, hourly average emissions on workday exceeded those of weekend and holiday by 8 % and 5 %
26 during the morning peak, with these differences increasing to 12% and 18% during the evening peak.
27 Current traditional emission methodology might underestimate emissions by 31.5%. We also used the
28 WRF-Chem model for simulation validation. This hourly-scale inventory provides quantitative support
29 for the precise implementation of pollution control and early warning.



30

31

Graphical abstract

32 1. Introduction

33 The number of vehicles in China grew from 14.53 million to 260 million over the past two decades,
 34 with an average annual growth rate of 16.39% (MEE, 2020a). This growth has driven economic
 35 development while adversely impacting air quality and human health (Anenberg et al., 2017). Premature
 36 deaths attributable to PM_{2.5} in China amounted to 1.33 million in the year 2020, of which motor vehicle
 37 emissions contributed approximately 12.5% (Li et al., 2023b; Luo et al., 2022). In 2019, passenger
 38 vehicles accounted for about 80% of the total vehicle population in China (NBS, 2020b) and contributed
 39 significantly to vehicular emissions (e.g., VOCs accounted for more than 50% of the total) (Li et al.,
 40 2023a). Quantification of passenger vehicle emission characteristics is imperative for the evaluation of
 41 relevant emission reduction policies.

42 With the advancement of regional air quality simulation technology and the increasing demand for
 43 atmospheric environmental management, traditional traffic emission statistical methods have become

44 inadequate to meet current refined management requirements (Gao et al., 2020). To address this issue,
45 previous studies have developed numerous methods for constructing refined vehicle emission inventories.
46 The first category involves constructing high spatiotemporal resolution traffic emission inventories by
47 using complex emission models, such as COPERT, MOVES, and IVE (Yang et al., 2018; Yu et al., 2021;
48 Latini et al., 2005; Huo et al., 2009). For example, Dey et al. (2019) estimated the emission levels of 8
49 types of pollutants from passenger cars in the Greater Dublin Area of Ireland based on the COPERT5
50 model. The second category utilizes big data on transportation. For instance, Dias et al. (2018) improved
51 the characterization of the spatial variation of vehicle speeds at the city scale through GPS modeling, and
52 Deng et al. (2020) utilized the BeiDou Navigation Satellite System (BDS) to establish an emission
53 inventory with lower uncertainty for the Beijing-Tianjin-Hebei (BTH) region. Yeganeh et al. (2025)
54 quantified the high-resolution spatiotemporal characteristics of traffic-related PM_{2.5} and black carbon
55 (BC) using long-term mobile monitoring data collected along five representative routes in Tehran, Iran.
56 However, due to the difficulties in obtaining large-scale and long-term traffic data, most studies are also
57 limited to roads, cities or urban agglomerations, such as Chengdu, Beijing, and the Pearl River Delta
58 (PRD) (Li et al., 2020b; Zheng et al., 2009; Wen et al., 2022), for emission calculations. There is a lack
59 of hourly-resolution emission estimates at the national level.

60 Emission factors are generally considered to be one of the primary sources of uncertainty in
61 emission inventories (Charis et al., 2010). Many scholars focus merely on the impact of vehicle
62 technology improvements, fuel types, and vehicle aging on emission factors, while often neglecting the
63 influence of speed (Xu et al., 2021; Andrew et al., 2003). Speed has the greater impact on emission
64 factors compared to other correction factors, as it fluctuates dynamically within the same region, while
65 other correction factors remain relatively constant over time. This difference is primarily attributed to
66 variations in engine workload and combustion efficiency at different speeds (Sun et al., 2020; Andrew
67 et al., 2003). The impact of speed on vehicle emissions is both significant and complex. For NO_x, the
68 emission rate of light-duty passenger vehicles at high speeds (>50 km h⁻¹) is 1.6 times that at low speeds
69 (10-20 km h⁻¹), while the emission rates of HC and CO at low speeds are 1.6 times and 2.3 times that of
70 high-speed driving, respectively (Guo et al., 2020). Given this impact, accurate calculation of speed
71 correction factors is important for reducing the uncertainty of emissions factors.

72 The temporal allocation method can also directly affect the accuracy of high-resolution emission
73 inventories. Previous studies have established emission inventories at monthly scales (Zheng et al., 2014;

74 Jiang et al., 2020; Zhou et al., 2016), or roughly obtained daily-scale data, followed by the construction
 75 of a regional-level hourly-scale inventory, such as Akash et al. (2022), who systematically analyzed
 76 hourly gridded road traffic emissions in Delhi city; Sun et al. (2021), who considered the influence of
 77 the vehicle age-annual average mileage curve and estimated hourly emissions on a $0.01^\circ \times 0.01^\circ$ grid in
 78 Tianjin. However, they have ignored the fluctuations in daily emissions caused by workday, weekend,
 79 and holiday, which has significant uncertainty.

80 To address these gaps, this study aims to improve the accuracy of emission estimations by utilizing
 81 big data of ride-hailing services to obtain nationwide speed distribution on a 0.01° grid for the first time
 82 and apply it to the speed correction of emission factors. We construct a high spatiotemporal resolution
 83 ($0.01^\circ \times 0.01^\circ$; 1h) emission inventory of atmospheric pollutants from passenger vehicles in China in
 84 2019 by further integrating traffic flow models and big data of the congestion delay index. The study
 85 also explores the spatiotemporal characteristics of pollutant emissions from passenger vehicles, compares
 86 the results with traditional calculation methods, and further evaluates the inventory improvement using
 87 WRF-Chem model.

88 2. Data and methodology

89 2.1. Estimation of emission inventories

90 The emission inventory for each pollutant (CO, VOCs, NO_x, PM, NH₃) for passenger cars was estimated
 91 with the following equation:

$$92 \quad E_j = \sum_{i,p,k,t} V_{p,i,k,t} \times BEF_{p,j} \times \varphi_{p,i,j,t} \times \gamma_{p,i,t} \times \lambda_{p,j} \times \theta_{p,j} \times 10^{-9} \quad (1)$$

$$93 \quad V_{p,i,k,t} = VP_{p,i,k,t} \times VKT_{p,i,t} \quad (2)$$

$$94 \quad TPE_s = \sum_j \frac{E_j}{PEV_j} \quad (3)$$

95 In Eq.(1) and Eq.(2), E represents pollutant emissions (t); i represents the grid; j represents the pollutant
 96 type, including CO, PM, VOCs, NO_x and NH₃; k represents the vehicle type, including small passenger
 97 cars and mini passenger cars; p represents the province; VP, VKT, and BEF represent the vehicle
 98 population, annual average vehicle kilometers traveled and baseline emission factors, with units of
 99 vehicles, km yr⁻¹, and g km⁻¹, respectively. φ is the environmental correction factor (including
 100 temperature correction factor, humidity correction factor, and altitude correction factor); γ is the speed
 101 correction factor; λ is the deterioration correction factor; θ represents other correction factors (including

102 sulfur content correction factor and ethanol blending correction factor). In Eq.(3), TPEs represents the
103 total pollutant equivalents (kt) (For assessing the extent of environmental and techno-economic hazards
104 posed by various pollutants), and PEV represents the pollutant equivalent value (kg) (MEE, 2018). This
105 study focused on gasoline-fueled passenger vehicles. This study focused on gasoline-fueled passenger
106 vehicles. This study adopted the VKT values for LDPVs in 2019 from the research of Ma et al. (2022).
107 The vehicle kilometers traveled (VKT) of light-duty gasoline passenger vehicles (LDPVs) in 2019 were
108 obtained from Ma et al. (2022). Based on the China Statistical Yearbook 2004–2019, we calculated the
109 proportion of passenger vehicles by emission standard, the total number of passenger vehicles in each
110 province in 2019 (Fig. S1), and the regional distribution of small and mini passenger vehicles by emission
111 standard (Fig. S2). The baseline emission factors were obtained based on other literature (Wen et al.,
112 2023; MEE, 2014; EEA, 2019), with specific details provided in Table.S1. Furthermore, the definition
113 of urban and rural areas involved in this study was based on the research of Li et al. (2020).

