



1 **Unheralded contributions of biogenic volatile organic compounds from urban greening**
2 **to ozone pollution: a high-resolution modeling study**

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19



20 **Abstract**

21 Urban Green Spaces (UGS) are widely advocated for mitigating urban atmospheric environment. However,
22 this study reveals that it can exacerbate urban ozone (O₃) levels under certain conditions, as demonstrated by
23 a September 2017 study in Guangzhou, China. Utilizing the Weather Research and Forecasting Model with
24 the Model of Emissions of Gases and Aerosols from Nature (WRF-MEGAN) and the Community Multiscale
25 Air Quality (CMAQ) model with a high horizontal resolution (1 km), we assessed the impact of UGS-related
26 biogenic volatile organic compound (BVOC) emissions on urban O₃. Our findings indicate that UGS-BVOC
27 emissions in Guangzhou amounted to 666.49 Gg, primarily from isoprene (ISOP) and terpenes (TERP). These
28 emissions contribute ~30% of urban ISOP concentrations and their incorporations to the model significantly
29 reduce the underestimation against observations. The study shows improvements in simulation biases for NO₂,
30 from 7.01 μg/m³ to 6.03 μg/m³, and for O₃, from 7.77 μg/m³ to -1.60 μg/m³. UGS-BVOC and UGS-LUCC
31 (land use cover changes) integration in air quality models notably enhances surface monthly mean O₃
32 predictions by 3.6-8.0 μg/m³ (+3.8-8.5%) and contributes up to 18.7 μg/m³ (+10.0%) to MDA8 O₃ during O₃
33 pollution episodes. Additionally, UGS-BVOC emissions alone increase the monthly mean O₃ levels by 2.2-
34 3.0 μg/m³ (+2.3-3.2%) in urban areas and contribute up to 6.3 μg/m³ (+3.3%) to MDA8 O₃ levels during O₃
35 pollution episodes. These impacts can extend to surrounding suburban and rural areas through regional
36 transport, highlighting the need for selecting low-emission vegetation and refining vegetation classification in
37 urban planning.

38 **Keywords**

39 Urban green space; BVOC; Ozone; Land use cover; CMAQ; MEGAN

40

41 **1. Introduction**

42 Exposure to air pollution now accounts for more fatalities than malaria, tuberculosis, and HIV/AIDS combined
43 (Lelieveld et al., 2020). As a result, the World Health Organization has declared air pollution the most
44 significant environmental threat to human health (WHO, 2021). Notably, over 70% global health burden of
45 air pollution stems from human-made emissions, leading to a policy focus predominantly on reducing these



46 emissions (Chowdhury et al., 2022; Lelieveld et al., 2019). Despite proactive measures to curb anthropogenic
47 emissions, the incidence of ozone episodes is escalating alongside rapid urbanization (Lu et al., 2020; Yim et
48 al., 2019). Numerous studies have investigated the effects of land use cover changes (LUCC) on air quality
49 during urbanization using numerical models and the majority of these studies conclude that urbanization
50 exacerbates air pollution (Qiu et al., 2023; Wang et al., 2022). However, such studies that depend on numerical
51 models usually face the coarse-resolution land use cover data limitation (Ma et al., 2022, 2019), which leads
52 these studies to frequently overlook a passive abatement approach distinct from reducing anthropogenic
53 sources—namely, the cultivation of urban green spaces (UGS) (Cohen et al., 2017).

54

55 The widely accepted notion that UGS can enhance air quality is substantiated by various strands of literature,
56 including public health (Burnett et al., 2018), urban planning (Solomon, 2007), and ecosystem services
57 (Lohmann et al., 2010). This concept is not only prevalent in scholarly circles but also gains traction in popular
58 media and is echoed in international standards and policy frameworks. For instance, the United Nations
59 System of Environmental-Economic Accounting advocates for vegetation as a nature-based approach to
60 mitigate air pollution (Le Page et al., 2015). Vegetation primarily contributes to air pollution reduction through
61 two mechanisms: deposition and dispersion (Shindell et al., 2012). Deposition involves the absorption of air
62 pollutants onto vegetative surfaces, while dispersion refers to the reduction of air pollutant concentrations
63 through aerodynamic effects caused by vegetation (Zhao et al., 2022). Notably, dispersion effects are
64 significantly more impactful than deposition, exceeding it by an order of magnitude (Ramanathan et al., 2001).

