

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

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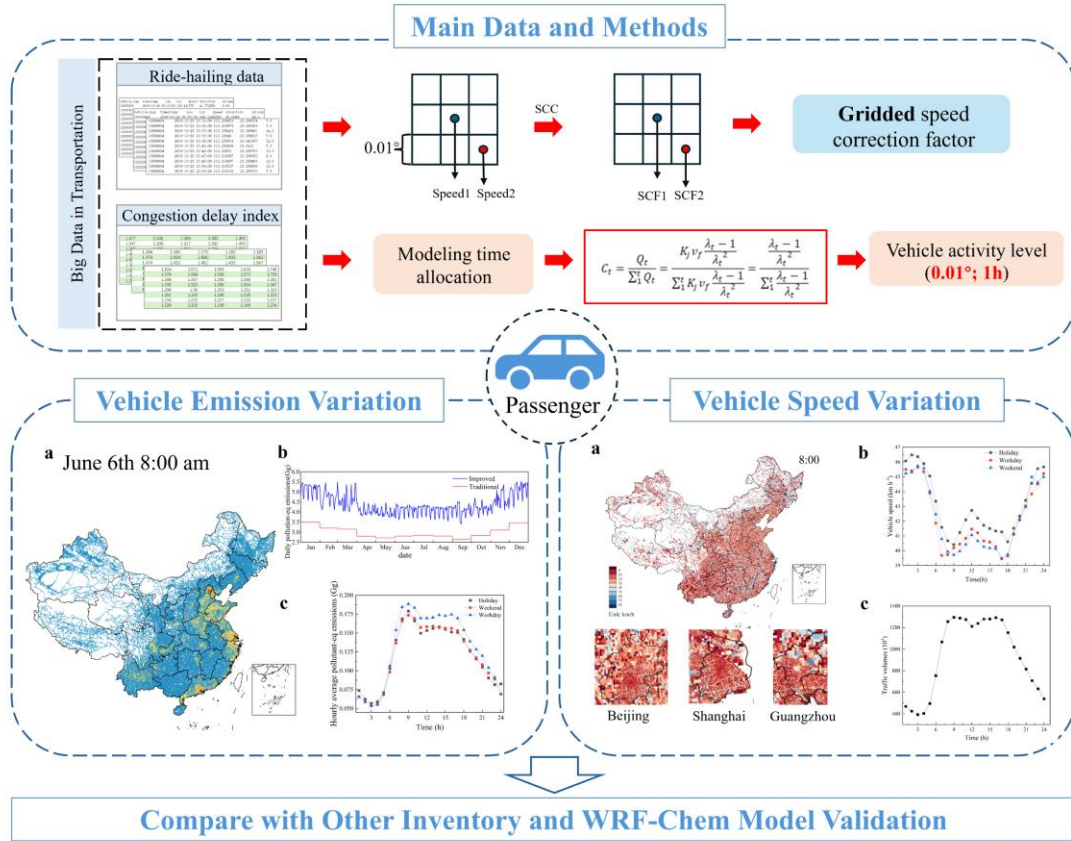
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15 **ABSTRACT:** As the global automotive industry continues to grow rapidly, the increasing number of
16 passenger vehicles has contributed to worsening air pollution. However, previous studies have
17 insufficiently addressed nationwide hourly vehicle 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. The vehicle kilometers traveled (VKT) of light-
106 duty gasoline passenger vehicles (LDPVs) in 2019 were obtained from Ma et al. (2022). Based on the
107 China Statistical Yearbook 2004–2019, we calculated the proportion of passenger vehicles by emission
108 standard, the total number of passenger vehicles in each province in 2019 (Fig. S1), and the regional
109 distribution of small and mini passenger vehicles by emission standard (Fig. S2). The baseline emission
110 factors were obtained based on other literature (Wen et al., 2023; MEE, 2014; EEA, 2019), with specific
111 details provided in Table.S1. Furthermore, the definition of urban and rural areas involved in this study
112 was based on the research of Li et al. (2020).

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

118 **2.2. Quantification of high-resolution emission factors based on big data of ride-hailing**

119 **2.2.1 Gridded speeds and determination of their correction factors**

120 A total of 23.6 billion vehicle trajectory data were collected in this study from Amap Ride-hailing
121 Platform (https://dache.amap.com/amap_mini#/), including workdays (September 24th, 2019, October
122 23rd, 2019), weekends (September 28th, 2019, October 26th, 2019) and holidays (September 13th, 2019,
123 October 1st, 2019) (Table S3). The platform data originates from mobile terminal users who have
124 activated GPS positioning. The data uploading behavior is primarily associated with the activation status
125 of the positioning function and has no direct connection with vehicle age. This dataset had covered all
126 major road types nationwide. To address the insufficient sample size of ride-hailing services in Western
127 China, we adopted the nearest neighbor interpolation method to supplement the speed information of
128 road segments with missing values across each road type. Moreover, we assumed that the vehicle speeds
129 on other dates did not vary significantly compared to these representative days, and that passenger
130 vehicles have consistent on-road driving speeds. Each vehicle sent data every 3 seconds. Using Python,

131 we processed the data to obtain hourly resolution vehicle speeds on a 0.01° grid. Finally, we obtained
132 gridded hourly vehicle speeds for three representative days: workdays, weekends, and holidays.

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

136 2.2.2 Corrections for other emission factors

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

142 2.3. High-resolution vehicle activity level data combined with traffic flow models

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

$$144 V_{p,t,k} = C_{p,t} \times V_{p,k} = C_{p,t} \times VP_{p,k} \times VKT \quad (4)$$

145 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
146 the number of vehicles of model k in province p (km·veh).

147 $C_{p,t}$ is the time allocation coefficient of province p at time period t . It is obtained by combining the
148 congestion delay index obtained from Baidu Map Traffic and Travel Big Data Platform
149 (<https://jiaotong.baidu.com/>) with the three-parameter model of traffic flow (Jinping et al., 2024), which
150 is constructed as follows:

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

$$154 \lambda = \frac{T}{T_f} = \frac{\frac{L}{v}}{\frac{L}{v_f}} = \frac{v_f}{v} \quad (5)$$

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

158
$$v = \frac{v_f}{\lambda} \quad (6)$$

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

161
$$Q = K_j \left(v - \frac{v^2}{v_f} \right) = K_j \left[\frac{v_f}{\lambda} - \frac{\left(\frac{v_f}{\lambda} \right)^2}{v_f} \right] = K_j v_f \frac{\lambda - 1}{\lambda^2} \quad (7)$$

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

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

166
$$C_t = \frac{Q_t}{\sum_1^t Q_t} = \frac{K_j v_f \frac{\lambda_t - 1}{\lambda_t^2}}{\sum_1^t K_j v_f \frac{\lambda_t - 1}{\lambda_t^2}} = \frac{\lambda_t - 1}{\sum_1^t \frac{\lambda_t - 1}{\lambda_t^2}} \quad (8)$$

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

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

172
$$V_{p,i,k,t} = \frac{L_{p,i}}{\sum_i L_{p,i}} \times V_{p,t,k} \quad (9)$$

173 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
 174 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
 175 grid of province p (km).

