

# A localized, plant-species-specific BVOC emission rate library for China using a statistical analysis of field measurements

Huijuan Han<sup>1</sup>, Yanqi Jia<sup>1</sup>, Rende Shi<sup>2</sup>, Changliang Nie<sup>1</sup>, Yoshizumi Kajii<sup>1</sup>, Yan Wu<sup>3</sup>,

Lingyu Li<sup>1\*</sup>

<sup>1</sup>College of Environment and Geography, Carbon Neutrality and Eco-Environmental

Technology Innovation Center of Qingdao, Qingdao University, Qingdao 266071, China

<sup>2</sup>Eco-environment Monitoring Center of Qingdao, Shandong Province, Qingdao 266003,

8 China

<sup>3</sup>School of Environmental Science and Engineering, Shandong University, Qingdao 266237,

## China

\*Corresponding author. E-mail: lilingyu@qdu.edu.cn;

Contributing authors: [hanhuijuan2022@163.com](mailto:hanhuijuan2022@163.com); [jiayanqi2022@163.com](mailto:jiayanqi2022@163.com);

yoymjh@126.com; changliangnie@163.com; kajii.yoshizumi.7e@kyoto-u.jp;

wuyan@sdu.edu.cn

## Abstract

Precise quantification of biogenic volatile organic compound (BVOC) emissions is essential for effective control of ozone and secondary organic aerosol pollution. However, the lack of a localized and detailed plant species-specific emission rate library poses significant challenges to accurate emission estimates in China. Additionally, large uncertainty exists in the representative emission rates used in inventory compilation. Here, a statistical approach for classifying emission intensity and assigning representative emission rates with higher accuracy was developed from our measurements and local field observations. Furthermore, a localized plant species-specific BVOC emission rate library for China covering 599 plant species was established. Critically, different reliability levels were assigned to each emission rate according to the measurement technique. Emission simulations were conducted to evaluate the implications of the developed library. Comparison with formaldehyde vertical

27 column density observations showed that our localized library improved the model  
28 performance in capturing the spatial variations of isoprene emissions. The newly estimated  
29 BVOC emissions were 27.70 Tg, 18% higher than estimates based on the global library.  
30 Updating the localized emission rates reduced underestimation in southern and overestimation  
31 in northeast and western China.

## 32 **1. Introduction**

33 Biogenic volatile organic compounds (BVOCs) are primarily emitted by vegetation in  
34 terrestrial ecosystems (Ciccioli et al., 2023; Guenther et al., 1995, 2012; Li et al., 2023, 2024;  
35 Simpson et al., 1999). These compounds are highly reactive (Atkinson et al., 2003), which  
36 can react with nitrogen oxides ( $\text{NO}_x$ ) to generate ozone ( $\text{O}_3$ ) and secondary organic aerosol  
37 (SOA) through atmospheric oxidation (Li et al., 2022; Wei et al., 2024), thereby affecting air  
38 quality, cloud formation, solar radiation transmission, and climate change (Blichner et al.,  
39 2024; Ndah et al., 2024). Furthermore, the  $\text{O}_3$  formation can be more sensitive to BVOCs than  
40 to  $\text{NO}_x$  in VOC-limited areas (Guo et al., 2024; Huang et al., 2024; Wang et al., 2023a). In  
41 China, both the reduction of anthropogenic VOCs and the growth of BVOC emissions in  
42 recent years (Cao et al., 2022; Gai et al., 2024) have enhanced the contribution of BVOCs to  
43  $\text{O}_3$  and SOA formation (Yang et al., 2023). Cao et al. (2022) reported that summertime BVOC  
44 emissions led to an average increase of 8.6 ppb (17%) in daily maximum 8 h (MDA8)  $\text{O}_3$   
45 concentration and  $0.84 \mu\text{g m}^{-3}$  (73%) in SOA over China. Accurately estimating BVOC  
46 emissions is essential for the precise control of complex air pollution in China.

47 Reported BVOC emission inventories for China have shown variable results and large  
48 uncertainties (Li et al., 2024). The quality of emission rates in an inventory substantially  
49 influences the accuracy of emission estimates (Wang et al., 2023b). In existing inventories,  
50 different emission rates have been applied to the same plant species due to variations in  
51 assignment methods. Mostly, global emission rates by plant function type (PFT) were used,  
52 although these include a few observations from China. Emissions from domestic and foreign  
53 plants often differ due to genetic, environmental, and climatic factors (Chatani et al., 2018).

54 Uncertainties will inevitably be introduced when foreign measurements are used in Chinese  
55 emission inventories. Therefore, it is essential to localize the emission rate library. Some  
56 inventories used limited local observations, but large uncertainties remained. In some cases,  
57 the emission rate was assigned based on a single observation or by directly averaging multiple  
58 observations. This approach introduces uncertainties because local measurements are limited  
59 and different studies may report varying emission rates for the same plant species (Chen et al.,  
60 2024; Zeng et al., 2024). Subsequently, some studies applied a method based on emission  
61 intensity categories to determine the emission rates used in inventory compilation (Klinger et  
62 al., 2002; Wang et al., 2007; Yan et al., 2005). In this method, different emission intensity  
63 categories (e.g., negligible, low, moderate, and high) are defined, each with a representative  
64 emission rate and a range of  $\pm 50\%$  (Simpson et al., 1999; Zhang et al., 2024). For each plant  
65 species, the emission rate is determined from the tendency of reported values to fall within  
66 certain categories. This method can substantially improve the accuracy of final emission rates;  
67 however, it has several limitations. First, the process of determining emission categories,  
68 representative emission rates, and ranges is not straightforward and lacks theoretical  
69 justification. Second, the various emission categories and representative values in different  
70 studies have led to disparate emission rates for the same plant species. For example, Klinger  
71 et al. (2002) assigned isoprene emission rates of 70, 70, and 14  $\mu\text{g C g}^{-1} \text{ h}^{-1}$  for *Salix*  
72 *character*, *Quercus mongolica*, and *Picea jezoensis*, respectively, whereas Wang et al. (2007)  
73 reported values of 20, 50, and 10  $\mu\text{g C g}^{-1} \text{ h}^{-1}$ . Third, most studies used coarse classifications  
74 of emission, typically five to seven categories (Klinger et al., 2002; Yan et al., 2005), which  
75 may result in imprecise classifications and overestimation or underestimation of emission  
76 rates for specific plant species. Significant uncertainties will be further introduced into BVOC  
77 emission estimates. Thus, detailed emission categories and accurate representative values and  
78 ranges are essential for accurately estimating emission rates. Additionally, a localized BVOC  
79 emission rate library should be established based on domestic observations to enhance  
80 inventory accuracy. Additionally, PFT-averaged emission rates were often used, which fail to  
81 capture the species specificity of BVOC emissions. Research has shown that isoprene

82 emission rates can vary by 220–330% among vegetation subtypes (Batista et al., 2019).

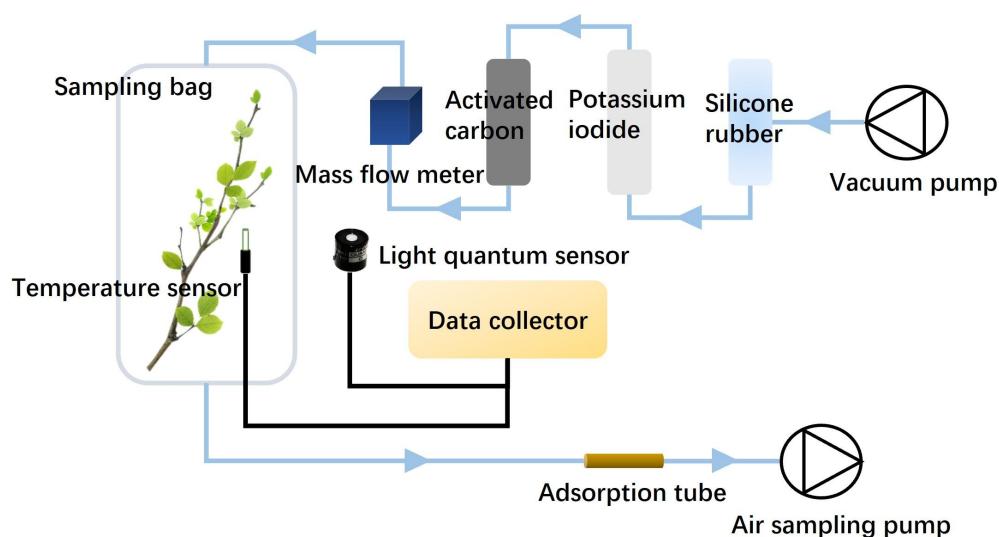
83 Therefore, it is also necessary to establish a plant species–specific emission rate library.

84 In this study, we first conducted the emission measurements for plants in China to  
85 provide more baseline data for the establishment of a localized emission rate library. Second,  
86 by summarizing our field measurements along with reported emission rates from China, we  
87 developed a statistical approach to determine plant species–specific emission rates. A  
88 localized BVOC emission rate library for China was established, and its features were  
89 analyzed. Differences in BVOC emission rates among vegetation types, families, genera, and  
90 species were examined. Then, the developed emission rate library was applied to establish a  
91 BVOC emission inventory for China using the Model of Emissions of Gases and Aerosols  
92 from Nature (MEGAN) v3.2. Its performance was further evaluated. Furthermore, the  
93 influence of emission rates with different reliability levels on the estimated BVOC emission  
94 was investigated. This study will be significant for improving the accuracy of local biogenic  
95 emission inventories and, in turn, air quality modeling. Additionally, our developed statistical  
96 approach can be extended to the establishment of BVOC emission rate libraries for other  
97 regions.