65

66 However, the efficacy of dispersion effects resulting from UGS-LUCC in reducing air pollution is not
67 straightforward. These effects can, under certain conditions, even increase local air pollution concentrations.
68 These conditions are influenced by several factors, such as the specific structure of the UGS vegetation
69 properties (e.g., height, leaf density), the site context (e.g., street canyon geometry, proximity to emission
70 sources), and prevailing meteorological conditions (e.g., wind speed and direction) (Ramanathan et al., 2001;
71 Solomon, 2007). For example, dense tree canopies might impede ventilation in urban street canyons, while
72 porous vegetation barriers in open-road settings could potentially intensify roadside air pollution
73 concentrations (Allen and Ingram, 2002; Cohen et al., 2017). Furthermore, Seinfeld et al., (1998) underscores
74 the complexity of these interactions, and they demonstrated that vegetation could exert nonlinear effects on
75 meteorological processes. These effects are particularly evident in their impact on the Planetary Boundary
76 Layer Height (PBLH) and the turbulent transport and advection of pollutants, which in turn influence
77 dispersion conditions.



78

79 UGS also have a complex role in air quality due to their production of biogenic volatile organic compounds
80 (BVOCs). For instance, in cities like Los Angeles, the UGS-BVOC emissions contribute to a quarter of the
81 secondary organic aerosol formation on hot days (Ramanathan et al., 2005). While Guenther et al., (2012)
82 noted that the majority of BVOC emissions are from natural land cover, Ma et al., (2022) indicates that in
83 metropolitan areas, the UGS-BVOC emissions can be significantly higher, ranging from 1 to 30 times those
84 from natural land use cover. This evidence suggests a dual nature of UGS vegetation in urban environments:
85 it can mitigate air pollution under certain conditions, but conversely, there is substantial experimental and
86 modelling evidence showing it can exacerbate pollution under different circumstances (Allen and Ingram,
87 2002; Burnett et al., 2018; Cohen et al., 2017). Moreover, metropolitan areas often encounter VOC-limited
88 conditions, or NO_x-saturation, where even minimal BVOC emissions can lead to notable O₃ production (Wang
89 et al., 2019). Additionally, urban areas typically experience higher temperatures than their surrounding natural
90 landscapes due to the urban heat island effect (Masson-Delmotte et al., 2021). This increase in temperature is
91 likely to further amplify the UGS-BVOC emissions (Zhou et al., 2015), influencing O₃ concentrations
92 significantly. This interaction might explain why many regional numerical models underestimate urban
93 surface ozone levels, as they often lack high-resolution land use cover data necessary to accurately estimate
94 the UGS-BVOC emissions (Qiu et al., 2023; Wang et al., 2021; Wu et al., 2020).

95

96 Currently, there is a growing research interest in characterizing the air quality impacts of UGS. While
97 Arghavani et al., (2019) investigating the effects of UGS on gaseous air pollutants in Tehran using the WRF-
98 Chem model, their focus was on the impact of meteorological changes on O₃ resulting from UGS (i.e., UGS-
99 LUCC effects), rather than the UGS-BVOC emissions effects on O₃. In contrast, Schlaerth et al., (2023a)
100 addressed the influence of the UGS-BVOC emissions on O₃ in Los Angeles and their findings indicate that
101 the UGS-BVOC emissions may increase O₃ by 0.95 ppb during the daytime and decrease it by 0.41 ppb at
102 night. Despite Schlaerth et al., (2023a) illustrating the significance of the UGS-BVOC emissions on O₃
103 concentrations, they did not investigate the impact of the UGS-LUCC effects.

104

105 The nonlinear correlation between O₃ and concentrations of BVOC and NO_x underscores the importance of
106 examining potential interactions between the UGS-BVOC emissions and anthropogenic emissions.
107 Furthermore, recent studies have highlighted the significance of the UGS-LUCC effects and the UGS-BVOC
108 emissions effects. Given the rise in urban O₃ pollution, investigating the influence of the UGS-LUCC effects
109 and the UGS-BVOC emissions effects on O₃ can assist in rationalizing UGS planning and formulating air



110 quality mitigation strategies. However, there is a lack of quantification regarding the combined effects of
111 UGS-LUCC and UGS-BVOC emissions on O₃.