176 2.4 WRF-Chem model setting

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

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

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

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

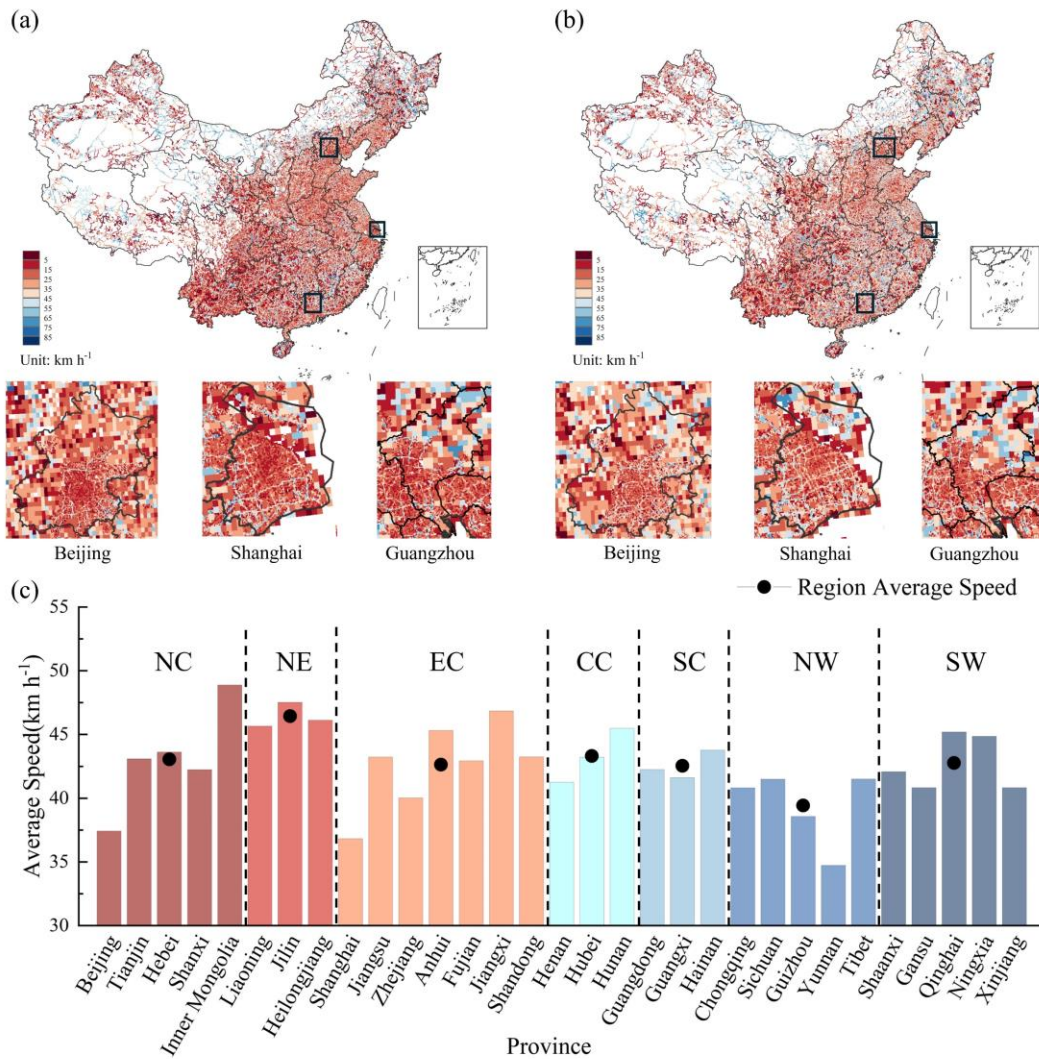
198 **3. Results and discussion**

199 **3.1. Spatiotemporal variation of vehicle speed and traffic flow**

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

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

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

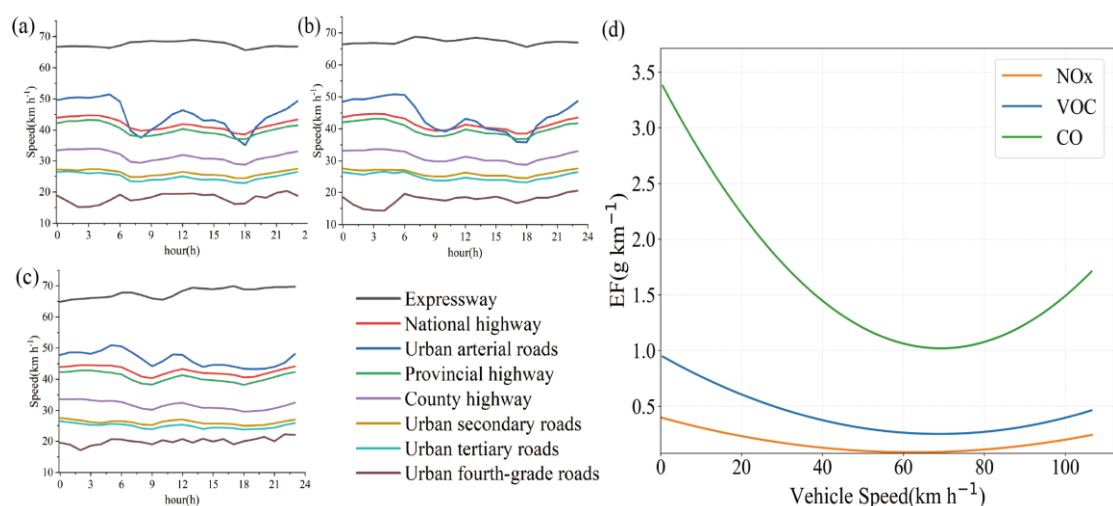


220
 221 **Figure 1.** The average vehicle speed of passenger vehicles in China in 2019: Spatial distribution of speeds on a 0.01°
 222 grid at (a) 8:00 and (b) 22:00 ; (c) Average speeds of provinces and regions, where NC: North China; NE: Northeast
 223 China; EC: East China; CC: Central China; SC: South China; NW: Northwest China; SW: Southwest China.