## 98 **2. Field measurements of emission rates**

99 Field measurements of BVOC emission rates were conducted from July 2020 to  
100 September 2023. The sites covered the south and north of China, including Shandong, Hebei,  
101 Jiangsu, and Anhui Provinces. Their specific locations are shown in Figure S1. Meanwhile,  
102 some pot experiments in the plant growth chamber were included. Emissions from 66 plant  
103 species—including 30 broadleaf trees, 12 coniferous trees, 20 shrubs, two crops, and two herb  
104 species—were measured (Table S1). The dynamic enclosure technique was used for the  
105 observations, as depicted in Figure 1 (Zhang et al., 2024). First, selected branches were  
106 enclosed within a Teflon bag (Welch Fluorocarbon, Inc., USA) with a volume ranging from  
107 15 to 60 L and a PAR transparency close to 100%. The bag was made of  
108 polytetrafluoroethylene, a material known for its inherent chemical inertness that minimizes

109 the generation and adsorption of VOCs without requiring additional treatment (Zhang et al.,  
110 2022). Clean air was continuously introduced into the bag at a constant flow rate of 10–20 L  
111 min<sup>-1</sup> after removing water, O<sub>3</sub>, and VOCs through silicone rubber, potassium iodide, and  
112 activated carbon. After equilibrium, the gases in the bag were collected into adsorption tubes  
113 filled with Tenax TA and Carbograph 5TD (Markes International, Bridgend, UK) using an  
114 air-sampling pump (Gilian Gilair Plus, Sensidyne, USA) with a flow rate of 200 mL min<sup>-1</sup> for  
115 30 minutes. For each plant species, three mature and healthy individuals were selected as  
116 replicates, and one blank sample was used as the background. During the whole enclosure, the  
117 temperature and photosynthetically active radiation (PAR) were recorded in real time. After  
118 the experiment, all leaves on the enclosed branch were collected and weighed after drying at  
119 75 °C for 48 hours.



120  
121 **Figure 1.** Schematic of dynamic enclosure technique. Vacuum pump was used to introduce  
122 air to the system; silicone rubber, potassium iodide, and activated carbon were used to remove  
123 O<sub>3</sub> and VOCs from the air; a mass flow meter was used to control flow rate; a temperature  
124 sensor and light quantum sensor were used to record temperature and photosynthetically  
125 active radiation; after equilibrium, the gases in the bag were collected into adsorption tubes  
126 using an air-sampling pump.  
127

128 The sampled tubes were analyzed using thermal desorption (TD)-gas  
129 chromatography–mass spectrometry (GC-MS) (TD, ATD II-26, Acrichi Inc., China; GC-MS,  
130 7890A-5975C, Agilent Technologies, USA). Detailed information about their operating  
131 conditions can be found in our previous study (Zhang et al., 2023, 2024). The Agilent DB-5  
132 chromatography column (30 m in height, inner diameter 0.25 mm, pore size 0.25  $\mu\text{m}$ ) was  
133 used. In the study, terpene mixed standards (Apelriemer Environmental, USA) and  
134 photochemical assessment monitoring station mixed standards (LINDE, USA) with a  
135 concentration of 1 ppm were used to quantify VOC concentrations. During compound  
136 quantification, the response factor (RF) method was used when the relative standard deviation  
137 of RFs was  $< 20\%$ . Otherwise, the external standard method was used, and the correlation  
138 coefficients of their curves were  $> 0.99$ . The quantified compounds included isoprene, 14  
139 monoterpenes, six sesquiterpenes, 21 alkanes, four alkenes, and 17 aromatics, as listed in  
140 Table S2.

141 The emission rates for each compound ( $\text{VOC}_i$ ) were calculated using equation (1).

$$142 \text{EF}_i = \frac{F \times C_i}{M} \quad (1)$$

143 where  $F$  ( $\text{L min}^{-1}$ ) and  $C_i$  ( $\mu\text{g m}^{-3}$ ) are the flow rate of the purged clean air into the Teflon bag  
144 and the mass concentration of  $\text{VOC}_i$ , respectively, and  $M$  (g) is the dry mass of the enclosed  
145 leaves.  $\text{EF}_i$  represents the emission rate of  $\text{VOC}_i$  under the observed temperature and PAR.

### 146 **3. Establishment of localized emission rate library**

#### 147 **3.1. Collection of basal observed emission rates**

148 Our field measurements and the published domestic measurements on plant  
149 species-specific BVOC emission rates in China were integrated to establish the localized  
150 emission rate library. Keywords including “plant volatile organic compounds”, “plant VOC  
151 emissions”, “BVOCs”, “isoprene”, and “biogenic VOCs” were utilized to query databases  
152 such as the China National Knowledge Infrastructure, Web of Science, Elsevier ScienceDirect,  
153 and Google Scholar. A total of 43 articles on BVOC emission measurements in China were

154 identified.

155 All the collected basal data observed under different environmental conditions were  
156 normalized to standard conditions (temperature = 30 °C, PAR = 1000  $\mu\text{mol m}^{-2} \text{s}^{-1}$ ) using the  
157 algorithm described in Guenther et al. (1993). Additionally, all emission rates were uniformly  
158 converted to values in units of  $\mu\text{g g}^{-1} \text{h}^{-1}$  (Zhang et al., 2024). The specific leaf area (SLA)  
159 values used for conversion were species-specific. For our measurements, we utilized SLA  
160 values derived from the general relationship between leaf area and leaf dry weight. For  
161 literature-sourced emission rates, we preferentially used SLA values from the original  
162 publication when available; otherwise, we obtained representative SLA values from  
163 measurements of the same species in China through an extensive literature review (Ghirardo  
164 et al., 2016; Ren et al., 2014; Wang et al., 2017). In total, we obtained the raw emission data  
165 of 599 plant species. Specifically, the sample size was 845 for isoprene, with emission rates  
166 ranging from 0.002 to 3699.61  $\mu\text{g g}^{-1} \text{h}^{-1}$ ; 846 for monoterpenes, with emission rates ranging  
167 from 0.006 to 4281.03  $\mu\text{g g}^{-1} \text{h}^{-1}$ ; and 140 for sesquiterpenes, with emission rates ranging  
168 from 0.002 to 143.84  $\mu\text{g g}^{-1} \text{h}^{-1}$ .

169 The collected emission rates included results measured using the static enclosure  
170 technique and the dynamic one. For the static enclosure technique, the branches or leaves  
171 were sealed within an enclosed space for collecting BVOCs. During the enclosure, there is no  
172 air exchange (Préndez et al., 2013; Tsui et al., 2009). The environment inside the chamber  
173 may change significantly due to the exposure to sunlight and physiological processes of plants,  
174 including temperature, humidity, and carbon dioxide (Stringari et al., 2023, 2024). These  
175 changes may lead to abnormal BVOC emissions by the enclosed plants. The dynamic  
176 enclosure technique involves air exchange in the chamber to maintain conditions that closely  
177 resemble the natural environment (Li et al., 2019). Thus, its measurements are expected to  
178 more accurately represent real emissions. In earlier studies, the static enclosure technique was  
179 commonly used in China, providing numerous observed results. In total, 473 isoprene and  
180 421 monoterpene emission rate values from 348 plant species were obtained using the static  
181 enclosure technique, and 372 isoprene, 425 monoterpene, and 140 sesquiterpene emission rate

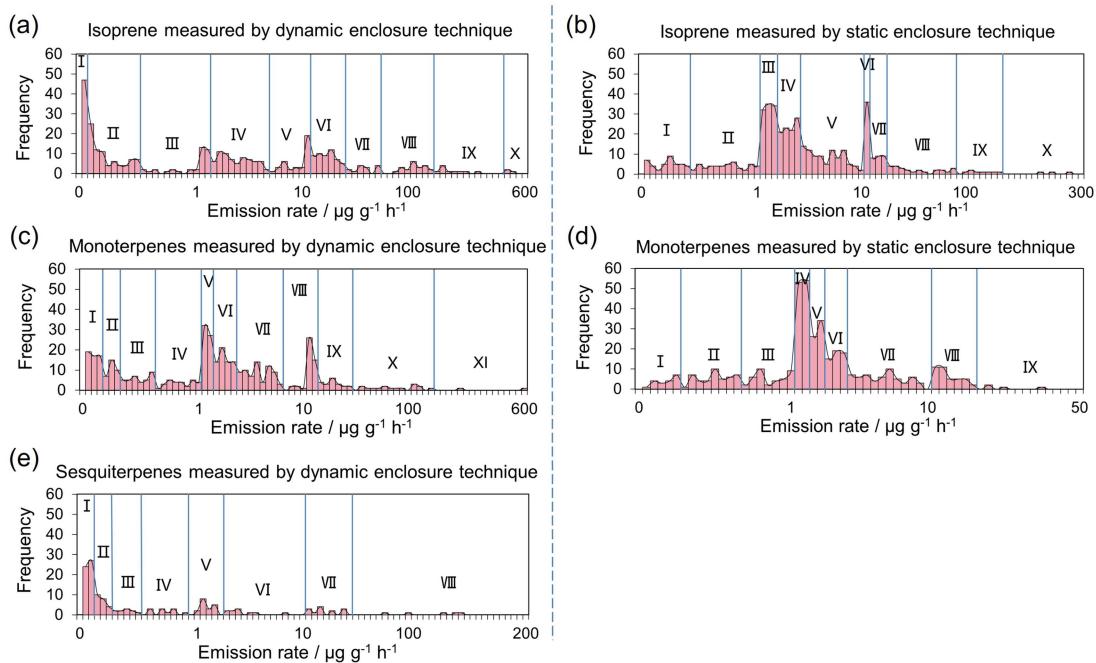
182 values from 330 plant species were obtained using the dynamic enclosure technique. A total  
183 of 79 plant species had emission rate observations using both techniques. Despite the large  
184 uncertainties associated with the static enclosure technique, these observations were included  
185 in establishing our localized rate library because of their larger sample size and ability to  
186 display plant emission patterns to a certain extent (Stringari et al., 2023). In the library,  
187 emission rates from observations using dynamic and static techniques were assigned different  
188 reliability (R) values of 1 and 2, respectively. An R-value of 1 indicates a higher reliability of  
189 emission rates than an R-value of 2.