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

119 **2.2. Quantification of high-resolution emission factors based on big data of ride-hailing**

120 **2.2.1 Gridded speeds and determination of their correction factors**

121 A total of 23.6 billion vehicle trajectory data were collected in this study from Amap Ride-hailing
122 Platform (https://dache.amap.com/amap_mini#/), including workdays (September 24th, 2019, October
123 23rd, 2019), weekends (September 28th, 2019, October 26th, 2019) and holidays (September 13th, 2019,
124 October 1st, 2019) (Table S3). The platform data originates from mobile terminal users who have
125 activated GPS positioning. The data uploading behavior is primarily associated with the activation status
126 of the positioning function and has no direct connection with vehicle age. This dataset had covered all
127 major road types nationwide. To address the insufficient sample size of ride-hailing services in western
128 China, we adopted the nearest neighbor interpolation method to supplement the speed information of
129 road segments with missing values across each road type. Moreover, we assumed that the vehicle speeds
130 on other dates did not vary significantly compared to these representative days, and that passenger

131 vehicles have consistent on-road driving speeds. Each vehicle sent data every 3 seconds. Using Python,
132 we processed the data to obtain hourly resolution vehicle speeds on a 0.01° grid. Finally, we obtained
133 gridded hourly vehicle speeds for three representative days: workdays, weekends, and holidays.

134 Furthermore, we adopted the improved speed correction curve (SCC) method proposed by Sun et
135 al. (2020) to obtain continuous speed correction factor values for VOC, NO_x, and CO, ultimately resulting
136 in gridded speed correction factors. For specific SCC of various pollutants, please refer to Table.S4.

137 2.2.2 Corrections for other emission factors

138 In the equations, ϕ utilizes daily temperature, humidity, and elevation data, all obtained from ERA5
139 (<https://cds.climate.copernicus.eu/datasets>). The deterioration correction factor λ is calculated using
140 relevant equations and coefficients from the EEA. (2019). θ includes the sulfur content correction factor
141 and the ethanol blending correction factor, which are based on the corresponding values from GEI (MEE,
142 2014). Specific values can be found in Table.S5.

143 2.3. High-resolution vehicle activity level data combined with traffic flow models

144 For time allocation for vehicle activity levels, the following formula can be used:

$$145 V_{p,t,k} = C_{p,t} \times V_{p,k} = C_{p,t} \times VP_{p,k} \times VKT \quad (4)$$

146 where $V_{p,t,k}$ is the vehicle activity level of model k in province p in time period t (km·veh); $V_{p,k}$ is
147 the number of vehicles of model k in province p (km·veh).

148 $C_{p,t}$ is the time allocation coefficient of province p at time period t . It is obtained by combining the
149 congestion delay index obtained from Baidu Map Traffic and Travel Big Data Platform
150 (<https://jiaotong.baidu.com/>) with the three-parameter model of traffic flow (Jinping et al., 2024), which
151 is constructed as follows:

152 The congestion delay index (λ) is defined as the ratio of the actual time spent by residents on one
153 trip to the time spent in a smooth state when the travelling distance is the same, and its calculation formula
154 is:

$$155 \lambda = \frac{T}{T_f} = \frac{\frac{L}{v}}{\frac{L}{v_f}} = \frac{v_f}{v} \quad (5)$$

156 Where, λ is the congestion delay index, dimensionless; T is the actual time spent travelling (h); T_f
157 is the time spent travelling at the smooth speed (h); L is the length of the road section (km), v is the actual
158 travelling speed (km h⁻¹), and v_f is the smooth speed of the vehicle (km h⁻¹), then:

159
$$v = \frac{v_f}{\lambda} \quad (6)$$

160 Combined with the basic three-parameter model of traffic flow, the relationship between flow rate
 161 and congestion index can be derived:

162
$$Q = K_j \left(v - \frac{v^2}{v_f} \right) = K_j \left[\frac{v_f}{\lambda} - \frac{\left(\frac{v_f}{\lambda} \right)^2}{v_f} \right] = K_j v_f \frac{\lambda - 1}{\lambda^2} \quad (7)$$

163 Where Q is the flow rate (veh h⁻¹); λ is the congestion delay index; K_j is the congestion density (veh
 164 km⁻¹); v_f is the unimpeded vehicle speed, and K_j and v_f are constants.

165 In turn, we obtain the formula for calculating the time allocation coefficient of motor vehicle
 166 emissions:

167
$$C_t = \frac{Q_t}{\sum_1^t Q_t} = \frac{K_j v_f \frac{\lambda_t - 1}{\lambda_t^2}}{\sum_1^t K_j v_f \frac{\lambda_t - 1}{\lambda_t^2}} = \frac{\lambda_t - 1}{\sum_1^t \frac{\lambda_t - 1}{\lambda_t^2}} \quad (8)$$

168 Where C_t is the motor vehicle emission time allocation coefficient, dimensionless; t is time; and Q_t
 169 denotes the volume of traffic in time period t.

170 Regarding the spatial allocation of the vehicle activity level, this study was done using the road
 171 length data provided by Golder Maps as an allocation index (Gómez et al., 2018), and the gridded vehicle
 172 activity level at 0.01° × 0.01° resolution was calculated according to the following formula:

173
$$V_{p,i,k,t} = \frac{L_{p,i}}{\sum_i L_{p,i}} \times V_{p,t,k} \quad (9)$$

174 where V_{p,i,k,t} is the activity level of model k in the i grid of province p in time period t; V_{p,t,k} is the
 175 number of vehicles of model k in province p in time period t; and L_{p,i} is the length of the road in the i
 176 grid of province p (km).

177 2.4 WRF-Chem model setting

178 To verify the superiority of the improved inventory, this study employed the WRF-Chem model to
 179 simulate the atmospheric concentrations of PM_{2.5} and O₃ in the Jiangsu and Shanghai regions (longitude
 180 range: 117.5°E ~ 122.0°E; latitude range: 30.0°N ~ 35.10°N) from February 1, 2019 to February 18,
 181 2019 (covering the Spring Festival period and the subsequent week). A two-layer nested model with
 182 spatial resolutions of 9×9 km and 3×3 km, respectively, was adopted for the simulation. The specific
 183 simulated region is illustrated in Figure S4(a).