112

113 Situated in South China, Guangzhou is one of the rapidly expanding cities in China since the initiation of the
114 reform and opening-up policy, undergoing swift urbanization (Yao and Huang, 2023). Being a key city in the
115 Guangdong-Hongkong-Macao Greater Bay Area, Guangzhou places significant emphasis on UGS
116 development. In this study, we aim to reconstruct the leaf area index (LAI) dataset for urban areas and estimate
117 the UGS-BVOC emissions utilizing the Model of Emissions of Gases and Aerosols from Nature version 3.1
118 (MEGANv3.1) (Guenther et al., 2020a). Subsequently, employing the Weather Research and Forecast model
119 version 4.1.1 (WRFv4.1.1) (Salamanca et al., 2011) – Community Multiscale Air Quality model version 5.4
120 (CMAQv5.4) (<https://zenodo.org/record/7218076>, last accessed: June 3, 2023), we intend to estimate the
121 improvements of the CMAQ simulation performance from considering UGS-LUCC and UGS-BVOC and
122 investigate the UGS-LUCC effects, the UGS-BVOC emissions effects, and their combined impacts on O₃ over
123 Guangzhou by configuring sensitivity scenarios.

124 **2. Methods and data**

125 **2.1 Leaf area index and land cover dataset**

126 The default LAI dataset to drive the MEGANv3.1 model is derived from the enhanced Moderate Resolution
127 Imaging Spectroradiometer (MODIS) /MOD15A2H in 2003 with 1 km spatial resolution (Myneni et al., 2015).
128 As MODIS/MOD15A2H assigns an LAI value of 0 to urban areas, MEGANv3.1 compensates by averaging
129 the LAI values in the vicinity of the urban area. However, this approach introduces considerable uncertainty
130 in the estimation of UGS-BVOC emissions. Hence, we opted for the Global Land Surface Satellite (GLASS)
131 LAI product for MEGANv3.1 in 2017 with 500-m spatial resolutions, derived from MODIS surface
132 reflectance data using the bidirectional long short-term memory (Bi-LSTM) model, which leverages existing
133 global LAI products (Ma and Liang, 2022) and effectively incorporates the temporal and spectral information
134 of MODIS surface reflectance. Consequently, the valid values of this data extend to urban areas, making it
135 suitable for simulating the UGS-BVOC emissions.

136

137 In this study, UGS are delineated as vegetation areas within the urban grid, and the urban grids are derived
138 from MODIS/MCD12Q1 (Friedl and Sulla-Menashe, 2019) in 2017, which corresponds to the simulation



139 period with 500 m spatial resolution. Furthermore, a high-resolution (10 m) land cover dataset in 2017 was
140 also obtained from the Geographic Remote Sensing Ecological Network Platform (accessible at
141 <http://www.gisrs.cn/infofordata?id=1c089287-909e-4394-b07f-c7004be60884>, last accessed: 20/11/2023)
142 and was employed to depict the spatial patterns of UGS. The processed land cover dataset is illustrated in
143 Figure S1. Meanwhile, the use of high-resolution land use cover data is pivotal for accurately depicting the
144 intricate details of land use cover, especially in areas broadly classified as urban by coarse-resolution data (i.e.,
145 MCD12Q1) and this refined approach allows for a more precise differentiation of UGS. Specifically, we
146 maintain a consistent urban area definition across both land use cover datasets, anchored by the urban
147 delineation provided by the MCD12Q1 dataset. However, the coarse resolution of MCD12Q1 is insufficient
148 for detailed spatial characterization of UGS. To address this limitation, we employ the high-resolution dataset
149 to refine the characterization of non-urban surfaces within the urban boundaries (i.e., UGS) defined by
150 MCD12Q1. This approach yields a sophisticated land cover dataset with 10 m spatial resolution that retains
151 the urban extent delineated by MCD12Q1 while incorporating detailed representations of UGS absent in the
152 original dataset. Consequently, while both datasets encompass identical urban extents, the default dataset lacks
153 representations of UGS, in contrast to the high-resolution dataset, which includes detailed depictions of UGS.

154 2.2 MEGANv3.1 configuration

155 The calculation of BVOC emissions was performed utilizing MEGANv3.1 (accessible at
156 <https://bai.ess.uci.edu/megan>, last accessed: 21 November 2023). MEGAN estimates BVOC emissions as the
157 product of an emission factor and an emission activity factor (Guenther et al., 2012a):

$$158 \text{ Emission} = \varepsilon \cdot \gamma \cdot \rho \quad (\text{Eq. 1})$$

159
160 In this equation, ε ($\text{mg} \cdot \text{m}^{-2} \cdot \text{h}^{-1}$) denotes an emission factor representing the emission rate under standard
161 conditions; ρ signifies the production and consumption within the canopy, typically set as 1. The emission
162 activity factor (γ) considers emission responses to changes in environmental and phenological conditions,
163 and its calculation is as follows:

$$164 \gamma_i = C_{CE} \cdot \text{LAI} \cdot \gamma_{P,i} \cdot \gamma_{T,i} \cdot \gamma_{A,i} \cdot \gamma_{SM,i} \cdot \gamma_{C,i} \quad (\text{Eq. 2})$$

165
166 In this equation, the activity factor for each compound class (i) denotes the emission response to light (γ_P),
167 temperature (γ_T), leaf age (γ_A), soil moisture (γ_{SM}), Leaf Area Index (LAI), and CO_2 inhibition (γ_C). The
168 canopy environment coefficient (C_{CE}) is assigned a value that ensures $\gamma = 1$ under standard conditions and



169 depends on the canopy environment model in use (Guenther et al., 2020a). In numerous applications of
170 MEGAN, the activity factors for soil moisture and CO₂ inhibition were disregarded (Guenther et al., 2012a;
171 Sindelarova et al., 2014).