## 190 **3.2. Determination of plant species-specific emission rates**

### 191 **3.2.1. Determination of emission categories**

192 All the available normalized isoprene, monoterpene, and sesquiterpene emission rates  
193 from all the plants were separately analyzed. Also, the values observed by dynamic and static  
194 enclosure techniques were separately analyzed. For each library described above, frequency  
195 distribution statistics were conducted. For the observations by the dynamic technique, the  
196 isoprene, monoterpene, and sesquiterpene emission rates fell predominantly within 0–600,  
197 0–600, and 0–200  $\mu\text{g g}^{-1} \text{ h}^{-1}$ , respectively, with a sparse distribution of higher emission rates.  
198 For the static technique, the isoprene and monoterpene emission rates fell predominantly  
199 within 0–300 and 0–50  $\mu\text{g g}^{-1} \text{ h}^{-1}$ , respectively. First, we divided the emission range (the  
200 x-axis) into various groups, which were further subdivided into 20 equal intervals (Figure 2).  
201 Then, we counted the frequency of values in each interval. Although individual plant emission  
202 rates were inconsistent, they exhibited a clear regularity in distribution, forming distinct  
203 intensity levels. Most measurements clustered around a mean value (the peak of the curve),  
204 revealing an underlying statistical structure despite individual variability. Second, ten  
205 categories (I–X) were defined for emission rates of isoprene and monoterpenes measured by  
206 the static enclosure technique, eleven (I–XI) for monoterpenes measured by dynamic one, and  
207 eight (I–VIII) for sesquiterpenes. Different categories represent different emission intensities,  
208 with categories I–XI representing emission levels from low to high. In the present study, more

209 emission categories were identified than those in previous studies (Klinger et al., 2002; Wang  
210 et al., 2007; Yan et al., 2005).



211

212 **Figure 2.** Frequency distribution of BVOC emission rates (Frequency distribution of BVOC  
213 emission rates observed by dynamic (left column: a, c, e) and static enclosure techniques  
214 (right column: b, d). The Roman numerals on each subgraph represent the emission categories  
215 identified by the frequency distribution.)

216

217 For each category, the ranges, frequency, mean, and standard deviation (SD) of emission  
218 rates are listed in Table 1. The frequencies of emission rates varied among emission categories.  
219 For the measurements by the dynamic enclosure technique, isoprene emission rates were  
220 concentrated in category II, ranging  $0.05\text{--}0.5 \mu\text{g g}^{-1} \text{h}^{-1}$ , with a frequency of 22%; categories  
221 VII–X, with higher emission intensity, comprised only 13% of the total measurements. This  
222 indicates that the categories with low and moderate emission intensity included the most plant  
223 species and samples. The distribution of monoterpene emission rates measured by the  
224 dynamic technique was relatively uniform, with frequencies ranging from 11% to 16% in  
225 most categories. For sesquiterpenes, category I, with the lowest emission intensity had the  
226 most measurements, accounting for 36% of the total, indicating the generally lower

227 sesquiterpene emissions for most plants. Among the emission rates measured by the static  
 228 technique, the highest frequencies of isoprene and monoterpene emission rates were found in  
 229 categories III and IV, respectively; their lowest frequencies occurred in categories with the  
 230 highest emission intensity, comprising less than 2% of the total measurements.

231 **Table 1.** Emission categories and their emission rate ranges and statistical results for each  
 232 BVOC component.

Enclosure technique	BVOC component	Emission category	Range of emission rate ( $\mu\text{g g}^{-1} \text{ h}^{-1}$ )	Frequency	Mean ( $\mu\text{g g}^{-1} \text{ h}^{-1}$ )	Standard deviation
Isoprene		I	0–0.05	47	0.02	0.01
		II	0.05–0.50	80	0.21	0.14
		III	0.50–2.0	38	1.23	0.42
		IV	2.0–7.0	68	4.20	1.35
		V	7.0–15.0	37	10.33	1.95
		VI	15.0–45.0	52	28.35	7.68
		VII	45.0–75.0	14	60.79	7.89
		VIII	75.0–200.0	21	127.66	31.92
		IX	200.0–500.0	10	276.17	52.56
Dynamic		X	>500.0	5	–	–
		I	0–0.15	53	0.08	0.04
		II	0.15–0.30	32	0.24	0.04
		III	0.30–0.60	35	0.47	0.09
		IV	0.60–1.0	28	0.83	0.11
		V	1.0–2.0	59	1.45	0.29
		VI	2.0–4.0	63	3.00	0.52
		VII	4.0–8.0	68	5.87	1.04
		VIII	8.0–20.0	46	13.60	2.80
		IX	20.0–50.0	20	32.68	7.63

	X	50.0–200.0	16	96.15	34.66
	XI	>200.0	5	—	—
Sesquiterpenes	I	0–0.1	51	0.05	0.03
	II	0.1–0.25	22	0.16	0.04
	III	0.25–0.50	10	0.37	0.07
	IV	0.50–0.90	11	0.71	0.10
	V	0.90–3.0	18	1.59	0.45
	VI	3.0–10.0	10	4.62	1.41
	VII	10.0–50.0	13	25.80	11.38
	VIII	>50.0	5	—	—
Isoprene	I	0–0.45	43	0.21	0.12
	II	0.45–1.0	45	0.72	0.16
	III	1.0–2.5	101	1.74	0.44
	IV	2.5–4.5	94	3.55	0.58
	V	4.5–10.0	92	6.72	1.44
	VI	10.0–15.0	36	12.07	1.60
	VII	15.0–30.0	26	21.74	4.23
	VIII	30.0–90.0	25	54.92	19.39
Static	IX	90.0–160.0	8	122.54	19.53
	X	>160.0	3	—	—
Monoterpene	I	0–0.25	19	0.16	0.07
	II	0.25–0.65	44	0.47	0.10
	III	0.65–1.0	38	0.84	0.10
	IV	1.0–2.0	107	1.49	0.26
	V	2.0–3.0	60	2.51	0.29
	VI	3.0–4.5	52	3.77	0.44
	VII	4.5–10.0	57	6.78	1.38

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VIII	10.0–22.0	39	14.42	3.07
IX	22.0–50.0	4	29.71	5.44
X	>50.0	1	—	—

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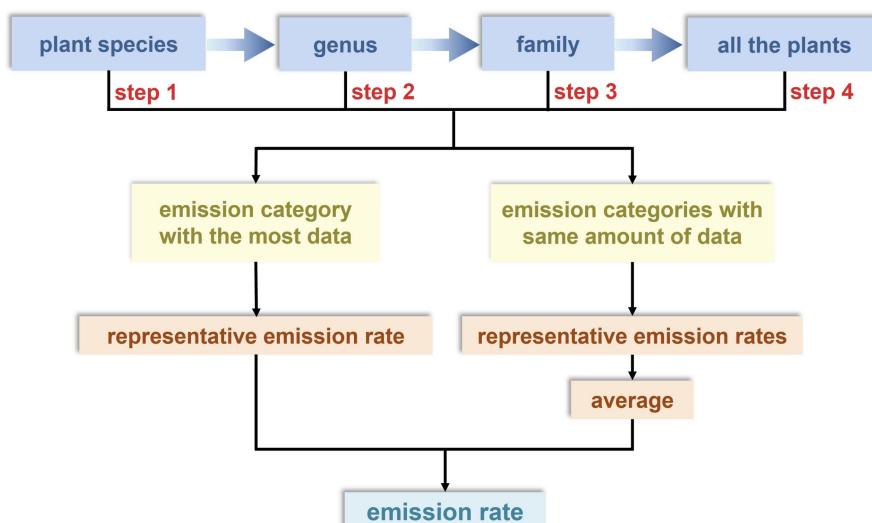
233

234 The emission rates exhibited a discrete distribution within each emission category,  
 235 characterized by large SDs relative to the mean. Using the mean as the representative  
 236 emission rate for each category would introduce uncertainty in emission rates for individual  
 237 plant species. Therefore, to obtain a robust estimate of the central tendency that is less  
 238 sensitive to potential outliers and the large observed variance, we implemented a two-step  
 239 statistical protocol to determine the representative emission rates for each category. First, the  
 240 95% confidence interval (CI) of each emission category was determined through a *t*-test  
 241 (Rivas-Ruiz et al., 2013). This allowed a 95% probability of the actual emission rates falling  
 242 within each category. Second, the values within the 95% CI for each category were averaged  
 243 as its representative emission rate. Third, the emission rate interval for each intensity category  
 244 was determined by  $\pm 50\%$  of its representative value. Notably, for the category with the  
 245 highest emission intensity, the lower limit of the interval was taken as the representative value  
 246 due to its limited samples and high dispersion. Thus, the emission rate intervals and  
 247 representative values for each intensity category were obtained specifically for each BVOC  
 248 component and for measurements by dynamic and static techniques separately, as listed in  
 249 Table S3.

250 For emission categories with lower emission intensity, the representative emission rates  
 251 from observations using static enclosure techniques were higher than those from observations  
 252 using the dynamic technique. The opposite was observed for emission categories with higher  
 253 emission intensity. Specifically, for isoprene, ten emission categories were classified for  
 254 observations by both techniques. The representative emission rates from the static technique  
 255 were higher than those from the dynamic one in categories I–V, which had lower emission  
 256 intensity, while they were lower in categories VI–X, which had higher emission intensity.