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

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

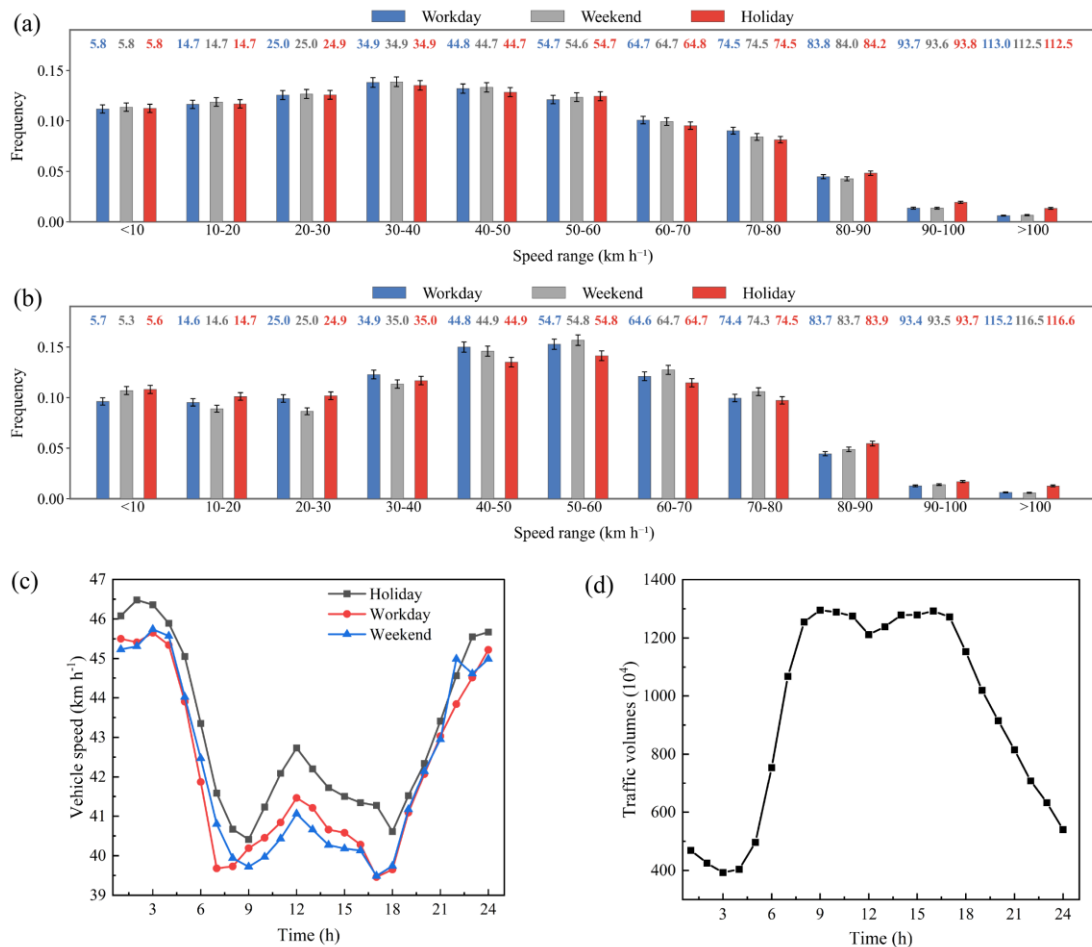
240 To further quantify the impact of average vehicle speed on the model results, this study conducted
241 a quantitative assessment of model uncertainty using Monte Carlo simulation. Across all speed intervals,
242 the emission factors and their corresponding uncertainties for CO, VOC, and NO_x were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



248

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

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



264

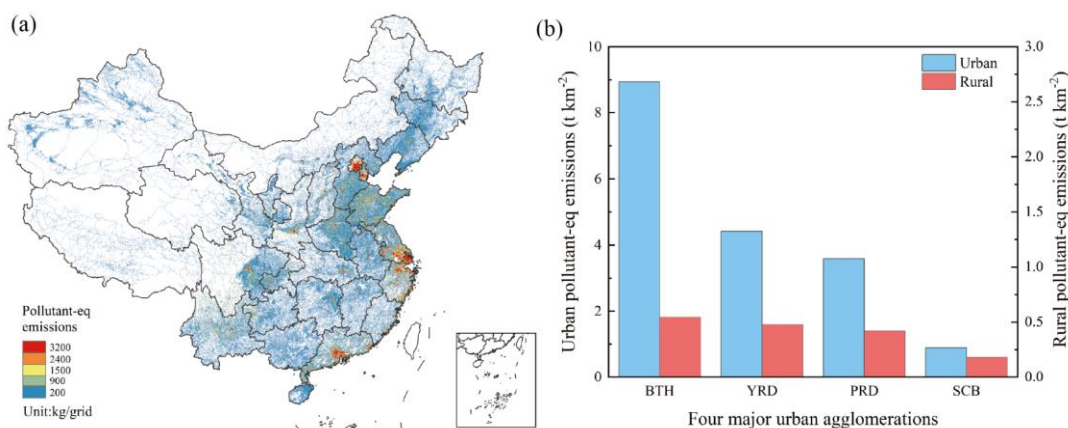
265 **Figure 3.** Characteristics of speed and traffic volume changes: speed distribution at (a) 8:00 and (b) 22:00 on
 266 workday, weekend and holiday. The values labeled in the figure represent the average speed of each interval; (c)
 267 Hourly speed variation on weekend, workday and holiday and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

268 **3.2. Total passenger vehicle emissions in 2019**

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

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

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



290
 291 **Figure 4.** Geospatial distribution of passenger vehicle emissions and the disparities between urban and rural areas:
 292 (a) total pollution-eq emissions (TPEs) at $0.01^\circ \times 0.01^\circ$ resolution and (b) urban-rural differences in vehicle emission
 293 densities in four major urban agglomerations (BTH: the Beijing-Tianjin-Hebei region; YRD: the Yangtze River
 294 Delta region; PRD: the Pearl River Delta region; SCB: the Sichuan Basin) in 2019.

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

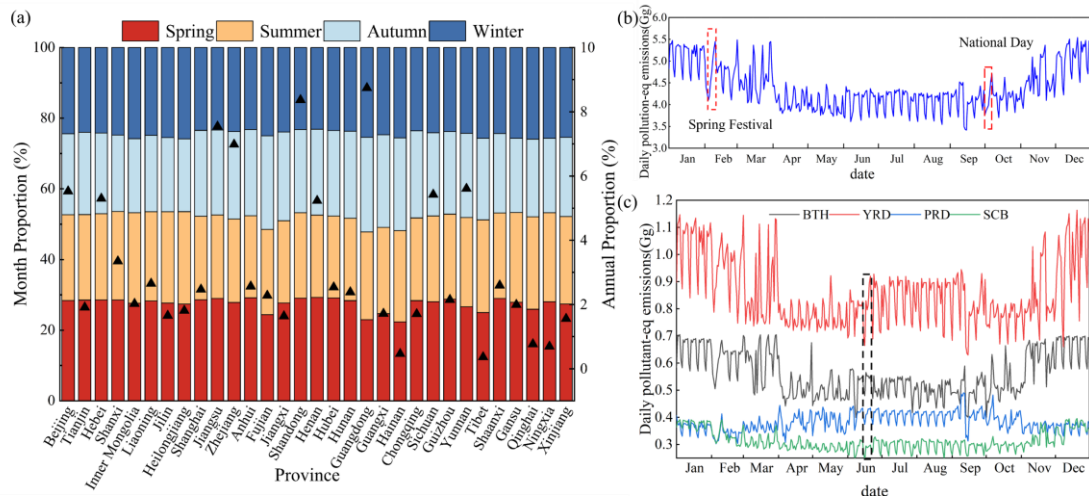
References	Year	CO	VOCs	NO _x	NH ₃	PM
This study	2019	4087.8	1069.4	211.7	77.5	1.95
Liu H. et al. (2017)	2015	—	674.4	—	—	—
Li S. et al. (2020a)	2017	—	—	—	75	—
Li S. et al. (2023a)	2019	4300	950	267.5	89	1.7
MEE (2020a)	2019	4564	1210	250	—	1.0

296 **3.3. Temporal variation of passenger vehicle emissions**

297 **3.3.1 Seasonal and daily variation**

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

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



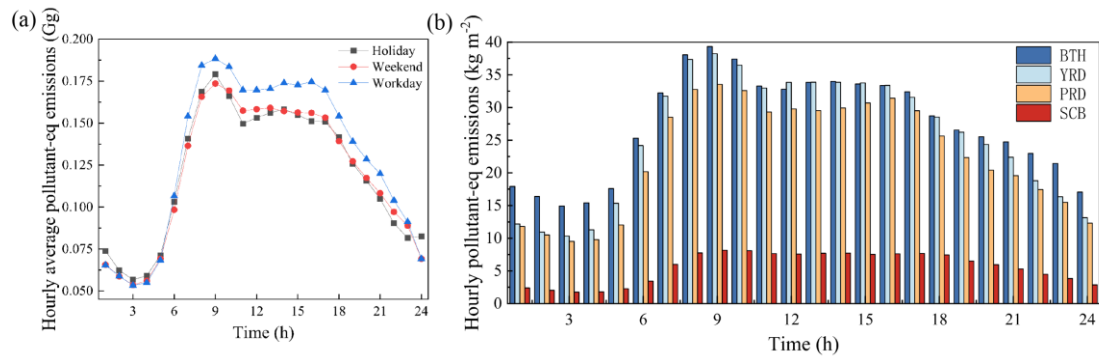
317
 318 **Figure 5.** Seasonal and daily scale variations in pollutant emissions: (a) TPEs by province in different months; (b)
 319 Daily changes in TPEs across the country and (c) in four major urban agglomerations (BTH, YRD, PRD, SCB).