184 The inventory developed in this study was used as the input data for traffic sources, while data from

185 the ABaCAS database was adopted for other emission sources; these two sets of data were jointly utilized
186 to generate the anthropogenic emission files required for the WRF-Chem model (Li et al., 2023a). The
187 $1^\circ \times 1^\circ$ Final Operational Global Analysis (FNL) data provided by the National Centers for Environmental
188 Prediction (NCEP, <https://rda.ucar.edu/datasets/ds083.2/>) was used to obtain the initial meteorological
189 conditions and boundary conditions. Real-time biomass burning emissions were derived from the Fire
190 Inventory from NCAR (FINN, <https://www2.aom.ucar.edu/modeling/finn-fire-inventory-ncar>). The
191 global simulation results from CAM-Chem (<https://www.aom.ucar.edu/cam-chem/cam-chem.shtml>)
192 were employed as the initial chemical conditions and boundary conditions. The specific parameterization
193 schemes are presented in Table S6.

194 This study used observational data from 114 national monitoring stations within the simulated area
195 to comprehensively evaluate the simulation results of the emission inventory developed in this study and
196 the traditional inventory, as well as the improvement effects at the 15 stations located in the regions with
197 the top 20% road density. The simulation results were verified by calculating the normalized mean
198 deviation (NMB) and correlation coefficient (R).

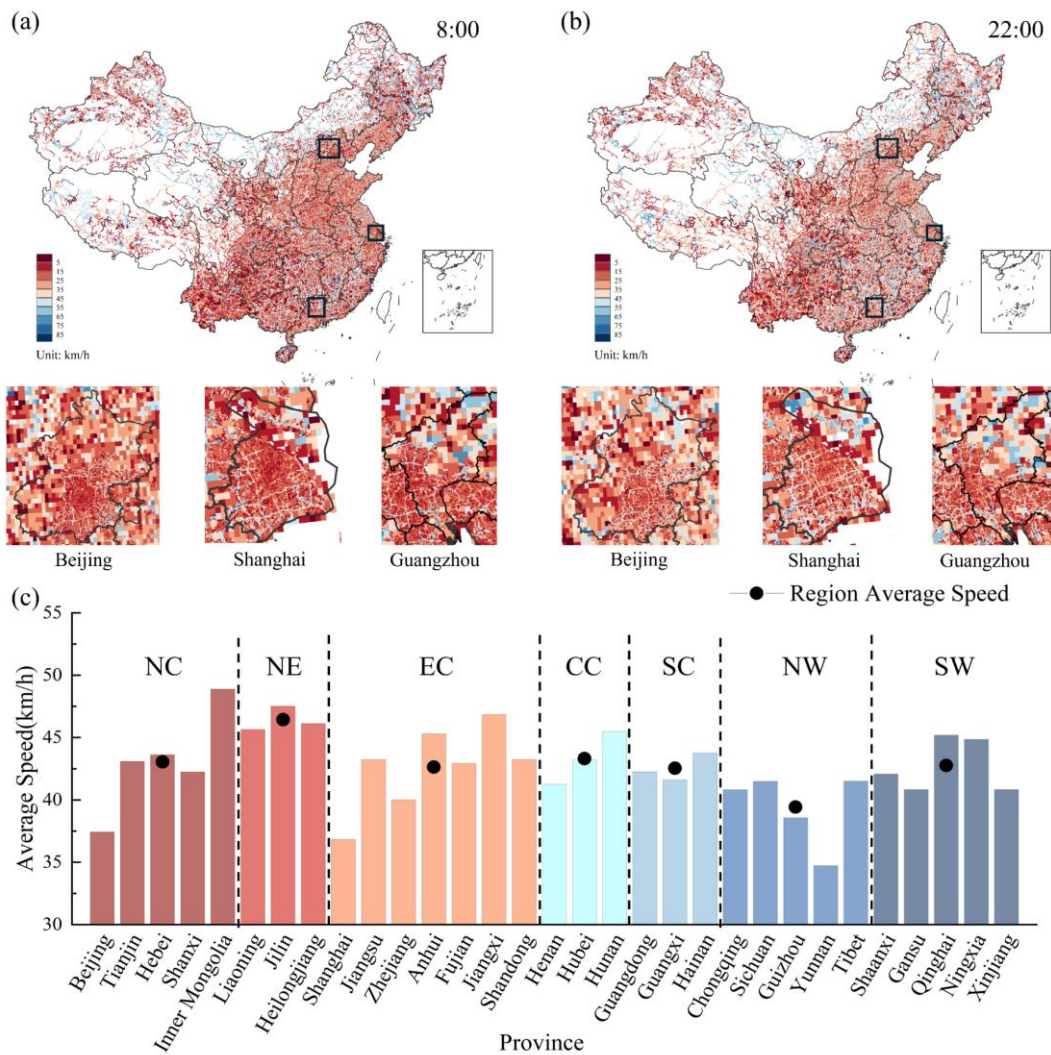
199 **3. Results and discussion**

200 **3.1. Spatiotemporal variation of vehicle speed and traffic flow**

201 Vehicle speed and traffic volume are important parameters for describing vehicle driving conditions
202 and traffic flow characteristics. The nationwide average passenger vehicle speed was 42.42 km h^{-1} . The
203 high concentration of work and business activities in the eastern China during the daytime, combined
204 with its large vehicle population, led to generally slower vehicle speeds at 8:00 compared to 22:00.
205 Especially in the key cities such as Beijing, Shanghai, and Guangzhou, city vehicle speeds at 8:00 a.m.
206 typically were $36.4 \pm 0.3 \text{ km h}^{-1}$ due to significantly increased traffic flow during the morning peak and
207 the circular radial road network which might concentrate traffic flow (Liu et al., 2018). During the off-
208 peak period at 22:00, differences in traffic flow speeds across various road types were more apparent.
209 The vehicle speeds on some provincial and county roads had increased significantly. This reflected the
210 non-uniformity of traffic flow distribution (Guan et al., 2024).

211 There were also differences in average vehicle speeds between provinces, with Inner Mongolia,
212 Jiangxi, and Qinghai having higher speeds (Fig. 1c). While Yunnan Province had the lowest average
213 vehicle speed, which might be related to its unique topography. Approximately 94% of Yunnan Province

214 was mountainous, with an average elevation exceeding 2,000 meters (Gu et al., 2016). These complex
 215 topographical conditions influenced the actual driving speed of vehicles (Hou et al., 2019). In addition,
 216 compared to the Northeast China (NE: 8:00: 44.18 km h⁻¹; 22:00: 48.37 km h⁻¹), the average vehicle
 217 speeds in the Northwest China (NW: 8:00: 36.89 km h⁻¹; 22:00: 40.41 km h⁻¹), the East China (EC:
 218 8:00:39.89 km h⁻¹; 22:00: 44.56 km h⁻¹), and the South China (SC: 8:00: 40.45 km h⁻¹; 22:00: 44.16 km
 219 h⁻¹) regions were lower, due to the NE was predominantly characterized by plains, and its population and
 220 transportation network were not as dense as those in the CC and SC (Fig. 1c) (Xu et al., 2023).