257 **3.2.2. Determination of emission rates**

258 Based on the established detailed categories of emission intensity with more accurate  
259 representative emission rates and intervals, the plant species-specific emission rates were  
260 determined. For a certain plant species, the assignment rule of emission rate is shown in  
261 Figure 3. The assignment is separate for the measurements by dynamic and static techniques.  
262 Then, a localized library including BVOC emission rates for 599 plant species was  
263 constructed, including those estimated based on the measurements by both dynamic and static  
264 enclosure techniques, labeled with R-values of 1 and 2, respectively. This library is available  
265 at <https://doi.org/10.5281/zenodo.14557394> (Han et al., 2024).



266

267 **Figure 3.** Determination of the emission rate for a certain plant species. Step 1–4 mean the  
268 order of priority when determining emission rates, namely using baseline data of the plant  
269 species primarily (step 1), then its belonging genus (step 2) and family (step 3), and at last all  
270 the plants in our dataset (step 4). For one of the steps, if no data fall within the interval of any  
271 emission category, then the observations of emission rates in the next step are used.

272

273 **3.3. Characteristics of localized emission rate library**

274 **3.3.1. Emission intensities of plants**

275 To characterize the emission capacities of different vegetation types, the number of plant  
276 species in each emission category was counted, with R-value = 1 as an example (Figure S2).

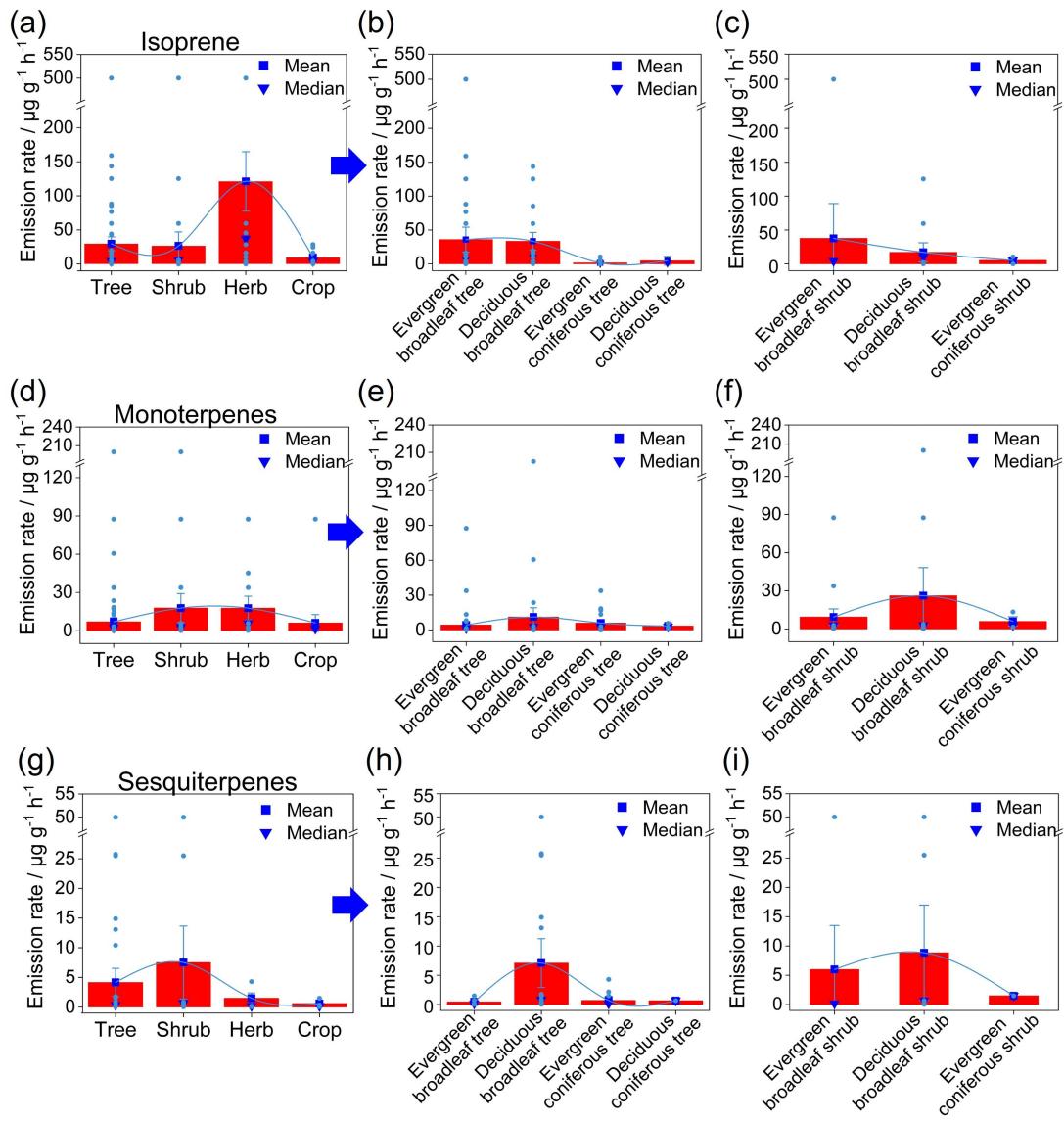
277 First, most plant species (57%) exhibited low-to-moderate isoprene emission intensities  
278 (Categories IV–VI). This emission profile was predominantly observed in evergreen broadleaf  
279 trees, deciduous broadleaf trees, and evergreen broadleaf shrubs, which together accounted  
280 for 69% of the species in these categories. Crops were uniformly distributed across Categories  
281 II–VI (low-to-moderate), whereas herbs showed a wide distribution, spanning all categories  
282 except Category II. Besides, monoterpene emissions were primarily characterized by  
283 moderate intensity (Categories V–VII), encompassing 53% of all species. Key contributors  
284 included evergreen broadleaf trees, deciduous broadleaf trees, and both evergreen and  
285 deciduous broadleaf shrubs. In contrast, only a small fraction of species (7%) displayed high  
286 emission intensities (Categories IX–XI). Most herb species (67%) showed moderate-to-high  
287 monoterpene emissions (Categories IV, VII, and VIII), while the majority of crop species  
288 (85%) fell into the low-to-moderate range (Categories III–VII). As for sesquiterpene  
289 emissions, over half of the plant species (52%) demonstrated low sesquiterpene emission  
290 intensities (Categories I–II), primarily consisting of evergreen broadleaf trees, evergreen  
291 coniferous trees, deciduous broadleaf trees, and crops. Deciduous broadleaf trees and shrubs  
292 showed a relatively uniform distribution across Categories I–VIII.

293 In general, most plant species emit isoprene at low to moderate intensities. Specifically,  
294 broadleaf plants predominantly exhibited a moderate emission intensity, whereas coniferous  
295 plants were mostly characterized by low-intensity emissions. Regarding monoterpenes, both  
296 broadleaf and coniferous plants primarily showed a moderate emission intensity. In contrast,  
297 herbaceous plants displayed a wide range of emission intensities for both isoprene and  
298 monoterpenes, covering low, moderate, and high levels. Meanwhile, the emission intensity of  
299 sesquiterpenes was relatively lower for most plant species, particularly trees and crops.

300 **3.3.2. Emission differences among vegetation types**

301 The distribution of emission rates across various vegetation types is illustrated in Figure  
302 4. Notably, considerable variation existed among vegetation types, characterized by a discrete  
303 distribution. For isoprene, the emission rates of trees were typically concentrated at 0.02–28.5

304  $\mu\text{g g}^{-1} \text{ h}^{-1}$ , those of shrubs concentrated around  $4.2 \mu\text{g g}^{-1} \text{ h}^{-1}$ , and those of crops mainly in  
305  $0.20\text{--}28.5 \mu\text{g g}^{-1} \text{ h}^{-1}$ , while emission rates of herbs showed a discrete distribution, with an  
306 average of  $26.5 \mu\text{g g}^{-1} \text{ h}^{-1}$ . Overall, herbs showed the highest isoprene emission, followed by  
307 trees and shrubs, based on their means and medians. For monoterpenes, emission rates of  
308 trees and shrubs were primarily concentrated at  $1.5\text{--}5.8 \mu\text{g g}^{-1} \text{ h}^{-1}$ , those of crops were mainly  
309  $0.46\text{--}5.8 \mu\text{g g}^{-1} \text{ h}^{-1}$ , while those of herbs were evenly distributed, with an average of  $17.7 \mu\text{g}$   
310  $\text{g}^{-1} \text{ h}^{-1}$ . Generally, herbs had the highest monoterpene emission, followed by shrubs, while the  
311 emissions of trees and crops were comparatively lower. As for sesquiterpenes, the emission  
312 rates for trees were mainly concentrated at  $0.05\text{--}0.17 \mu\text{g g}^{-1} \text{ h}^{-1}$  and secondarily in  $0.36\text{--}4.3$   
313  $\mu\text{g g}^{-1} \text{ h}^{-1}$ ; those of shrubs were mainly distributed around  $0.17$  and  $1.5 \mu\text{g g}^{-1} \text{ h}^{-1}$ , and those of  
314 crops and herbs were mainly  $0.05\text{--}0.17 \mu\text{g g}^{-1} \text{ h}^{-1}$ . Comparatively, trees and shrubs showed the  
315 highest sesquiterpene emission, followed by herbs, while crops had the lowest emission. As to  
316 the subtypes, broadleaf plants had relatively higher isoprene emission levels, while coniferous  
317 plants had higher monoterpene emission levels. This may be attributed to the broad and thick  
318 leaves of broadleaf plants, which possess stronger photosynthetic efficiency to produce  
319 isoprene (Benjamin et al., 1996; Li et al., 2021). Meanwhile, the thicker cuticle of coniferous  
320 plants can create favorable conditions for the storage of monoterpenes (Aydin et al., 2014),  
321 which are primarily regulated by temperature and less influenced by light (Bourtsoukidis et  
322 al., 2024). Moreover, the vegetation types with high sesquiterpene emissions were similar to  
323 those with high monoterpene emissions, which can be explained by the significant correlation  
324 between the emissions of monoterpenes and sesquiterpenes from plants ( $P < 0.05$ ) reported by  
325 Ormeño et al. (2010).