320 3.3.2 Hourly variation

321 The hourly average TPEs varied among workday, weekend, and holiday (Fig. 6a). Peak emission
 322 periods were mainly concentrated between 8:00 and 9:00 in the morning and between 16:00 and 17:00
 323 in the afternoon, similar to the daily variation trend of traffic volume (Yang et al., 2019; Shang et al.,
 324 2024). During the morning peak, hourly average emissions on workday exceeded those on weekend and
 325 holiday by 8% and 5%, respectively, increasing to 12% and 18% during the evening peak. This expanding
 326 difference was attributed to the more diverse types of nighttime travel activities, which included both
 327 work trips and daily consumption trips such as dining and shopping. This led to higher vehicle density
 328 and prolonged traffic congestion, thereby substantially increasing emission intensity (Azari et al., 2025;
 329 Choudhary et al., 2025). As most private and commercial activities occurred during daylight hours,
 330 daytime emissions on workday, weekend, and holiday constituted 85.2%, 84%, and 83.1% of the total
 331 daily emissions, respectively.

332 A distinct variation in the trend of hourly average TPE density is observed across different regions
 333 (Fig. 6b). The BTH region was highest, followed by the YRD, PRD, and SCB regions. This trend might
 334 be related to factors such as traffic conditions, population density, and meteorological conditions in each
 335 region (Xie et al., 2019; Yang et al., 2025). The data revealed that the daily average emission densities
 336 in the BTH and the YRD were 4.9 times and 4.6 times that of the SCB, respectively. Especially during
 337 the peak period at 8:00 in the morning, the hourly average emission densities ratios reached as high as
 338 5.4 times and 5.3 times (Fig.6b). This significant emission difference emphasized the necessity of

339 prioritizing traffic management measures in the BTH region.



340

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

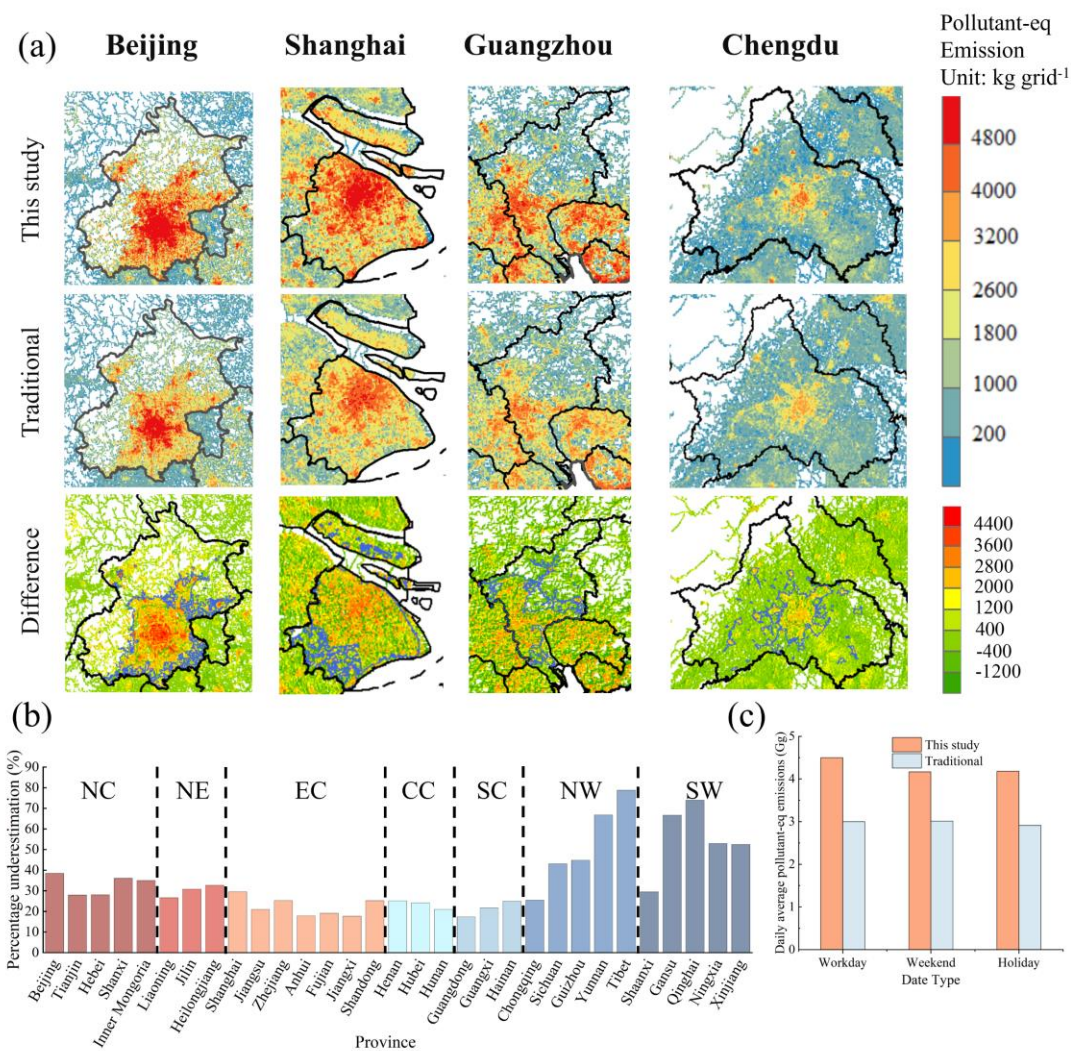
343 3.4. Comparison of passenger vehicle emissions with conventional algorithms

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

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

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

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



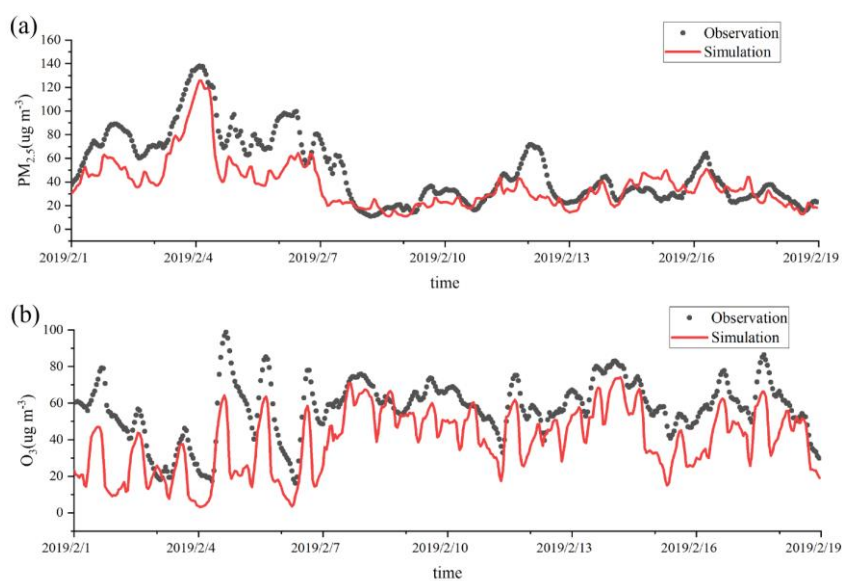
367
 368 **Figure 7.** Comparison of this study with traditional algorithms: (a) Beijing, Shanghai, Guangzhou to compare it with
 369 the results of the present study (Difference = This Study - Traditional); (b) Comparison of daily average results
 370 across (c) four seasons and (d) three date type; The percentage of underestimation for each province calculated with
 371 the traditional method. The purple boundary in (a) is the Urban Growth Boundary (UGB).