172

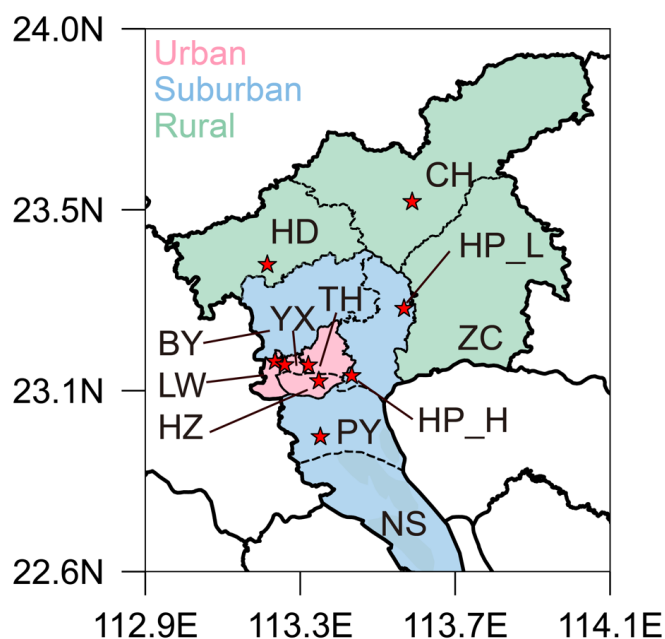
173 Hence, the input data to drive MEGANv3.1 comprises meteorological variables (e.g., temperature, solar
174 radiation, relative humidity, soil moisture), LAI, and three types of land cover data (i.e., ecotype, growth
175 form, and relative vegetation composition for each ecotype/growth form). Meanwhile, the growth form
176 datasets in MEGANv3.1 contain considerations of evergreen broadleaf forests, grasslands, and crops, which
177 cover all types of UGS in Guangzhou city (Figure S1). Meteorological data are obtained from the WRF
178 simulation results, and the LAI dataset is detailed in Section 2.1 as well as additional default land cover data
179 provided by MEGANv3.1 were employed.

180 **2.3 WRF-CMAQ and Scenario Configuration**

181 Both the WRFv4.1.1 model and the CMAQv5.4 model are compiled and operated on a server with a Linux
182 environment. The WRFv4.1.1 model was employed to simulate meteorological conditions, utilizing initial and
183 boundary conditions sourced from the NCEP 1° × 1° Final (FNL) reanalysis dataset (National Centers for
184 Environmental Prediction, National Weather Service, NOAA, U.S. Department of Commerce, 2000). As
185 illustrated in Figure S2, four nested domains with horizontal resolutions of 27, 9, 3, and 1 km, respectively,
186 were employed. The outermost domain encompasses mainland China, while the innermost domain zooms in
187 Guangzhou city, and the physical parameterization configured for the WRF simulation is listed in Table S1.
188 CMAQv5.4 utilized meteorological fields provided by WRF to model O₃ concentrations. The initial and
189 boundary conditions for CMAQ were derived from the default profiles representing a clean atmosphere. In
190 addition, we acquired anthropogenic emissions for the CMAQ domain from the Multi-resolution Emission
191 Inventory for China (MEIC) 2017 developed by Tsinghua University, which contains monthly gridded (0.25°
192 × 0.25°) emissions information for anthropogenic emissions. Moreover, CMAQ was configured with the
193 Carbon Bond chemical mechanism (CB06) (Luecken et al., 2019) and AERO7 (Pye et al., 2017). In this study,
194 we incorporated the Modular Emission Inventory Allocation Tools for the Community Multiscale Air Quality
195 model (MEIAT-CMAQ, <https://github.com/Airwhf/MEIAT-CMAQ>, last accessed: February 27, 2024) to
196 allocate spatial and species-specific emissions within the raw inventories, addressing discrepancies in
197 resolution and species compared to the modeled configurations. Moreover, MEIAT-CMAQ can directly
198 generate the hourly model-ready emission files for CMAQ via temporal allocation. The model simulation