326

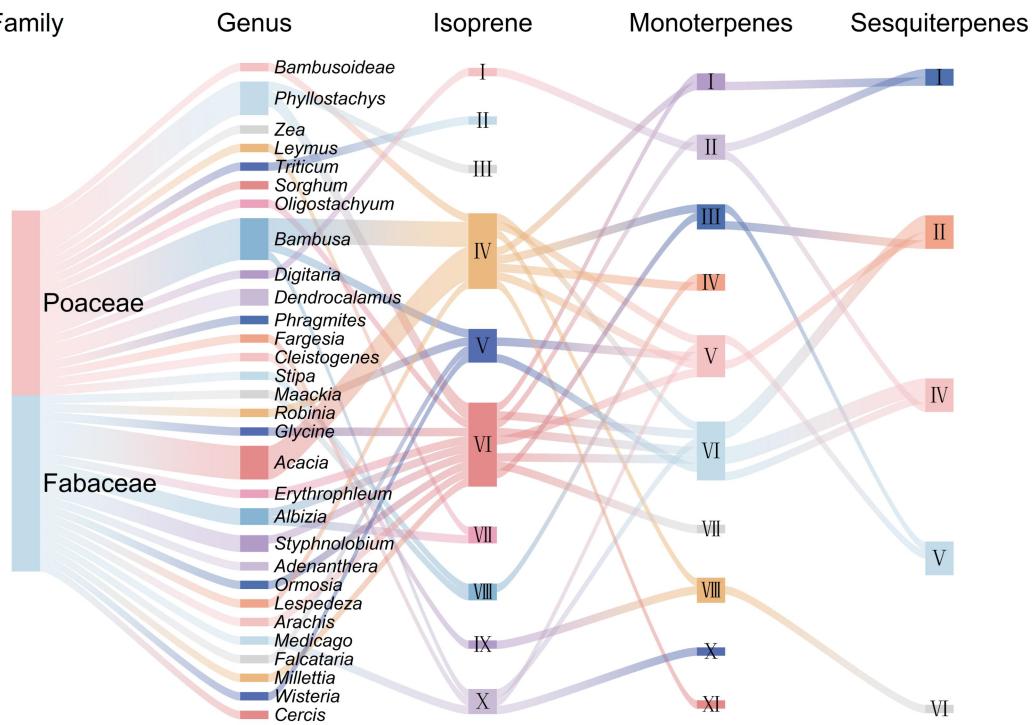
327 **Figure 4.** Statistics of BVOC emission rates in various vegetation types. a–i: Distribution of  
 328 emission rates for isoprene (a), monoterpenes (d), and sesquiterpenes (g) across vegetation  
 329 types (trees, shrubs, herbs, and crops). Differences in BVOC emission rates between various  
 330 subtypes of trees (b, e, h) and shrubs (c, f, i). Bar charts display median and mean of the  
 331 distribution; bar ends represent the 25th and 75th percentiles, and outliers are also displayed.

332

### 333 3.3.3. Interspecific differences in the same family/genus

334 Plants within the same family or genus usually share similar morphological and  
 335 biological traits (Lun et al., 2020; Wu, 2021). However, BVOC emissions are influenced by  
 336 genes and interactions with the environment (Peñuelas and Staudt, 2010), leading to

337 variations in the components and quantities of BVOC emissions. From our developed  
338 emission rate library, higher BVOC emissions were discovered in the families Poaceae and  
339 Fabaceae, which respectively had higher isoprene and monoterpene emissions. Exceptionally,  
340 the crop isoprene emission rates in Fabaceae were overall higher than those in Poaceae  
341 (Figure 5). Specifically, the emission rates of *Arachis hypogaea* and *Glycine max* ( $28.5 \mu\text{g g}^{-1}$   
342  $\text{h}^{-1}$ )—belonging to Fabaceae—were higher than those of *Zea mays* and *Sorghum bicolor* ( $16.4 \mu\text{g g}^{-1} \text{h}^{-1}$ ), belonging to Poaceae. Differences may exist among genera within the same family.  
343 Plants of Poaceae are widely distributed in China and worldwide (Sun et al., 2024;  
344 Wanasinghe et al., 2024), including the dominant crops like *Triticum aestivum*, *Oryza sativa*,  
345 and *Z. mays*, as well as herbs and bamboo. The plant species, genera, and BVOC emission  
346 rates within Poaceae are listed in Table S4. The evergreen broadleaf trees and bamboo  
347 species—such as *Fargesia spathacea* and *Bambusa textilis*—are widely distributed and  
348 commonly used for afforestation (Yan et al., 2024). They possessed the highest isoprene  
349 emission rate of  $500.0 \mu\text{g g}^{-1} \text{h}^{-1}$ . In the selection of plant species for future afforestation,  
350 lower-emission bamboo species like *Bambusa ventricosa* and *Bambusa vulgaris* var. *striata*  
351 should be preferred. Herbs usually showed higher isoprene and monoterpene emissions, but  
352 *Phragmites australis* had higher sesquiterpene emissions. Crops showed higher sesquiterpene  
353 emissions than other vegetation types. Also, it is worth mentioning that considerable  
354 differences in emission rates were exhibited even among plants belonging to the same genus.  
355 Thus, it may introduce uncertainties to our developed emission rate library when assigning  
356 based on the observations of all the plants within the same genus or family. Meanwhile, the  
357 limited samples in the same family likely resulted in an incomplete conclusion. Therefore,  
358 expanding emission observations to cover a wider range of plant species is imperative for the  
359 development of a more precise emission rate library. Also, the accuracy of the emission rates  
360 in the developed library derived by this assignment could be verified through field  
361 observations in a future study.



363

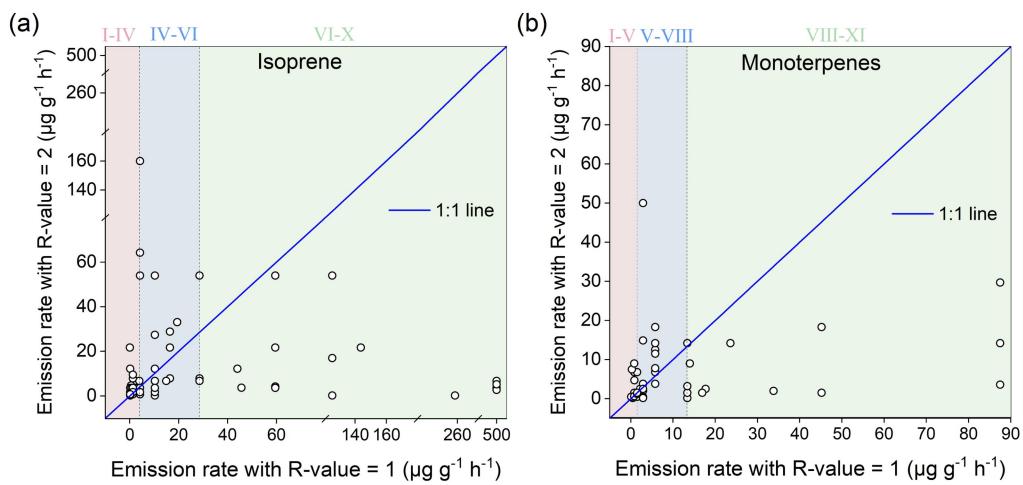
364 **Figure 5.** Emission categories of the plant species in different genera of the families Poaceae  
 365 and Fabaceae. Box length represents the number of species, and colors at the start and end of  
 366 each connecting line correspond to the two connected ends.

367

368 **3.3.4. Variability in emission rates derived from dynamic and static enclosure  
 369 measurements**

370 In the localized emission rate library, the subsets of emission rates with R-values of 1  
 371 and 2 were separately established. For isoprene emission rates, 51% of plant species exhibited  
 372 higher values with R-value = 2 than with R-value = 1. Among these plants, 66% had an  
 373 emission rate of  $0.02\text{--}4.2 \mu\text{g g}^{-1} \text{h}^{-1}$  (in lower emission intensity) (Figure 6). In contrast, for  
 374 plants with emission rates of R-value = 1 higher than those of R-value = 2, 78.1% had  
 375 emission rates of  $28.5\text{--}500.0 \mu\text{g g}^{-1} \text{h}^{-1}$  (in moderate and high emission intensity). For  
 376 monoterpenes emission rates, 49% of plant species displayed higher values with R-value = 2  
 377 than with R-value = 1, with all emission rates below  $13.4 \mu\text{g g}^{-1} \text{h}^{-1}$  (in lower emission

378 intensity). In contrast, for plants with emission rates of R-value = 1 higher than those of  
 379 R-value = 2, 48% had emission rates of  $13.4\text{--}200.0 \mu\text{g g}^{-1} \text{h}^{-1}$  (in moderate and high emission  
 380 intensity). To conclude, the emission for plants with high intensity may be underestimated  
 381 when measured by the static enclosure technique, while those for plants with low intensity  
 382 may be overestimated. The discrepancy between emission rates derived from dynamic and  
 383 static enclosure measurements is likely attributed to two factors. First, static enclosure  
 384 technique, which may induce a large buildup of BVOCs and release of stressed compounds  
 385 due to altered chamber conditions; its detection limit causes more compounds to be detected  
 386 (Li et al., 2019), leading to higher emission rates than dynamic measurement for plants with  
 387 low emission intensity. Second, plants with high emission intensity often have strong  
 388 transpiration, leading to moisture condensation on the walls within the static enclosure,  
 389 followed by stomatal closure and reduced emissions (Kfouri et al., 2017). In addition, high  
 390 BVOCs concentrations may undergo reactions and degradation in the chamber (Antonsen et  
 391 al., 2020), together contributing to underestimates by the static technique for plants with high  
 392 emission intensity.