372 3.5. Model validation

373 The simulation results of the inventories reflected the temporal variation of pollutant concentrations
 374 well. The improved inventory were more consistent with the observed data from the perspective of hourly
 375 change ($PM_{2.5}$: $R^2 = 0.850$, $NMB = -27.4\%$; O_3 : $R^2 = 0.771$, $NMB = -32.5\%$) (Fig. 8 and Fig. S8). The
 376 bias may be caused by the underestimation of the input anthropogenic emission inventory, and it falls
 377 within an acceptable and reasonable range verified by comparison with other literature (Ma et al., 2018;

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

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



391
392 **Figure 8.** Comparison of temporal variations between simulated results from the improved inventory and observed
393 data.(a) $PM_{2.5}$; (b) O_3 .

394 4. Conclusions

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

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

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

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

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

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

436 At present, this study focuses on passenger vehicles; to improve its accuracy and applicability,
437 future research will be further extended to freight trucks, industrial vehicles, agricultural vehicles, and
438 the entire transportation sector. The speed-emission coupling method verified in this study can not only
439 be extended to such transportation sub-sectors as freight trucks and urban public transport. This improves
440 the accuracy of emission quantification, distinguishes the emission contributions of different vehicle
441 types, and helps to clarify the impacts of anthropogenic nitrogen inputs on the nitrogen cycle (Shen et
442 al., 2026). Meanwhile, the method can also provide revised schemes for aviation and water transportation
443 with different power structures, supporting the establishment 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 **Code and data availability**

460 The ride-hailing GPS data, congestion delay index, input files for the WRF-Chem model, as well as
461 observational data of meteorology, PM_{2.5} and O₃, are all available via the links and cited references
462 provided in the method section of this paper. The Python scripts used for data processing and emission
463 inventory development can be made available upon reasonable request from the corresponding author.

464 **Supporting Information**

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

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.

478 **Competing interests**

479 The contact author has declared that none of the authors has any competing interests.

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497 **References**

- 498 Abediasl, H., Balazadeh Meresht, N., Alizadeh, H., Shahbakhti, M., Koch, C. R., and Hosseini, V.: Road
499 transportation emissions and energy consumption in cold climate cities, *Urban Clim.*, 52,
500 doi:10.1016/j.uclim.2023.101697, 2023.
- 501 Akash, B., Vikas, S., Leeza, M., Geetam, T., Khaiwal, R., and Suman, M.: Spatially resolved hourly
502 traffic emission over megacity Delhi using advanced traffic flow data, *Earth Syst. Sci. Data.*, 1-37,
503 doi:10.5281/zenodo.6553770, 2022.
- 504 Andrew, J. K., Robert, A. H., Gary, A. Kendall.: Effects of Vehicle Speed and Engine Load on Motor
505 Vehicle Emissions, *Environ. Sci. Technol.*, 37, 3739–3746, doi:10.1021/es0263588 2003.
- 506 Azari, M., Hatami, M., Hosseini, M., Flood, I.: Revealing non-work travel patterns under the influence
507 of multiple actors: An integrated geospatial agent-based approach, *Cities*, 159: 105750,
508 doi:10.1016/j.cities.2025.105750, 2025.
- 509 Anenberg, S. C., Miller, J., Minjares, R., Du, L., Henze, D. K., Lacey, F., Malley, C. S., Emberson, L.,
510 Franco, V., Klimont, Z., and Heyes, C.: Impacts and mitigation of excess diesel-related NO_x emissions
511 in 11 major vehicle markets, *Nature*, 545, 467-471, doi:10.1038/nature22086, 2017.
- 512 Charis, K., Dimitrios, G., Ntziachristos, I. K. L., Pastorello, C., and Dilara, P.: Uncertainty estimates and
513 guidance for road transport emission calculations., Publications Office of the European Union, EUR,
514 doi:10.2788/78236, 2010.
- 515 Chen, X., Jiang, L., Xia, Y., Wang, L., Ye, J., Hou, T., Zhang, Y., Li, M., Li, Z., Song, Z. and Li, J.:
516 Quantifying on-road vehicle emissions during traffic congestion using updated emission factors of light-
517 duty gasoline vehicles and real-world traffic monitoring big data. *Sci. Total. Environ.*, 847, 157581,
518 doi:10.1016/j.scitotenv.2022.157581, 2022.
- 519 China Mobile Source Environmental Management Annual Report, Ministry of Ecology and Environment

520 of the People's Republic of China, 2020a.

521 China Mobile Source Environmental Management Annual Report, Ministry of Ecology and Environment
522 of the People's Republic of China, 2025.

523 China Statistical Yearbook, NBS (National Bureau of Statistics of China), China Statistics Press, Beijing,
524 2020b.

525 Choudhary, A., Gokhale, S.: Urban real-world driving traffic emissions during interruption and
526 congestion, *Transport. Res. D-Tr.*, 43: 59-70, doi:10.1016/j.trd.2015.12.006, 2016.

527 Deng, F., Lv, Z., Qi, L., Wang, X., Shi, M., and Liu, H.: A big data approach to improving the vehicle
528 emission inventory in China, *Nat. Commun.*, 11, 2801, doi:10.1038/s41467-020-16579-w, 2020.

529 Dey, S., Caulfield, B., & Ghosh, B.: Modelling uncertainty of vehicular emissions inventory: A case
530 study of Ireland. *J. Clean. Prod.*, 213, 1115-1126, doi: 10.1016/j.jclepro.2018.12.125, 2019.

531 Dias, D., Amorim, J. H., Sá, E., Borrego, C., Fontes, T., Fernandes, P., Pereira, S. R., Bandeira, J., Coelho,
532 M. C., and Tchepel, O.: Assessing the importance of transportation activity data for urban emission
533 inventories, *Transport. Res. D-tr. E.*, 62, 27-35, doi:10.1016/j.trd.2018.01.027, 2018.

534 Ding, J., Ren, C., Wang, J., Feng, Z., & Cao, S. J.: Spatial and temporal urban air pollution patterns based
535 on limited data of monitoring stations, *J. Clean. Prod.*, 434, 140359, doi:10.1016/j.jclepro.2023.140359,
536 2024.

537 Duan, L., Song, L., Wang, W., Jian, X., Heijungs, R., and Chen, W.: Urbanization inequality: evidence
538 from vehicle ownership in Chinese cities. *Humanit. Soc. Sci. Commun.*, 11(1), 1-12,
539 doi:10.1057/s41599-024-03173-4, 2024.