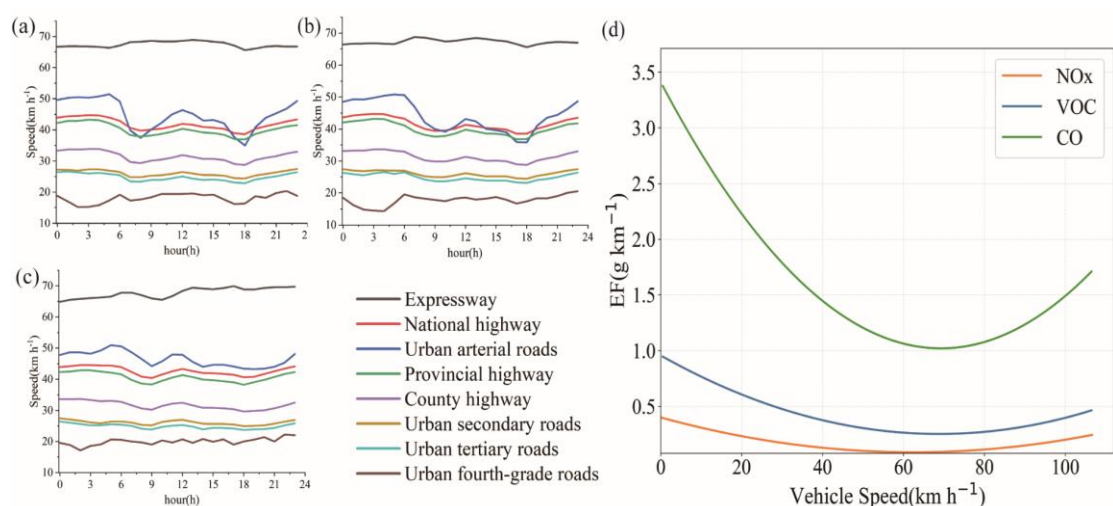


221
 222 **Figure 1.** The average vehicle speed of passenger vehicles in China in 2019: Spatial distribution of speeds on a 0.01°
 223 grid at (a) 8:00 and (b) 22:00 ; (c) Average speeds of provinces and regions, where NC: North China; NE: Northeast
 224 China; EC: East China; CC: Central China; SC: South China; NW: Northwest China; SW: Southwest China.

225 Specific to the road type, the average driving speeds were higher on expressways (workday: 8:00:
 226 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

227 h⁻¹) and national highways (workday: 8:00: 40.05 km h⁻¹; 22:00: 42.92 km h⁻¹) compared to other types
228 of roads (Figs. 2a, 2b, 2c). Notably, urban arterial roads speeds fluctuated sharply during workdays and
229 weekends, with fluctuation magnitudes of 25.3 km h⁻¹ and 12.8 km h⁻¹ respectively; this was attributable
230 to the heavy intercity and interregional commuting traffic they carry, which caused a rapid surge in road
231 saturation and thus a sharp speed drop, followed by a swift rebound (by 63.2% and 41.2% respectively)
232 during midday off-peak hours as commuting demand wanes (Wang et al., 2016). By contrast, holiday
233 travel was dominated by interregional family visits and tourism, with highly dispersed travel timings,
234 leading to mitigated speed fluctuations across all road types. The emission factor of CO, VOCs, and NO_x
235 all exhibited a trend of sharp decrease followed by gradual increase in response to vehicle speed, which
236 was consistent with the combustion kinetics of internal combustion engines (Fig. 2d). Among them, the
237 EFs of incomplete combustion pollutants (CO and VOCs) showed more significant responses to speed
238 variations, while the EFs of thermal-generated NO_x were mainly controlled by the temperature and
239 oxygen concentration inside the cylinder and thus showed relatively moderate responses to speed
240 changes (Chen et al., 2022).

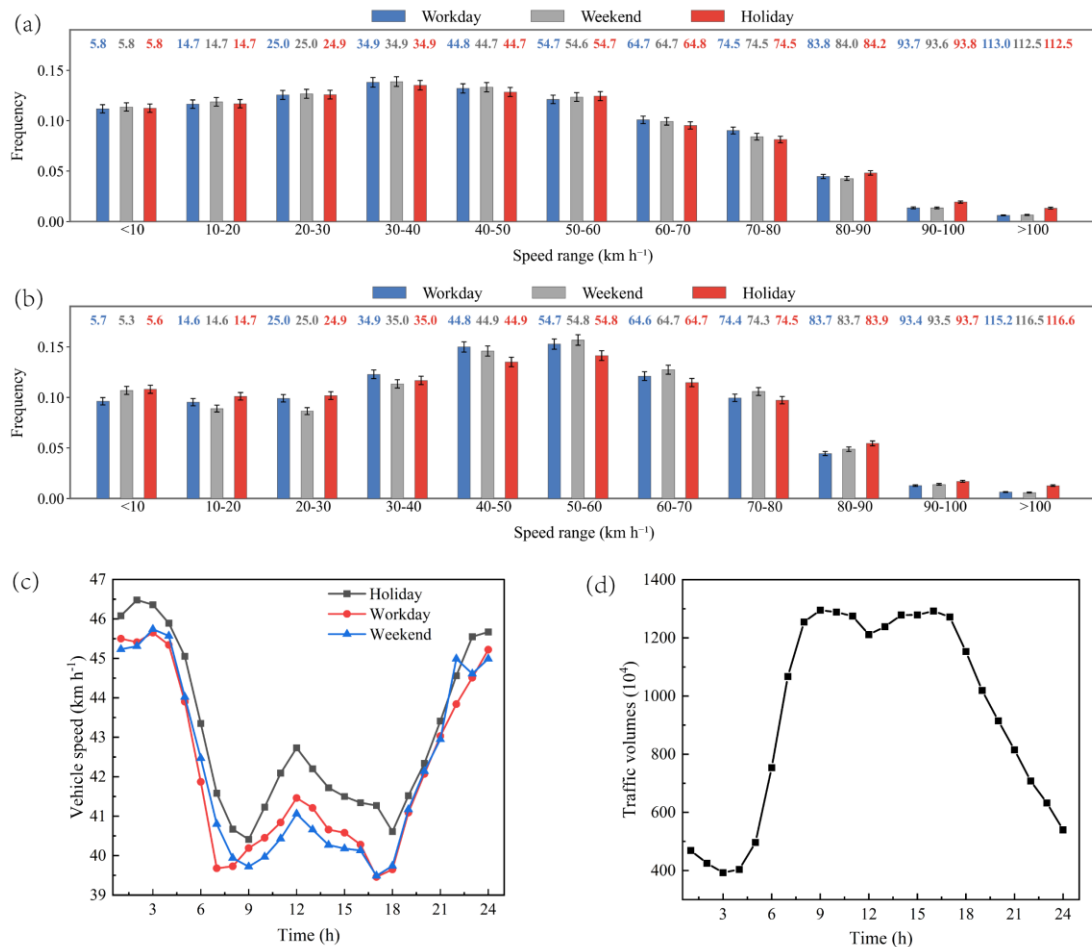
241 To further quantify the impact of average vehicle speed on the model results, this study conducted
242 a quantitative assessment of model uncertainty using Monte Carlo simulation. Across all speed intervals,
243 the emission factors and their corresponding uncertainties for CO, VOC, and NO_x were $1.4866 \pm 21.42\%$
244 $\text{g}\cdot\text{km}^{-1}$, $0.4042 \pm 22.56\%$ $\text{g}\cdot\text{km}^{-1}$, and $0.1507 \pm 28.30\%$ $\text{g}\cdot\text{km}^{-1}$, respectively. Furthermore, uncertainty
245 analysis was performed for each speed interval. Although the 40–80 km·h⁻¹ interval exhibited the lowest
246 emission factors, it represented the dominant driving range for passenger vehicles, with the highest
247 probability density. In contrast, the uncertainty of emission factors reached its maximum when vehicle
248 speeds exceeded 80 km·h⁻¹ (Fig. S3).