393  
 394 **Figure 6.** Comparison of emission rates derived from dynamic (R-value = 1) and static  
 395 (R-value = 2) enclosure measurements for isoprene (a) and monoterpenes (b). (The solid line  
 396 represents the 1:1 relationship, and the Roman numerals on each subgraph represent the  
 397 emission category.)

398

399 **3.3.5 Comparison with global emission rate library of MEGANv3.2**

400 Comparison between our library and MEGANv3.2 global library was performed. For  
401 consistency, the comparison was conducted at the genus level, as the global library often  
402 assigns uniform values across species within a genus. Our results revealed consistent  
403 identification of high-emitting genera but quantitative differences (Figure S4). For isoprene,  
404 while genera like *Populus* and *Quercus* are high-emitters in both libraries, our localized  
405 emission rates for *Populus* ( $78.51 \text{ nmol m}^{-2} \text{ s}^{-1}$ ) and *Salix* ( $11.64 \text{ nmol m}^{-2} \text{ s}^{-1}$ ) differ  
406 significantly from the global value (37 and  $37 \text{ nmol m}^{-2} \text{ s}^{-1}$ , respectively). The discrepancies  
407 are even more pronounced for monoterpenes. Genera *Lespedeza* and *Spiraea* have the highest  
408 emissions in both libraries, but the localized values (40.87 and  $21.0 \text{ nmol m}^{-2} \text{ s}^{-1}$ ) are nearly  
409 an order of magnitude higher than the global values (5.30 and  $2.73 \text{ nmol m}^{-2} \text{ s}^{-1}$ ). In contrast,  
410 sesquiterpene emissions show closer agreement in both libraries.

411 **4. Application of localized emission rate library**

412 **4.1. BVOC emission simulation**

413 MEGANv3.2 was applied to estimate BVOC emissions, including 199 compounds  
414 (isoprene, 40 monoterpenes, 45 sesquiterpenes, and 113 other VOCs). The simulation was  
415 driven by key inputs, including vegetation data, species-specific emission rates, and  
416 externally sourced meteorological fields such as Weather Research and Forecasting (WRF)  
417 output. Specifically, the vegetation data include the distribution of four growth forms, their  
418 species speciation, ecological types, canopy types, and leaf area index (LAI). In the study, the  
419 database of high-resolution vegetation distribution (HRVD) with a horizontal resolution of  $1 \times$   
420 1 km established by Cao et al. (2024) (<https://zenodo.org/records/10830151>), was used to  
421 produce the distributions of growth forms and canopy types. It integrates multiple sources of  
422 land cover data—including the China multi-period land use/cover change remote sensing  
423 monitoring data set (CNLUCC) (Xu et al., 2020), MODIS MCD12Q1 land cover product  
424 (Friedl and Sulla-Menashe, 2019), as well as the Vegetation Atlas of China  
425 (1:1,000,000)—which shows a significant correlation with the field investigation. The

426 vegetation speciation was derived from the Vegetation Atlas of China (1:1,000,000). LAI was  
427 from the MODIS version 6.1 LAI product reprocessed by Lin et al. (2023)  
428 (<http://globalchange.bnu.edu.cn/research/laiv061>) and further updated based on the HRVD.  
429 Hourly meteorological fields driving MEGANv3.2 were simulated by WRF v3.8.1. The  
430 simulation covered the whole of China at a horizontal resolution of 36 × 36 km for the year  
431 2020.

432 In MEGAN version 3.2 used in this study, both PFT distribution and detailed vegetation  
433 species composition in grids are entered. Based on the vegetation composition, the gridded  
434 PFT-averaged emission factors can be calculated from the species-specific emission factors  
435 using the emission factor processing module of MEGANv3.2 and are then included in the  
436 emission calculator. Notably, plant species in our library did not cover all the plants in the  
437 vegetation speciation file; for species not included in our library, we assigned their emission  
438 factors using the global values. To match the input for MEGANv3.2, where monoterpenes and  
439 sesquiterpenes were categorized into five and two categories, respectively, the emission rates  
440 of monoterpenes and sesquiterpenes were assigned to separate categories based on the  
441 relationships of the global ones in MEGANv3. In total, emission rates of 283 plant species  
442 were updated, including 257, 280, and 101 species for isoprene, monoterpenes, and  
443 sesquiterpenes, respectively. Specifically, 202 plant species the emission rates with R-value =  
444 1, while an additional 81 species had those with R-value = 2. The application of emission  
445 rates with R-value = 1 was assessed by calculating the plant species coverage percentage of  
446 the total vegetation. Emission rates with R-value = 1 cover a high percentage of the dominant  
447 vegetation, specifically 93% of the total tree area and 94% of the total crop area. In contrast,  
448 their coverage is substantially lower for shrubs and herbs, with 34% and 21% of their  
449 respective areas. This is a common challenge in regional BVOC modeling, as comprehensive  
450 field measurements for all shrub and herb species are often limited.

451 To systematically evaluate the performance of the localized emission library developed  
452 in this study, four simulation experiments (Simulation 1–4) were conducted under identical  
453 model configurations, with the only variation being the source of emission rates. Simulation 1

454 incorporated all available species-specific emission rates in our localized library, prioritizing  
 455 those with high accuracy (R-value = 1) and supplementing with lower-accuracy records  
 456 (R-value = 2) where necessary, thereby maximizing localization. Simulation 2 used only  
 457 R-value = 1 emission rates to establish a baseline under the most reliable data scenario.  
 458 Simulation 3 also employed the full localized library but favored R-value = 2 data and  
 459 supplemented it with R-value = 1. This design enabled a controlled assessment of data  
 460 quality influence through comparison with Simulation 1. In Simulations 1–4, for plants  
 461 without assigning localized emission rates, global data were used. Finally, Simulation 4 relied  
 462 on the default global emission rate library embedded in MEGANv3.2, serving as a reference  
 463 to quantify the net effect of emission rate localization when compared with Simulation 1. A  
 464 summary of the simulation design is provided in Table 2 for clarity.

465 **Table 2.** Simulation experiments for evaluation of the localized emission rate library.

Emission rate				Objective
Simulations	Local data with R-value =1	Local data with R-value =2	Global data in MEGANv3.2	
To maximize localization and represent the basic estimate using all available local data				
Simulation 1	✓✓✓	✓✓	✓	
To provide an estimate based solely on the high-quality local data				
Simulation 2	✓✓✓	-	✓✓	
To investigate the sensitivity of results to the data quality of emission rates, comparing with Simulation 1				
Simulation 3	✓✓	✓✓✓	✓	
To serve as a benchmark for quantifying the impact of localization				
Simulation 4	-	-	✓✓✓	

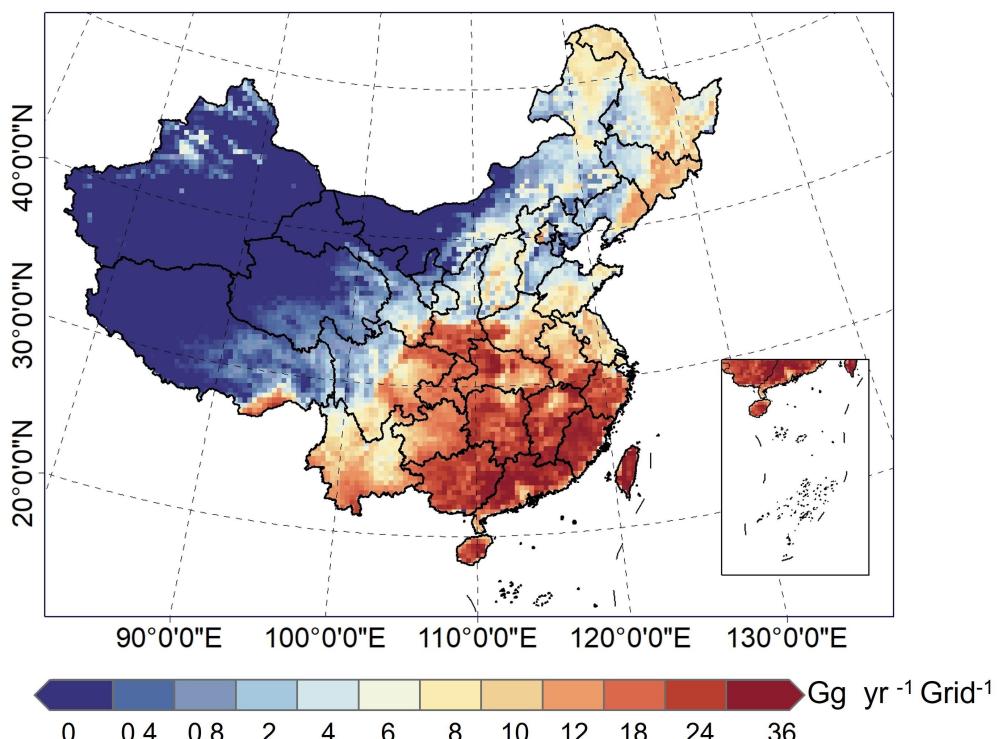
466 Note: The number of ✓ symbols shows the priority from high to low. Taking Simulation 1 as  
467 an example, the plant species-specific emission rates are assigned from the localized library  
468 with R-value = 1 primarily (labeled ✓✓✓), then those with R-value = 2 as a supplement  
469 (labeled ✓✓), and global data are used for plants without localized emission rates (labeled ✓).  
470

## 471 **4.2. BVOC emissions in China**

472 Based on the results in Simulation 1 where our developed emission rate library was fully  
473 applied—including the emission rates with R-values of both 1 and 2 (as in Table 2)—the  
474 annual total BVOC emission in China for the year 2020 was 27.70 Tg (detailed composition  
475 shown in Figure S5). In the four BVOC categories, other VOCs contributed the most,  
476 accounting for 47% of the total emissions. The large contribution was attributable to their  
477 large number of compound species, comprising more than half of the total simulated  
478 compounds in MEGANv3.2. Isoprene and monoterpenes exhibited comparable contributions,  
479 accounting for 23% and 25% of the total, respectively. Specifically, isoprene, butane, and  
480 isobutene emerged as the most substantial contributors to BVOC emissions, jointly  
481 accounting for 44%. Notably, in our study, the emission estimates for butane and isobutene  
482 used global emission factors without localization. They were even higher than the isoprene  
483 and monoterpene emission factors from our localized library for some tree species. This  
484 might have introduced uncertainties, and local observations for their emission rates are  
485 required in the future.