540 EMEP/EEA air pollutant emission inventory guidebook 2019 : technical guidance to prepare national
541 emission inventories., European Environment Agency, 2019.

542 Environmental Protection Tax Law of the People's Republic of China., MEE (Ministry of Ecology and
543 Environment), 2018.

544 Gao, C., Gao, C., Song, K., Xing, Y., and Chen, W.: Vehicle emissions inventory in high spatial-temporal
545 resolution and emission reduction strategy in Harbin-Changchun Megalopolis, *Process Saf. Environ.*,
546 138, 236-245, doi:10.1016/j.psep.2020.03.027, 2020.

547 Georgiou, G. K., Christoudias, T., Proestos, Y., Kushta, J., Pikridas, M., Sciare, J., Savvides, C., and
548 Lelieveld, J.: Evaluation of WRF-Chem model (v3.9.1.1) real-time air quality forecasts over the Eastern
549 Mediterranean, *Geosci. Model Dev.*, 15, 4129-4146, doi:10.5194/gmd-15-4129-2022, 2022.

550 Gómez, C. D., González, C. M., Osses, M., and Aristizábal, B. H.: Spatial and temporal disaggregation
551 of the on-road vehicle emission inventory in a medium-sized Andean city. Comparison of GIS-based top-
552 down methodologies, *Atmos. Environ.*, 179, 142-155, doi:10.1016/j.atmosenv.2018.01.049, 2018.

553 Gu, Z., Duan, X., Liu, B., Hu, J., and He, J.: The spatial distribution and temporal variation of rainfall
554 erosivity in the Yunnan Plateau, Southwest China: 1960-2012, *Catena*, 145, 291-300,
555 doi:10.1016/j.catena.2016.06.028, 2016.

556 Guan, D., Ren, N., Wang, K., Wang, Q., and Zhang, H.: Checkpoint data-driven GCN-GRU vehicle
557 trajectory and traffic flow prediction, *Sci. Rep.*, 14, 30409, doi:10.1038/s41598-024-80563-3, 2024.

558 Guo, D., Zhao, J., Xu, Y., Sun, F., Li, K., Wang, J., and Sun, Y.: The Impact of Driving Conditions on
559 Light-Duty Vehicle Emissions in Real-World Driving, *Transport*, 35, 379-388,
560 doi:10.3846/transport.2020.12168, 2020.

561 Hou, G., Chen, S., and Chen, F.: Framework of simulation-based vehicle safety performance assessment
562 of highway system under hazardous driving conditions, *Transport. Res. C-Em.*, 105, 23-26,
563 doi:10.1016/j.trc.2019.05.035, 2019.

564 Huo, H., Zhang, Q., He, K., Wang, Q., Yao, Z., and Street, D. G.: High-Resolution Vehicular Emission
565 Inventory Using a Link-Based Method: A Case Study of Light-Duty Vehicles in Beijing, *Environ. Sci.*
566 *Technol.* 43, 7, 2394–2399, doi:10.1021/es802757a, 2009.

567 Jiang, P., Zhong, X., and Li, L.: On-road vehicle emission inventory and its spatio-temporal variations in
568 North China Plain, *Environ. Pollut.*, 267, 115639, doi:10.1016/j.envpol.2020.115639, 2020.

569 Jing, B., Wu, L., Mao, H., Gong, S., He, J., Zou, C., Song, G., Li, X., and Wu, Z.: Development of a
570 vehicle emission inventory with high temporal–spatial resolution based on NRT traffic data and its impact
571 on air pollution in Beijing – Part 1: Development and evaluation of vehicle emission inventory, *Atmos.*
572 *Chem. Phys.*, 16, 3161-3170, doi:10.5194/acp-16-3161-2016, 2016.

573 Jinping, W., Haixia, F., Huanhuan, Z., Guohua, H., Miaomiao, H., Qingli, S., and Er-wei, N.: A temporal
574 allocation method of motor vehicle emission inventories, *J. Automot. Saf. Energy.*, 15, 387-394,
575 doi:10.3969/j.issn.1674-8484.2024.03.012, 2024.

576 Krotkov, N. A., McLinden, C. A., Li, C., Lamsal, L. N., Celarier, E. A., Marchenko, S. V., Swartz, W. H.,
577 Bucsela, E. J., Joiner, J., Duncan, B. N., Boersma, K. F., Veefkind, J. P., Levelt, P. F., Fioletov, V. E.,
578 Dickerson, R. R., He, H., Lu, Z., and Streets, D. G.: Aura OMI observations of regional SO₂ and NO₂
579 pollution changes from 2005 to 2015., *Atmos. Chem. Phys.*, 16, 4605-4629, doi:10.5194/acp-16-4605-
580 2016, 2016.

581 Latini, G., Passerini, G., and Tascini, S.: Roundabouts and traffic emissions at crossroads, *WIT Trans.*
582 *Ecol. Environ.*, 84, doi:10.2495/SPD050912, 2026.

583 Li, S., Lang, J., Zhou, Y., Liang, X., Chen, D., and Wei, P.: Trends in ammonia emissions from light-duty
584 gasoline vehicles in China, 1999-2017, *Sci. Total Environ.*, 700, 134359,
585 doi:10.1016/j.scitotenv.2019.134359, 2020a.

586 Li, S., Wang, S., Wu, Q., Zhang, Y., Ouyang, D., Zheng, H., Han, L., Qiu, X., Wen, Y., Liu, M., Jiang, Y.,
587 Yin, D., Liu, K., Zhao, B., Zhang, S., Wu, Y., and Hao, J.: Emission trends of air pollutants and CO₂ in
588 China from 2005 to 2021, *Earth Syst. Sci. Data.*, 15, 2279-2294, doi:10.5194/essd-15-2279-2023, 2023a.

589 Li, X., Gong, P., Zhou, Y., Wang, J., Bai, Y., Chen, B., Hu, T., Xiao, Y., Xu, B., Yang, J. and Liu, X.:
590 Mapping global urban boundaries from the global artificial impervious area (GAIA) data. *Environ. Res.*
591 *Let.*, 15(9), 094044, doi:10.1088/1748-9326/ab9be3, 2020.

592 Li, Y., Lv, C., Yang, N., Liu, H., and Liu, Z.: A study of high temporal-spatial resolution greenhouse gas
593 emissions inventory for on-road vehicles based on traffic speed-flow model: A case of Beijing, *J. Clean.*
594 *Prod.*, 277, doi:10.1016/j.jclepro.2020.122419, 2020b.

595 Li, Y., Li, B., Liao, H., Zhou, B. B., Wei, J., Wang, Y., Zang, Y., Yang, Y., Liu, R., and Wang, X.: Changes
596 in PM_{2.5}-related health burden in China's poverty and non-poverty areas during 2000-2020: A health
597 inequality perspective, *Sci. Total Environ.*, 861, 160517, doi:10.1016/j.scitotenv.2022.160517, 2023b.

598 Liang, X., Zhang, S., Wu, Y., Xing, J., He, X., Zhang, K. M., Wang, S. and Hao, J.: Air quality and health
599 benefits from fleet electrification in China, *Nat. Sustain.*, 2(10), 962-971, doi:10.1038/s41893-019-0398-
600 8, 2019.

601 Liu, H., Man, H., Cui, H., Wang, Y., Deng, F., Wang, Y., Yang, X., Xiao, Q., Zhang, Q., Ding, Y., and He,
602 K.: An updated emission inventory of vehicular VOCs and IVOCs in China, *Atmos. Chem. Phys.*, 17,
603 12709-12724, doi:10.5194/acp-17-12709-2017, 2017.