249

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

253 Based on ride-hailing big data, the average speed of passenger vehicles fluctuated across different
 254 times. The daily average traffic speeds on workday and weekend were consistent, with both lower than
 255 on holiday, at 42.108, 42.111, and 43.032 km h⁻¹, respectively. The higher holiday speed (Fig. 3c) can
 256 be attributed to reduced urban congestion resulting from increased public transportation use for leisure
 257 travel on holidays (Zhang et al., 2023b). All three-day types exhibited two low-speed valleys from 7:00-
 258 9:00 and 17:00-19:00, with the workday morning valley occurring one hour earlier compared to weekend,
 259 consistent with findings by Yang et al. (2017). The national average speed frequency distribution differed
 260 at 8:00 and 22:00 on workday (Fig. 3a and Fig. 3b), primarily concentrated at 34.9 ± 0.2 km h⁻¹ and 44.8
 261 ± 0.3 km h⁻¹, respectively. Compared with weekday, there were no morning and evening rush hours on
 262 holiday, resulting in a higher proportion in high-speed intervals (Yang et al., 2016). The large difference
 263 in speed between these two periods is due to the variation in traffic volumes, as illustrated by the inverse
 264 relationship between hourly traffic volume and speed distribution (Fig. 3d).



265

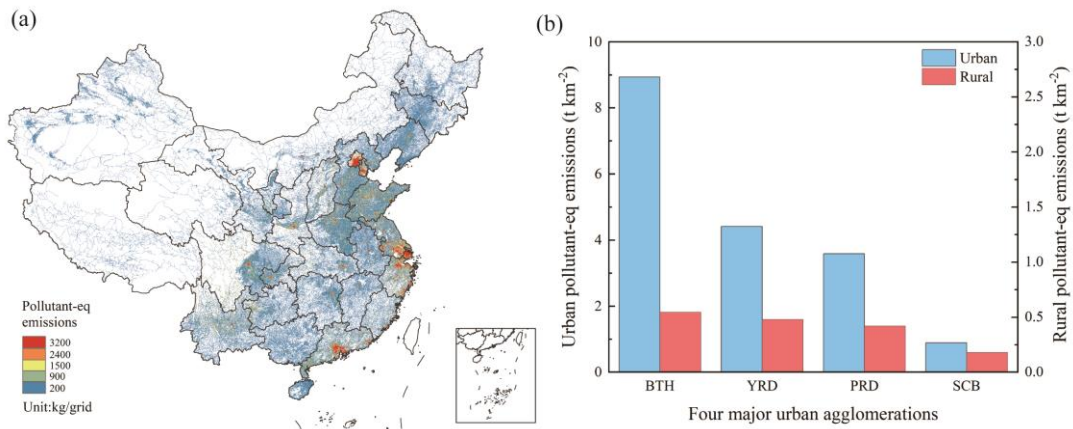
266 **Figure 3.** Characteristics of speed and traffic volume changes: speed distribution at (a) 8:00 and (b) 22:00 on
 267 workday, weekend and holiday. The values labeled in the figure represent the average speed of each interval; (c)
 268 Hourly speed variation on weekend, workday and holiday and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

269 **3.2. Total passenger vehicle emissions in 2019**

270 The annual amount of CO, VOCs, NO_x, PM and NH₃ emitted from national passenger vehicles in
 271 2019 were 4087.8, 1069.4, 211.7, 1.9, 77.5 kt, respectively and TPEs was 1.6×10³ kt. Considering these
 272 pollutants exhibited similar emission patterns, this study focused on analyzing the total pollutant
 273 equivalent emissions. Pollutant emissions from passenger vehicles showed significant spatial
 274 heterogeneity. Urban areas, despite occupying only 0.8% of the country's total land area, accounted for
 275 a high 35.3% of total vehicle emissions. High-pollution areas mainly concentrated in four urban
 276 agglomerations (BTH、YRD、PRD、SCB) (Fig. 4a). These areas were densely populated with high
 277 vehicle usage frequency, contributing significantly to the total emissions at 48.54%. Specific emissions
 278 by province are shown in Table S7. The urban emission density of vehicles within four urban
 279 agglomerations was significantly higher compared to rural areas (Fig. 4b), as most passenger vehicles

280 primarily operated in urban (Loder et al., 2019). However, variations in urban-rural vehicle ownership
 281 and land area across different urban agglomerations led to different urban-rural emission density gaps
 282 (Zhao et al., 2019). Notably, the Beijing-Tianjin-Hebei (BTH) urban agglomeration exhibited the largest
 283 urban-rural emission density ratio of 16.4, which was 13.5 higher than the national average. This gap
 284 stemmed from its higher per capita vehicle ownership than the national average, and smaller urban built-
 285 up areas than other agglomerations (Duan et al., 2024).

286 This study conducted a comparative analysis of the results from different studies to verify the
 287 accuracy of the emission inventory. Compared with previous research results, this research considered
 288 the impact of vehicle driving speed on emissions and the differences in emissions between holiday,
 289 workday, and weekend, and its estimated emissions in this study fell within the ranges of other estimation
 290 results (Table 1).



291
 292 **Figure 4.** Geospatial distribution of passenger vehicle emissions and the disparities between urban and rural areas:
 293 (a) total pollution-eq emissions (TPEs) at $0.01^\circ \times 0.01^\circ$ resolution and (b) urban-rural differences in vehicle emission
 294 densities in four major urban agglomerations (BTH: the Beijing-Tianjin-Hebei region; YRD: the Yangtze River
 295 Delta region; PRD: the Pearl River Delta region; SCB: the Sichuan Basin) in 2019.

296 **Table 1** Comparison and validation with previous studies. (Unit: kt)

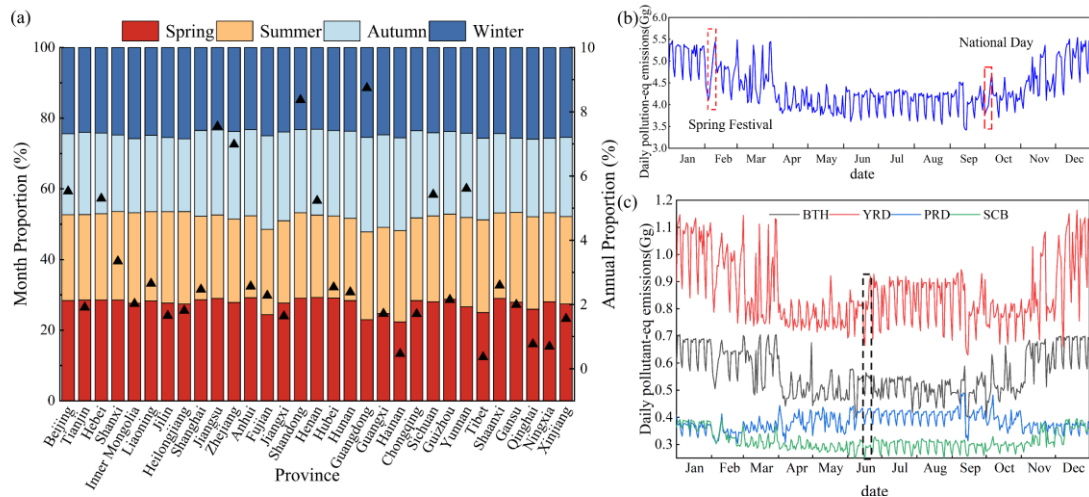
References	Year	CO	VOCs	NO _x	NH ₃	PM
This study	2019	4087.8	1069.4	211.7	77.5	1.95
Liu H et al.(2017)	2015	—	674.4	—	—	—
Li S et al.(2020a)	2017	—	—	—	75	—
Li S et al.(2023a)	2019	4300	950	267.5	89	1.7
MEE(2020a)	2019	4564	1210	250	—	1.0