486 BVOC emissions in China exhibited large spatial variations, higher in the southeast and  
487 lower in the northwest (Figure 7). Specifically, high emissions in the Southeast Hill,  
488 Yunnan–Guizhou Plateau, and Taiwan Province, located in southeastern China, were  
489 primarily attributed to the extensive coverage of evergreen broadleaf trees (Cai et al., 2024).  
490 Among them, the widely distributed plants *Quercus fabri*, *Bambusa textilis*, and *Lithocarpus*  
491 *amygdalifolius* had higher isoprene emission rates of 85.5, 500.0, and 125.4  $\mu\text{g g}^{-1} \text{ h}^{-1}$ ,  
492 respectively. Suitable environments characterized by high temperatures were also major

493 contributors to the high emissions in these regions (Duan et al., 2023). Furthermore, the  
 494 Greater and Lesser Khingan Mountains and Changbai Mountains were rich in forest resources,  
 495 including both coniferous and broadleaf trees, accounting for over 77% of the total vegetation  
 496 distribution in those regions, resulting in relatively higher BVOC emissions. The North China  
 497 Plain and Sichuan Basin, with their widespread crop cultivation, accounting for 74% and 54%  
 498 of the total vegetation coverage, also exhibited high emissions. The lower emissions in the  
 499 northwest were likely due to the predominance of herb species with lower emission rates,  
 500 such as *Festuca ovina*, *Krascheninnikovia compacta*, and *Elymus nutans*.



501  
 502 **Figure 7.** Spatial distribution of BVOC emissions estimated based on the localized emission  
 503 rate library in China in 2020.

504  
 505 Compared with the results in Simulation 4, BVOC emissions were 18% higher after  
 506 updating the emission rates using our developed library than the emissions (23.44 Tg)  
 507 estimated using the global emission rates without localization. By BVOC categories, the  
 508 emissions of isoprene, monoterpenes, and sesquiterpenes increased by 55%, 29%, and 48%,

509 respectively. The contributions of isoprene, monoterpenes, sesquiterpenes, and other VOCs to  
510 total BVOC emissions changed from 18%, 23%, 4%, and 55% to 23%, 25%, 5%, and 47%,  
511 respectively. A discrepancy was also found in the spatial distribution (Figure 8c). In  
512 southeastern China, especially the Sichuan Basin, Simulation 1 showed higher emissions than  
513 Simulation 4. This was likely due to the widespread distribution of crops, which had higher  
514 emission rates in our library compared with the global one. Conversely, in western and  
515 northeastern China, particularly in the Greater and Lesser Khingan Mountains and Changbai  
516 Mountains, emissions in Simulation 1 were lower than in Simulation 4. This was mainly due  
517 to the extensive distribution of the genera *Pinus* and *Betula*. Their isoprene emission rates  
518 with R-value = 1 were used in Simulation 1, which were 80% and 86% lower than the global  
519 ones, respectively. Also, the plants of the two genera were widespread, accounting for 70% of  
520 the total vegetation coverage area in the Greater and Lesser Khingan Mountains and Changbai  
521 Mountains. To evaluate the spatial patterns of simulated BVOC emissions based on various  
522 emission rates, the correlation between emissions and observed formaldehyde (HCHO)  
523 vertical column density (VCD) was analyzed. HCHO in the atmosphere can serve as a reliable  
524 proxy for tracing the biogenic source of isoprene, especially in summer (Liu et al., 2024).  
525 Here, the Sentinel-5p TROPOspheric Monitoring Instrument (TROPOMI) Spaceborne HCHO  
526 products, which can be accessed through the Google Earth Engine platform  
527 (<https://code.earthengine.google.com/>), were used. It is important to note that in our study  
528 region, which is subject to anthropogenic influences, a substantial fraction of the atmospheric  
529 HCHO is expected to originate from anthropogenic VOCs (Ren et al., 2022). This likely  
530 caused uncertainty in our analysis, in summer. Meanwhile, satellite HCHO products also  
531 exhibit uncertainties (Chong et al., 2024). As shown in Figure S7, the isoprene emissions in  
532 July in Simulation 1 correlated more strongly with HCHO concentration spatially (correlation  
533 coefficient = 0.73,  $P < 0.05$ ) than in Simulation 4 (correlation coefficient = 0.67,  $P < 0.05$ ).  
534 This suggests that the application of our localized emission rate library could simulate the  
535 spatial variations of BVOC emissions better. Using the global emission rate library, there  
536 might be an underestimate in the south and an overestimate in the northeast and west, which

537 could be abated by updating the localized emission rates.

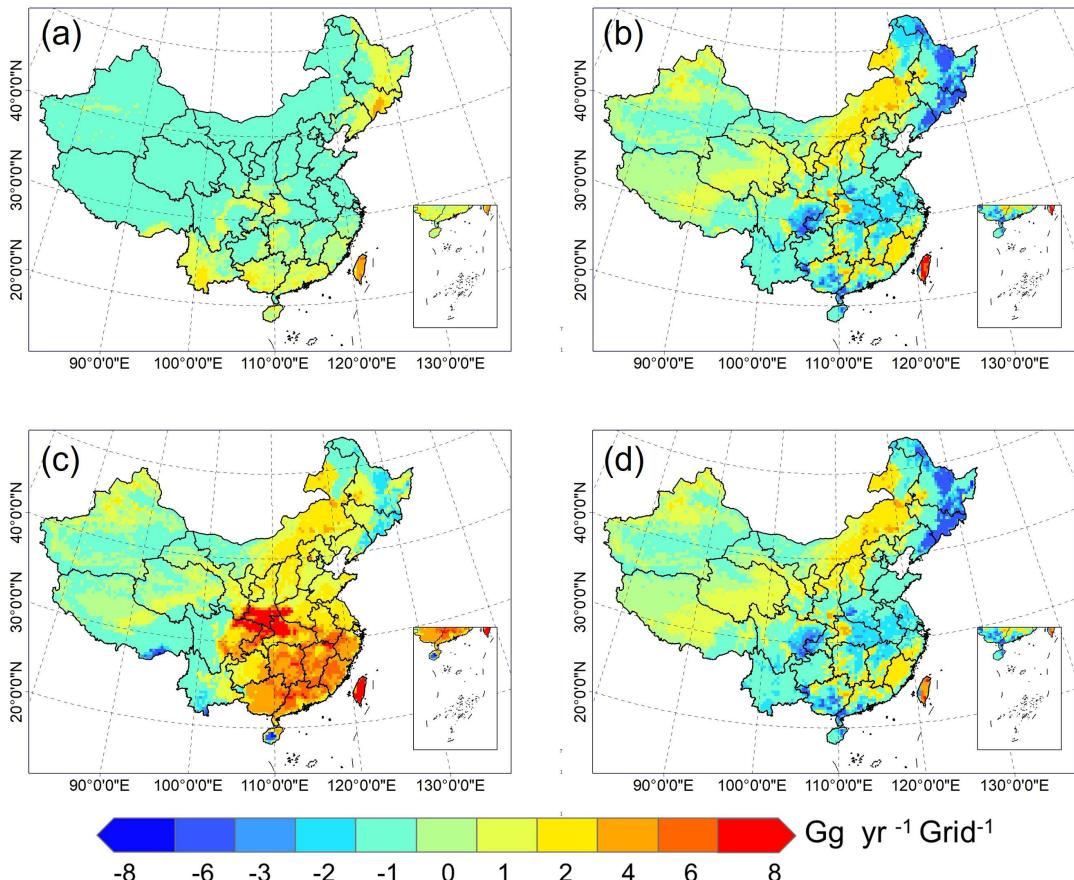
538 **4.3. Impact of emission rates with different reliability on BVOC  
539 emission estimates**

540 To apply more accurate emission rates, Simulation 2 was conducted employing only the  
541 emission rates with R-value = 1 from the localized library. For the plant species having  
542 emission rates with R-value = 2 in Simulation 1, the global emission rates were assigned in  
543 Simulation 2. Compared with the estimation from Simulation 1, there was a similar total  
544 emission (27.46 Tg). By BVOC categories, isoprene emissions increased by 4%, while  
545 monoterpene emissions decreased by 2%; the emissions of sesquiterpenes and other VOCs  
546 remained unchanged. The BVOC composition changed little. Spatially, in most regions of  
547 China, the emissions of Simulation 1 were slightly lower than those from Simulation 2 by  
548  $-1$  to  $0$  Gg  $\text{yr}^{-1}$  grid $^{-1}$  (Figure 8a). The main reason for this discrepancy was that plant  
549 emission rates were updated using R-value = 2 in Simulation 1, which was lower than the  
550 global ones in Simulation 2. Among these plants, herbs accounted for 84%, while trees  
551 and shrubs only accounted for 3% and 14%, respectively. The average isoprene and  
552 monoterpene emission rates of these herb species derived from our library were 7% and  
553 67% lower than those from the global library, respectively. In contrast, the emissions of  
554 Simulation 2 exceeded those of Simulation 1 in certain areas by  $0\text{--}6$  Gg  $\text{yr}^{-1}$  grid $^{-1}$ , which  
555 were concentrated in South China, the Lesser Khingan Mountains, and the Changbai  
556 Mountains. This was primarily due to the herb distribution belonging to the *Carex* genus,  
557 whose isoprene emission rates with R-value = 2 were 24% higher than the global values.  
558 These plants comprised 31% of the total herb coverage. The above resulted in only small  
559 changes in the national total BVOC emissions when excluding emission rates with lower  
560 reliability.