604 Liu, P., Wu, Y., Li, Z., Lv, Z., Zhang, J., Liu, Y., Song, A., Wang, T., Wu, L., Mao, H., and Peng, J.:
605 Tailpipe volatile organic compounds (VOCs) emissions from Chinese gasoline vehicles under different
606 vehicle standards, fuel types, and driving conditions, *Atmos. Environ.* 323, 120348,
607 doi:10.1016/j.atmosenv.2024.120348, 2024.

608 Liu, Y. H., Ma, J. L., Li, L., Lin, X. F., Xu, W. J., and Ding, H.: A high temporal-spatial vehicle emission
609 inventory based on detailed hourly traffic data in a medium-sized city of China, *Environ. Pollut.*, 236,
610 324-333, doi:10.1016/j.envpol.2018.01.068, 2018.

611 Liu, Z., Yang, H., and Wei, X.: Spatiotemporal Variation in Relative Humidity in Guangdong, China,
612 from 1959 to 2017, *Water*, 12, doi:10.3390/w12123576, 2020.

613 Loder, A., Ambuhl, L., Menendez, M., and Axhausen, K. W.: Understanding traffic capacity of urban
614 networks, *Sci. Rep.*, 9, 16283, doi:10.1038/s41598-019-51539-5, 2019.

615 Lu, Z., Kwon, T. J., and Fu, L.: Effects of winter weather on traffic operations and optimization of
616 signalized intersections, *Journal of Traffic and Transportation Engineering (English Edition)*, 6, 196-208,
617 doi:10.1016/j.jtte.2018.02.002, 2019.

618 Luo, Z., Wang, Y., Lv, Z., He, T., Zhao, J., Wang, Y., Gao, F., Zhang, Z., and Liu, H.: Impacts of vehicle
619 emission on air quality and human health in China, *Sci. Total Environ.*, 813, 152655,
620 doi:10.1016/j.scitotenv.2021.152655, 2022.

621 Ma, D., Wu, X., Sun, X., Zhang, S., Yin, H., Ding, Y., and Wu, Y.: The Characteristics of Light-Duty
622 Passenger Vehicle Mileage and Impact Analysis in China from a Big Data Perspective, *Atmosphere*, 13,
623 doi:10.3390/atmos13121984, 2022.

624 Ma, X.Y., Sha, T., Wang, J.Y., Jia, H.L., Tian, R.: Investigating impact of emission inventories on PM_{2.5}
625 simulations over North China Plain by WRF-Chem. *Atmos. Environ.*, 195, 125–
626 140, doi:10.1016/j.atmosenv.2018.09.058, 2018.

627 Qi, Z., Zheng, Y., Feng, Y., Chen, C., Lei, Y., Xue, W., Xu, Y., Liu, Z., Ni, X., Zhang, Q., Yan, G., and
628 Wang, J.: Co-drivers of Air Pollutant and CO₂ Emissions from On-Road Transportation in China 2010-
629 2020, *Environ. Sci. Technol.*, 57, 20992-21004, doi:10.1021/acs.est.3c08035, 2023.

630 Shang, W.-L., Song, X., Chen, Y., Yang, X., Liang, L., Deveci, M., Cao, M., Xiang, Q., and Yu, Q.:
631 Congestion and Pollutant Emission Analysis of Urban Road Networks Based on Floating Vehicle Data,
632 *Urban. Clim.*, 53, doi:10.1016/j.uclim.2023.101794, 2024.

633 Shao, M., Zhang, Y., Zeng, L., Tang, X., Zhang, J., Zhong, L., and Wang, B.: Ground-level ozone in the
634 Pearl River Delta and the roles of VOC and NO_x in its production, *J. Environ. Manage.*, 90, 512-518,
635 doi:10.1016/j.jenvman.2007.12.008, 2009.

636 Shen, Q., Tang, B., Wu, X., Kang, J., Li, J., Pan, Y., Liu, X., Xu, W.: A large net source revealed by the
637 atmospheric reactive nitrogen budget in a subtropical plateau lake basin, southwest China, *Nitrogen Cycl.*,
638 2: e006 doi: 10.48130/nc-0025-0018, 2026.

639 Sun, J., Qin, M., Xie, X., Fu, W., Qin, Y., Sheng, L., Li, L., Li, J., Sulaymon, I. D., Jiang, L., Huang, L.,
640 Yu, X., and Hu, J.: Seasonal modeling analysis of nitrate formation pathways in Yangtze River Delta
641 region, China, *Atmos. Chem. Phys.*, 22, 12629-12646, doi:10.5194/acp-22-12629-2022, 2022.

642 Sun, S., Sun, L., Liu, G., Zou, C., Wang, Y., Wu, L., and Mao, H.: Developing a vehicle emission
643 inventory with high temporal-spatial resolution in Tianjin, China, *Sci. Total Environ.*, 776,
644 doi:10.1016/j.scitotenv.2021.145873, 2021.

645 Sun, S., Jin, J., Xia, M., Liu, Y., Gao, M., Zou, C., Wang, T., Lin, Y., Wu, L., Mao, H., and Wang, P.:
646 Vehicle emissions in a middle-sized city of China: Current status and future trends, *Environ. Int.*, 137,
647 105514, doi:10.1016/j.envint.2020.105514, 2020.

648 The Announcement about Releasing Five National Technical Guidelines of the Air Pollutant Emissions
649 Inventory., MEE (Ministry of Ecology and Environment), 2014.

650 Tong, R., Liu, J., Wang, W., and Fang, Y.: Health effects of PM_{2.5} emissions from on-road vehicles during
651 weekdays and weekends in Beijing, China, *Atmos. Environ.*, 223, doi:10.1016/j.atmosenv.2019.117258,

652 2020.

653 Wang, H., Wen, Y., Wu, J., Cai, R., Shen, Y., Deng, C., Li, Y., Li, Y., Wu, H., Huang, D., Cheng, H., Yan,
654 C., Gao, J., Zheng, M., Liu, Y., Kulmala, M., Mao, F., Smith, J. N., Zhang, S., Hao, J., Li, X., and Jiang,
655 J.: Accelerated reduction of atmospheric ultrafine particles since China VI vehicle emission standards,
656 *Npj Clim. Atmos. Sci.*, 9(55), doi: 10.1038/s41612-026-01327-6, 2026.

657 Wang, P., Qiao, X., Zhang, H. L.: Modeling PM_{2.5} and O₃ with aerosol feedbacks using WRF/Chem over
658 the Sichuan Basin, southwestern China, *Chemosphere*, 254, 126735,
659 doi:10.1016/j.chemosphere.2020.126735, 2020.

660 Wang, X., Fan, T., Li, W., Yu, R., Bullock, D., Wu, B. and Tremont, P.: Speed variation during peak and
661 off-peak hours on urban arterials in Shanghai. *Transport. Res. C-Em*, 67, 84-94,
662 doi:10.1016/j.trc.2016.02.005, 2016.

663 Wen, Y., Liu, M., Zhang, S., Wu, X., Wu, Y., and Hao, J.: Updating On-Road Vehicle Emissions for China:
664 Spatial Patterns, Temporal Trends, and Mitigation Drivers, *Environ. Sci. Technol.*, 57, 14299-14309,
665 doi:10.1021/acs.est.3c04909, 2023.