297 **3.3. Temporal variation of passenger vehicle emissions**

298 **3.3.1 Seasonal and daily variation**

299 Analysis of passenger vehicle emissions revealed distinct seasonal patterns across different regions
300 (Fig. 5). Specifically, the PRD experienced higher emissions in summer, while the YRD, BTH, and SCB
301 regions had higher emissions in winter (Fig. 5c) (Shao et al., 2009; Jiang et al., 2020; Sun et al., 2022).
302 This high winter emission pattern was primarily attributed to adverse weather conditions, which induced
303 prolonged vehicle idling, and reduced driving speeds (Lu et al., 2019). Moreover, vehicles often needed
304 to turn on additional heating equipment, which increased engine load and consequently affected
305 emissions (Abediasl et al., 2023). Notably, Guangdong recorded the highest emissions (Fig.5a), due to
306 its subtropical climate with approximately 80% relative humidity (Liu et al., 2020)and had a high volume
307 of traffic (Yang et al., 2022; Krotkov et al., 2016).

308 This study considered the impact of workday, weekend, and holiday on daily emissions. During the
309 Spring Festival and National Day, people opted for public transportation for long-distance travel or
310 returning home at the holiday's onset, resulting in the lowest passenger vehicle emissions on the first
311 day, gradually increasing in the following days (Fig. 5b) (Zhang et al., 2023b). Passenger vehicle
312 emissions normally exhibited a notable weekend effect, with reduced levels on weekend relative to
313 workday (Fig. S5), and daily average pollutant emissions on holiday were 0.92 times those of workday
314 (Wu et al., 2022; Tong et al., 2020). Specifically at daily emissions, for example, from June 17 to June
315 22, the BTH, YRD, PRD, and SCB regions exhibited notable differences in emission variations. The
316 YRD and PRD regions experienced emission peaks on Friday, while the BTH reached its highest
317 emission level on Monday, corroborating the findings of Wu et al. (2022) and Zheng et al. (2009).



318

319

Figure 5. Seasonal and daily scale variations in pollutant emissions: (a) TPEs by province in different months; (b)

320

Daily changes in TPEs across the country and (c) in four major urban agglomerations (BTH, YRD, PRD, SCB).

321

3.3.2 Hourly variation

322

The hourly average TPEs varied among workday, weekend, and holiday (Fig. 6a). Peak emission

323

periods were mainly concentrated between 8:00 and 9:00 in the morning and between 16:00 and 17:00

324

in the afternoon, similar to the daily variation trend of traffic volume (Yang et al., 2019; Shang et al.,

325

2024). During the morning peak, hourly average emissions on workday exceeded those on weekend and

326

holiday by 8% and 5%, respectively, increasing to 12% and 18% during the evening peak. This expanding

327

difference was attributed to the more diverse types of nighttime travel activities, which included both

328

work trips and daily consumption trips such as dining and shopping. This led to higher vehicle density

329

and prolonged traffic congestion, thereby substantially increasing emission intensity (Azari et al., 2025;

330

Choudhary et al., 2025). As most private and commercial activities occurred during daylight hours,

331

daytime emissions on workday, weekend, and holiday constituted 85.2%, 84%, and 83.1% of the total

332

daily emissions, respectively.

333

A distinct variation in the trend of hourly average TPE density is observed across different regions

334

(Fig. 6b). The BTH region was highest, followed by the YRD, PRD, and SCB regions. This trend might

335

be related to factors such as traffic conditions, population density, and meteorological conditions in each

336

region (Xie et al., 2019; Yang et al., 2025). The data revealed that the daily average emission densities

337

in the BTH and the YRD were 4.9 times and 4.6 times that of the SCB, respectively. Especially during

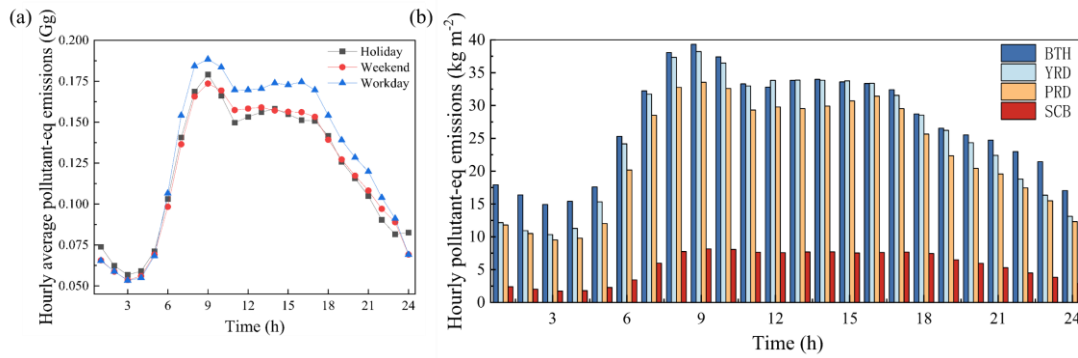
338

the peak period at 8:00 in the morning, the hourly average emission densities ratios reached as high as

339

5.4 times and 5.3 times (Fig.6b). This significant emission difference emphasized the necessity of

340 prioritizing traffic management measures in the BTH region.



341

342 **Figure 6.** Hourly emission changes for three-day types and regions:(a) hourly total pollutant emission characteristics
343 for weekend, workday and holiday and (b) in four major urban agglomerations (BTH, YRD, PRD, SCB).