561 Furthermore, to investigate the impact of using emission rates with R-value = 1 versus  
562 R-value = 2 on the estimated emissions, Simulation 3 was conducted by using those with  
563 R-value = 2 preferentially and then those with R-value = 1 supplementally. The results in

564 Simulations 1 and 3 were compared. Simulation 3 produced an increase in BVOC emissions  
565 by 7%. By BVOC categories, isoprene and monoterpene emissions rose by 17% and 11%,  
566 respectively, while those of sesquiterpenes and other VOCs remained similar. Their  
567 contributions to the total BVOC emissions changed little. Spatially, in most regions, the  
568 emissions in Simulation 3 were higher than those in Simulation 1 (Figure 8b), particularly in  
569 the Sichuan Basin. *O. sativa*, a single crop species, accounted for 93% of the total crop  
570 coverage. Its isoprene and monoterpene emission rates for R-value = 2 were 1.2 and 14.2  $\mu\text{g}$   
571  $\text{g}^{-1} \text{h}^{-1}$ , respectively, much higher than those with R-value = 1 (0.18 and 5.8  $\mu\text{g g}^{-1} \text{h}^{-1}$ ). In the  
572 Lesser Khingan Mountains and Changbai Mountains, the isoprene emission rate for the  
573 widely distributed genus *Larix* with R-value = 2 was 166% higher than that with R-value = 1;  
574 for the species *Pinus koraiensis*, the monoterpene emission rate with R-value = 2 was 390%  
575 higher. Conversely, in areas where herbs were widely distributed, especially in the northwest  
576 of China, the emissions in Simulation 3 were lower than those in Simulation 1. This was  
577 likely because, for most herb species, emission rates at R-value = 2 were lower than those at  
578 R-value = 1. For instance, the applied isoprene emission rates for the genera *Stipa*,  
579 *Cleistogenes*, and *Leymus* in Simulation 1 were 125.8, 258.9, and 59.5  $\mu\text{g g}^{-1} \text{h}^{-1}$ , respectively,  
580 while they were 1.2, 1.2, and 4.2  $\mu\text{g g}^{-1} \text{h}^{-1}$ , respectively, in Simulation 3. For emissions  
581 estimated in Simulation 3, the correlation between emissions and observed HCHO VCD was  
582 analyzed, with a correlation coefficient of 0.63 ( $P < 0.05$ ). Meanwhile, the correlation  
583 coefficient (0.72) for the emissions estimated in Simulation 2 was also higher than that in  
584 Simulation 3. Their correlation coefficient was 0.63 ( $P < 0.05$ ), lower than that in Simulation  
585 1. Meanwhile, the correlation coefficient (0.72) for the emissions estimated in Simulation 2  
586 was also higher than that in Simulation 3. Therefore, it can be concluded that greater  
587 application of emission rates from dynamic measurements leads to better implications for  
588 emission estimates. Together with maximizing localization, namely using emission rates from  
589 static measurements as a supplement, better results will be obtained. Notably, similar national  
590 total BVOC emissions and spatial accuracy were observed between Simulations 1 and 2  
591 because most of the species (84%) with emission rates of R-value = 2 were herbs, whose

592 coverage was limited. Overall, using emission rates with R-value = 2 could overestimate total  
 593 BVOC emissions in China. Therefore, additional high-reliability emission observations using  
 594 dynamic techniques are strongly encouraged to further improve the accuracy of the localized  
 595 emission rate library and emission inventory.



596  
 597 **Figure 8.** Spatial distribution of differences among BVOC emissions simulated using  
 598 different emission rates: (a–d) Simulation 1 minus Simulation 2 (a), Simulation 1 minus  
 599 Simulation 3 (b), Simulation 1 minus Simulation 4 (c), Simulation 2 minus Simulation 3 (d).

600

## 601 **5. Conclusion**

602 By integrating our field measurements with reported local measurements, a statistical  
 603 approach for classifying emission categories and determining plant species-specific emission  
 604 rates for BVOC emission inventory compilation was developed. It produced more detailed

605 categories of emission intensity, accurate emission rate intervals, and representative values  
606 compared to previous studies, namely ten, ten or eleven, and eight categories respectively for  
607 isoprene, monoterpene, and sesquiterpene emission rates. The detailed categories for emission  
608 intensity can further improve the determined representative emission rates. Based on this, a  
609 localized plant species-specific BVOC emission rate library for China was developed,  
610 including isoprene, monoterpene, and sesquiterpene emission rates for 599 plant species. In  
611 this library, observations from both dynamic and static techniques were included and  
612 separated with different reliability. Variability was found in the emission rates derived from  
613 dynamic and static enclosure measurements. Specifically, measurements by static enclosure  
614 technique may underestimate the emissions of plants with higher emission intensity and  
615 overestimate the emissions of plants with lower emission intensity. Analyzing the emission  
616 rates derived from the dynamic technique measurements in our library, and comparing the  
617 means and medians among vegetation types, herbs showed the highest isoprene emission  
618 level, followed by trees and shrubs; herbs also had the highest monoterpene emission level,  
619 followed by shrubs, while trees and crops were comparatively lower; trees and shrubs showed  
620 the highest sesquiterpene emission levels, followed by herbs and crops. Interspecific  
621 differences were exhibited within the same type, family, or genus.

622 Furthermore, our localized emission rate library was applied in China's BVOC emission  
623 inventory compilation, with performance evaluation. By updating the localized emission rates,  
624 the simulated BVOC emission in China in 2020 was 27.70 Tg, 18% higher than that using the  
625 global emission rate library. Isoprene, monoterpenes, sesquiterpenes, and other VOCs  
626 contributed 23%, 25%, 5%, and 47% to the total emissions, respectively. It had better  
627 performance in emission estimation, with the higher correlation coefficient of 0.73 ( $P < 0.05$ )  
628 between isoprene emission and HCHO VCD observations spatially. The underestimates in the  
629 south and overestimates in the northeast and west when using global emission rates could be  
630 reduced by updating the localized ones. Using emission rates with different reliability could  
631 result in different emission estimates and model performance. The use of emission rates  
632 measured by static enclosure technique could decrease the accuracy of estimation and result

633 in an overestimation of BVOC emissions. Therefore, in BVOC emission inventory  
634 compilation, it is suggested to use emission rates measured by the dynamic enclosure  
635 technique more to achieve more accurate results.

636 Although our developed localized emission rate dataset is beneficial for improving the  
637 accuracy of the emission inventory, uncertainties still exist in the dataset and its application.  
638 First, the dataset includes only a limited number of plant species, making it difficult to cover  
639 all the plants in China. Researchers must use global emission rates for plants without  
640 localized observations. Second, uncertainties may be introduced when assigning emission  
641 rates based on observations of plants within the same genus or family. For the emission rates  
642 with R-value = 1, 16% were allocated by genus and 13% by family; for those with R-value =  
643 2, 3% were allocated by genus and 5% by family. Third, for monoterpene and sesquiterpene  
644 emission rates separately, some of the raw observed results are the sum of their studied  
645 dominant compounds rather than the whole category of monoterpenes and sesquiterpenes.  
646 Therefore, in the application of our dataset, there may be an underestimation of their  
647 emissions. Meanwhile, the MEGAN model requires more detailed categories for them; it is  
648 better to conduct compound-specific observations and obtain their emission rates. Fourth, the  
649 determined emission categories can be more detailed, and the emission rate intervals and  
650 representative values can be more accurate if more local observation samples are available.  
651 The above uncertainties would be reduced by including more reliable local emission  
652 measurements, specifically by plant species and compounds, in the future. Notably, despite  
653 the current uncertainties, our study starts the effort to establish a reliable localized dataset of  
654 BVOC emission rates used in inventory compilation. Undeniably, it helps improve the  
655 regional representativeness of model inputs for China and better captures the spatial  
656 variations of BVOC emissions. Meanwhile, our developed statistical approach can be  
657 extended to the establishment of localized BVOC emission rate datasets for other regions.

658

659 **Data availability**

660 All datasets used in this study are publicly available. The localized plant species-specific  
661 BVOC emission rate dataset is available from *Zenodo* at  
662 <https://doi.org/10.5281/zenodo.14557394>. Spaceborne HCHO products is available from  
663 Google Earth Engine platform at <https://code.earthengine.google.com>. Database of  
664 high-resolution vegetation distribution (HRVD) is available from *Zenodo* at  
665 <https://zenodo.org/records/10830151>. LAI is available from the MODIS version 6.1 LAI  
666 product at <http://globalchange.bnu.edu.cn/research/laiv061>.

667

668 **Author contributions**

669 LL conceived and designed the study, HH performed the data analysis, carried out the  
670 model simulations, and drafted the manuscript with the help of RS, CN, and YK. YJ  
671 conducted data field measurements and collection, YW provided analysis of the measured  
672 data.

673

674 **Competing interests**

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

676

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