666 Wen, Y., Zhang, S., Zhang, J., Bao, S., Wu, X., Yang, D., and Wu, Y.: Mapping dynamic road emissions
667 for a megacity by using open-access traffic congestion index data, *Appl. Energ.*, 260,
668 doi:10.1016/j.apenergy.2019.114357, 2020.

669 Wen, Y., Wu, R., Zhou, Z., Zhang, S., Yang, S., Wallington, T. J., Shen, W., Tan, Q., Deng, Y., and Wu,
670 Y.: A data-driven method of traffic emissions mapping with land use random forest models, *Appl. Energ.*,
671 305, doi:10.1016/j.apenergy.2021.117916, 2022.

672 Wu, H., Tang, X., Wang, Z., Wu, L., Lu, M., Wei, L., & Zhu, J.: Probabilistic automatic outlier detection
673 for surface air quality measurements from the China national environmental monitoring network, *Adv.*
674 *Atmos. Sci.*, 35(12), 1522–1532, doi:10.1007/s00376-018-8067-9, 2018.

675 Wu, L., Xie, J., and Kang, K.: Changing weekend effects of air pollutants in Beijing under 2020 COVID-
676 19 lockdown controls, *npj Urban Sustainability*, 2, 23, doi:10.1038/s42949-022-00070-0, 2022.

677 Xie, R., Wei, D., Han, F., Lu, Y., Fang, J., Liu, Y., and Wang, J.: The effect of traffic density on smog
678 pollution: Evidence from Chinese cities, *Technol. Forecast. Soc.*, 144, 421-427,
679 doi:10.1016/j.techfore.2018.04.023, 2019.

680 Xu, X., Tan, M., Liu, X., Wang, X., and Xin, L.: Stability and Changes in the Spatial Distribution of
681 China's Population in the Past 30 Years Based on Census Data Spatialization, *Remote Sens.*, 15,
682 doi:10.3390/rs15061674, 2023.

683 Xu, Y., Liu, Z., Xue, W., Yan, G., Shi, X., Zhao, D., Zhang, Y., Lei, Y., and Wang, J.: Identification of on-
684 road vehicle CO₂ emission pattern in China: A study based on a high-resolution emission inventory,
685 *Resour. Conserv. Recy.*, 175, doi:10.1016/j.resconrec.2021.105891, 2021.

686 Yang, D., Zhang, S., Niu, T., Wang, Y., Xu, H., Zhang, K. M., and Wu, Y.: High-resolution mapping of
687 vehicle emissions of atmospheric pollutants based on large-scale, real-world traffic datasets, *Atmos.*
688 *Chem. Phys.*, 19, 8831-8843, doi:10.5194/acp-19-8831-2019, 2019.

689 Yang, L., Shen, Q., and Li, Z.: Comparing travel mode and trip chain choices between holidays and
690 weekdays, *Transport. Res. A-Pol.*, 91, 273-285, doi:10.1016/j.tra.2016.07.001, 2016.

691 Yang, L., Wu, D., Cao, S., Zhang, W., Zheng, Z., and Liu, L.: Transportation Interrelation Embedded in
692 Regional Development: The Characteristics and Drivers of Road Transportation Interrelation in
693 Guangdong Province, China, *Sustainability*, 14, doi:10.3390/su14105925, 2022.

694 Yang, S., Wu, J., Qi, G., and Tian, K.: Analysis of traffic state variation patterns for urban road network
695 based on spectral clustering, *Adv. Mech. Eng.*, doi:10.1177/1687814017723790, 2017.

696 Yang, W., Yu, C., Yuan, W., Wu, X., Zhang, W., and Wang, X.: High-resolution vehicle emission
697 inventory and emission control policy scenario analysis, a case in the Beijing-Tianjin-Hebei (BTH)
698 region, China, *J. Clean. Prod.*, 203, 530-539, doi:10.1016/j.jclepro.2018.08.256, 2018.

699 Yang, X., Wang, Q., Liu, L., Tian, J., Xie, H., Wang, L., Cao, Y., and Ho, S. S. H.: Impacts of emission
700 reduction and meteorological conditions on air quality improvement from 2016 to 2020 in the Northeast
701 Plain, China, *J. Environ. Sci.*, 151, 484-496, doi:10.1016/j.jes.2024.04.017, 2025.

702 Yeganeh, B., Shakerdonyavi, A., Zafarmomen, N. and Taheri, A.: Comprehensive spatiotemporal
703 analysis of long-term mobile monitoring for traffic-related particles in a complex urban environment.
704 *Atmos. Pollut. Res.*, 102870, doi:10.1016/j.apr.2025.102870, 2025.

705 Yu, K. A., McDonald, B. C., and Harley, R. A.: Evaluation of Nitrogen Oxide Emission Inventories and
706 Trends for On-Road Gasoline and Diesel Vehicles, *Environ. Sci. Technol.*, 55, 6655-6664,
707 doi:10.1021/acs.est.1c00586, 2021.

708 Zhang, J., Peng, J., Song, A., Lv, Z., Tong, H., Du, Z., Guo, J., Wu, L., Wang, T., Hallquist, M., and Mao,
709 H.: Marked impacts of transient conditions on potential secondary organic aerosol production during
710 rapid oxidation of gasoline exhausts, *npj Clim. Atmos. Sci.* 6, doi:10.1038/s41612-023-00385-4, 2023a.

711 Zhang, X. and Gao, J.: The analysis and solution for intercity travel behaviors during holidays in the
712 post-epidemic era based on big data, *PLoS One*, 18, e0288510, doi:10.1371/journal.pone.0288510,
713 2023b.

714 Zhao, J., Tang, Y., Zhu, X., & Zhu, J.: National environmental monitoring and local enforcement
715 strategies, *Nat. Cities*, 2(1), 58-69, doi:10.1038/s44284-024-00173-y, 2025.

716 Zheng, B., Huo, H., Zhang, Q., Yao, Z. L., Wang, X. T., Yang, X. F., Liu, H., and He, K. B.: High-
717 resolution mapping of vehicle emissions in China in 2008, *Atmos. Chem. Phys.*, 14, 9787-9805,
718 doi:10.5194/acp-14-9787-2014, 2014.

719 Zheng, J., Zhang, L., Che, W., Zheng, Z., and Yin, S.: A highly resolved temporal and spatial air pollutant
720 emission inventory for the Pearl River Delta region, China and its uncertainty assessment, *Atmos.*
721 *Environ.*, 43, 5112-5122, doi:10.1016/j.atmosenv.2009.04.060, 2009.

722 Zhao, P., and Bai, Y.: The gap between and determinants of growth in car ownership in urban and rural
723 areas of China: A longitudinal data case study. *J. Transp. Geogr.*, 79, 102487,
724 doi:10.1016/j.jtrangeo.2019.102487, 2019.

725 Zhou, Y., Zhao, Y., Mao, P., Zhang, Q., Zhang, J., Qiu, L., and Yang, Y.: Development of a high-resolution
726 emission inventory and its evaluation through air quality modeling for Jiangsu Province, China, *Atmos.*
727 *Chem. Phys.*, 17, 211–233, doi:10.5194/acp-2016-567, 2016.

728 Zhu, X. H., He, H. D., Lu, K. F., Peng, Z. R., & Gao, H. O.: Characterizing carbon emissions from China
729 V and China VI gasoline vehicles based on portable emission measurement systems, *J. Clean. Prod.*, 378,
730 134458, doi:10.1016/j.jclepro.2022.134458, 2022.