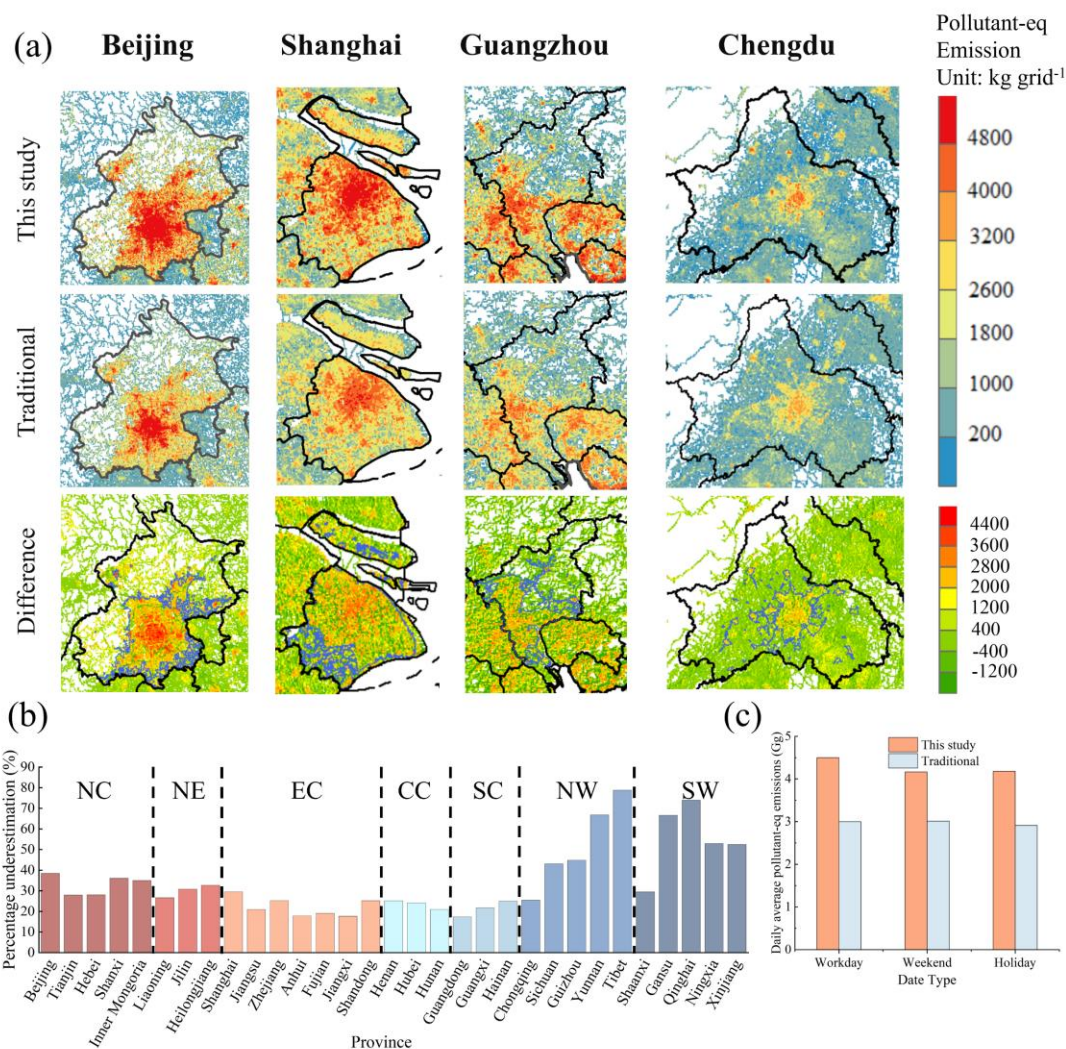
344 3.4. Comparison of passenger vehicle emissions with conventional algorithms

345 To improve estimation accuracy, this study obtained gridded speed-corrected emission results based
346 on real-time vehicle driving data and compared them with passenger vehicle emission data obtained using
347 traditional methods.

348 The improved methodology reflected a more accurate and detailed characterization of passenger
349 vehicle emissions, which were primarily concentrated in urban centers, with emission intensity gradually
350 decreasing from the city center outwards (Jing et al., 2016). Spatially, the improved method avoided
351 the limitation of using fixed speeds in traditional approaches. It can accurately identify higher
352 emissions on crowded urban roads caused by frequent acceleration and deceleration, and properly
353 show lower emissions on outside roads (Fig. 7a) (Zhang et al., 2023a; Wen et al., 2020; Choudhary
354 et al., 2016). Overall, the estimation using the traditional method underestimated the total emissions by
355 31.5%, with Sichuan, Beijing, Shanghai, and Guangdong being underestimated by 43.1%, 38.4%, 29.6%,
356 and 17.4%, respectively. In Tibet, the average vehicle speed stabilized at around 42.5 km h⁻¹, and the
357 SCC analysis revealed a speed correction factor 2.09 times that of the traditional speed correction factor
358 (SCF), leading to the most serious underestimation in this region (Fig. 7b) (Sun et al., 2020).

359 The traditional method exhibited a significant underestimation of passenger vehicle emissions
360 across distinct seasons and day types (Fig. 7c). From a seasonal perspective, this method underestimated
361 the average daily passenger vehicle emissions by 31.6%, 31.0%, 32.7% and 31.8% in spring, summer,
362 autumn and winter, respectively, with a relatively small overall fluctuation range. In contrast, the
363 discrepancy in underestimation across different day types was more pronounced, and the method's
364 underestimation of passenger vehicle emissions on weekends (33.4%) was significantly higher than that

365 on weekdays (27.7%). The formation of this characteristic difference was not only associated with refined
 366 vehicle speed correction, but also stemmed from the quantitative analysis of vehicle activity levels across
 367 different day types based on congestion indices in this study.



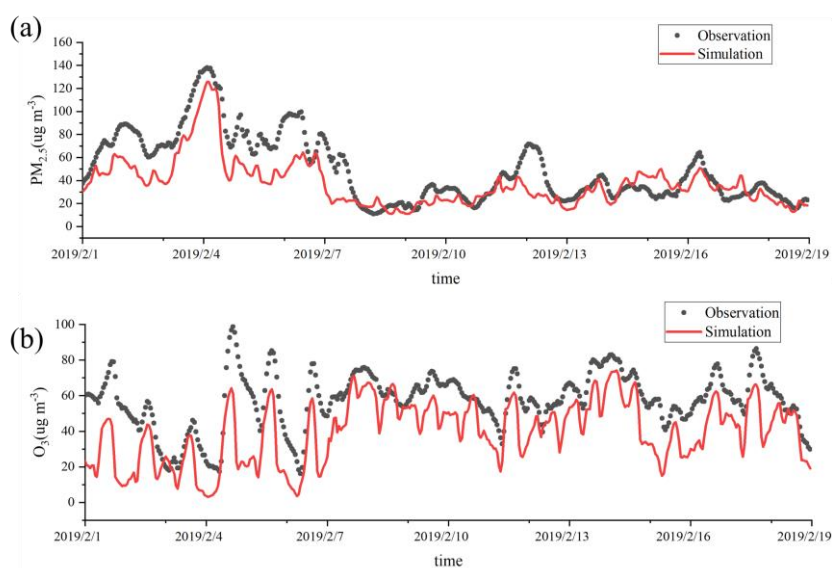
368
 369 **Figure 7.** Comparison of this study with traditional algorithms: (a) Beijing, Shanghai, Guangzhou to compare it with
 370 the results of the present study (Difference = This Study - Traditional); (b) Comparison of daily average results
 371 across (c) four seasons and (d) three date type; The percentage of underestimation for each province calculated with
 372 the traditional method. The purple boundary in (a) is the Urban Growth Boundary (UGB).

373 3.5. Model validation

374 The simulation results of the inventories reflected the temporal variation of pollutant concentrations
 375 well. The improved inventory were more consistent with the observed data from the perspective of hourly
 376 change (PM_{2.5}: R² = 0.850, NMB = -27.4%; O₃: R² = 0.771, NMB = -32.5%) (Fig. 8 and Fig. S8). The
 377 bias may be caused by the underestimation of the input anthropogenic emission inventory, and it falls
 378 within an acceptable and reasonable range verified by comparison with other literature (Ma et al., 2018;

379 Wang et al., 2020 and Georgiou et al., 2022). This result indicated that the accuracy of the emission
380 inventory refined through detailed vehicle speed correction was superior to that constructed by traditional
381 algorithms.

382 The inventory optimization effect was relatively notable in heavily polluted traffic-intensive areas
383 (Fig. S4b), with an overall 0.36% improvement in NMB ($PM_{2.5}$) and 0.02 improvement in R^2 (O_3). This
384 effect is attributable to the complex characteristics of speed fluctuations in these areas. Specifically, the
385 NMB of $PM_{2.5}$ at the Administrative Center Monitoring Station and Putuo Monitoring Station increased
386 by 0.7% and 0.45%, respectively. Meanwhile, the R^2 of O_3 at the Pudong Chuansha Monitoring Station
387 and Xinghu Garden Monitoring Station rose by 0.05 and 0.04, respectively (Fig. S9). However, this study
388 merely achieved a slight improvement, which may be attributed to the small proportion of emissions
389 from passenger vehicles (e.g., approximately 3.2% for CO, 4.7% for VOC, and 1.2% for NO_x) (Li et al.,
390 2023a). The performance of its simulations would be significantly enhanced when the accuracy of vehicle
391 speed correction for the entire traffic source could be further improved.



392
393 **Figure 8.** Comparison of temporal variations between simulated results from the improved inventory and observed
394 data.(a) $PM_{2.5}$; (b) O_3 .

395 4. Conclusions

396 With the rapid growth of the global automobile industry, the proliferation of passenger vehicles has
397 exacerbated the air pollution problem. Current research lacks a nationwide hourly-scale emissions study
398 for passenger vehicles. Therefore, this study introduces an innovative approach by utilizing big data of
399 ride-hailing services and traffic flow models to obtain nationwide hourly gridded speed and traffic

400 volume, which facilitated the derivation of refined speed correction factors based on actual nationwide
401 driving behavior at both spatial and temporal scales, enabling the construction of a high-resolution (0.01°
402 $\times 0.01^\circ$; 1h) emission inventory for passenger vehicle atmospheric pollutants in China. Our emission
403 inventory revealed that passenger vehicles in China emitted approximately 4087.8, 1069.4, 211.7, 1.9,
404 and 77.5 kt of CO, VOCs, NO_x, PM, and NH₃, respectively, in 2019.

405 This research showed significant spatial heterogeneity in passenger vehicle emissions in China.
406 Despite occupying merely 0.8% of the national territory, urban areas generated 35.3% of the country's
407 total vehicle emissions. High-pollution areas were predominantly concentrated in four major urban
408 agglomerations (BTH, YRD, PRD, SCB), which contributed significantly to the total emissions at
409 48.54%, due to high local traffic volumes and relatively low vehicle speeds. Emission density analysis
410 revealed a hierarchical pattern among urban agglomerations, with the BTH region exhibiting the highest
411 density, followed by the YRD, PRD, and SCB regions. And the urban emission density of vehicles within
412 four urban agglomerations was significantly higher compared to rural areas.

413 Passenger vehicle emissions also exhibit multiscale temporal variations. Higher emissions observed
414 in winter due to weather and driving conditions. In addition, vehicle emissions normally exhibited a
415 notable weekend effect, with reduced levels on weekend relative to workday, and daily average pollutant
416 emissions on holiday were 0.92 times those of workday. There are also differences in the hourly average
417 pollutant emissions across the above three-day types. During the morning peak, hourly average emissions
418 on workday exceeded those on weekend and holiday by 8% and 5%, respectively, increasing to 12% and
419 18% during the evening peak. Compared with traditional algorithms, this study could more accurately
420 identify the actual emission status of urban roads, reducing the deviation in emission estimation. Current
421 traditional methodology might underestimate by 31.5 %, which is more serious in areas with very little
422 speed variation. The simulated results for PM_{2.5} and O₃ in this study inventory exhibited good
423 performance.

424 Our study has limitations in the simulation: Instead of the MEIC anthropogenic emission inventory
425 commonly used in WRF-Chem simulations, we adopted the ABaCAS database for both traffic and non-
426 traffic sources. This is because MEIC does not provide the passenger vehicle emission ratio, which is
427 essential for our accurate estimation of passenger vehicle emission contributions. However, compared
428 with MEIC, ABaCAS underestimates NO_x and VOCs by approximately 20%, which affects the
429 simulation results to some extent. Previous studies also have reported that the uncertainty ranges of PM_{2.5},

430 VOCs and NO_x emissions estimated by ABaCAS are [-58%, 60%], [-54%, 102%] and [-29%, 32%],
431 respectively (Li et al., 2023a). In addition, this may also be related to the insufficient spatial
432 representativeness of national environmental monitoring data during actual acquisition and the influence
433 of local pollution sources around monitoring sites, which slightly affect the validation results (Ding et
434 al., 2024; Zhao et al., 2025; Wu et al., 2018). For these reasons, the simulation results based on ABaCAS
435 database show weak correlation with the temporal variation trend of observed values and strong
436 discrepancies.

437 At present, this study focuses on passenger vehicles; to improve its accuracy and applicability,
438 future research will be further extended to freight trucks, industrial vehicles, agricultural vehicles, and
439 the entire transportation sector. The speed-emission coupling method verified in this study can not only
440 be extended to such transportation sub-sectors as freight trucks and urban public transport, improving
441 the accuracy of their emission quantification and distinguishing the differences in emission contributions
442 of different vehicle types; but also provide modification ideas for aviation and water transportation
443 sectors with different power forms, facilitating the construction of refined emission inventories. In the
444 future, with the continuous increase in the proportion of China V and China VI vehicles, as well as
445 the rising penetration rate of electric vehicles (EVs) (China's stock of electric vehicles reached 31.4
446 million by 2024, a year-on-year increase of 53.84%) (MEE, 2025; Liang et al., 2019; Wang et al.,
447 2026), coupled with the implementation of policies for the elimination and renewal of old vehicles,
448 the overall "speed-emission" relationship in the passenger vehicle sector will be gradually weakened
449 (Liu et al., 2024; Zhu et al., 2022). These above-mentioned measures coordinate the upgrading of
450 emission standards with the transformation of the energy structure, providing an important reference for
451 other countries to balance environmental governance, energy security and transportation development.
452 Additionally, a more comprehensive big data will be obtained to provide support for the quality of
453 emission inventories. Overall, the analytical framework developed in this study accurately quantifies
454 emissions of key atmospheric pollutants from China's passenger vehicle sector. The findings provide an
455 important scientific basis for intelligent transportation and the formulation of more refined control
456 policies and offer a methodological reference for precise emission management in the transportation
457 sector through its high-resolution data approach.

458 **Associated content**

459 **Supporting Information**

460 Figures showing distribution of passenger car ownership; weekly change in emission equivalents; the
461 distribution of passenger vehicles by emission standard in different regions; the probability density
462 distribution and frequency statistics of passenger vehicle emission factors; spatial distribution of
463 passenger car emissions for a given three-day period; spatial distribution under conventional algorithms;
464 comparison of simulated values and observed values of some stations and tables showing emission
465 factors for each emission standard; average speed correction factors for passenger vehicles under the
466 traditional algorithm; sample data for ride-hailing big data; speed correction curves; deterioration, sulfur
467 correction factors; provincial emissions from passenger cars; parameter settings and verification results
468 of the model simulation.

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473

474 **Author contributions**

475 BL and ZS conceived the study and wrote the paper; BL, ZS, YL, YZ processed the data required for
476 emission estimation and analyzes the processing results; WG, JL, YY, WZ, ZM optimized the research
477 methodology and collected relevant data; HL reviewed the manuscript.

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