199 spanned a month, from 21 August 2017 to 30 September 2017. To mitigate bias resulting from meteorological
200 and chemical drift, the initial 10 days of this simulation were designated as spin-up and were not included in
201 the analysis for this study. Given the spatial heterogeneity in the distribution of UGS across different areas,
202 this study categorizes Guangzhou into urban, suburban, and rural regions (Figure 1). Specifically, the urban
203 areas comprise Haizhu (HZ), Liwan (LW), Yuexiu (YX), and Tianhe (TH) districts. The suburban areas
204 encompass Huangpu (HP), Baiyun (BY), Panyu (PY), and Nansha (NS) districts. Lastly, the rural regions
205 include Zengcheng (ZC), Conghua (CH), and Huadu (HD) districts. To facilitate clear differentiation between
206 the two sites in the HP region, they have been designated as HP_L and HP_H, respectively.



207

208 **Figure 1** The innermost domain of WRF-CMAQ with various areas and the air quality station locations map.

209

210 In this study, four distinct scenarios, as listed in Table 1 were established to investigate the impacts of UGS-
211 LUCC, UGS-BVOC, and their combined effects on the ozone simulation. These scenarios also focused on the
212 performance of the CMAQ simulation and the influence on O₃ episodes. The Gdef_N scenario considered as
213 the base case, employs default land use cover data—specifically, data excluding UGS, and utilizes the LAI
214 dataset with urban areas omitted (N-LAI). In contrast, the Gdef_Y scenario is similar to Gdef_N but
215 incorporates the LAI dataset that includes urban areas (T-LAI). This adjustment allows for the assessment of
216 the UGS-BVOC emission effects on O₃ concentrations. The Ghr_N scenario mirrors Gdef_N but differs by
217 integrating high-resolution land use cover data, which encompasses UGS land use cover. This scenario aims



218 to examine the UGS-LUCC effects on O₃ concentrations. Finally, the Ghr_Y scenario combines high-
219 resolution land use cover data with the LAI dataset inclusive of urban areas, thereby enabling an exploration
220 of the combined effects of UGS-BVOC emissions and UGS-LUCC on O₃ concentrations.

221 **Table 1 Scenario configurations**

Name	LC dataset	LAI dataset	Description
Gdef_N	Default data	N-LAI	Base
Gdef_Y	Default data	T-LAI	UGS-BVOC effects
Ghr_N	High-resolution data	N-LAI	UGS-LUCC effects
Ghr_Y	High-resolution data	T-LAI	combined effects

222 **2.4 Observation Dataset**

223 We utilize hourly ground-level meteorological observations, encompassing 2-m temperature (T2) and 10-m
224 wind speed (WS10), sourced from national basic meteorological stations provided by the Guangdong
225 Provincial Meteorological Service (Figure S3). Hourly ambient concentrations of O₃ from national monitoring
226 stations are gathered from the China National Environmental Monitoring Centre (CNEMC). The locations of
227 these air quality stations are depicted in Figure 1, and the air quality data and meteorological data both undergo
228 thorough quality control. Subsequently, they are utilized to assess the model performance of WRF-CMAQ.

229 **3. Results and discussion**

230 **3.1 Model Evaluation**

231 Evaluation of the WRF-CMAQ model performance is undertaken through comparison against ground-level
232 observations and the evaluation metrics of meteorological parameters are listed in Table S2, which shows that
233 the meteorological fields were faithfully reproduced in this study and can be used to drive the air quality model.
234

235 The primary sources of isoprene (ISOP) and monoterpenes (TERP) are BVOCs, rendering the assessment of
236 their concentrations a pivotal method for indirectly verifying the accuracy of BVOC emission estimates. Table
237 2 delineated within this study presents the mean concentrations of ISOP and TERP derived from various
238 scenarios juxtaposed with the observed average concentrations. This comparative analysis reveals that after
239 the incorporation of UGS-BVOC emissions, there is an augmentation in the ISOP concentration from 0.24
240 ppb to 0.31 ppb and from 0.21 ppb to 0.28 ppb under distinct land use cover scenarios (Gdef and Ghr), relative



241 to an observed concentration of 0.33 ppb. This increment signifies a substantial diminution in the discrepancy
 242 between the modeled and observed concentrations attributable to UGS-BVOC emissions. Analogously, the
 243 integration of UGS-BVOC emissions yields a refinement in the estimation accuracy of ISOP concentrations
 244 at both Modiesha and Wanqinsha sites, as evidenced by a reduced bias.

245

246 These findings reveal that ISOP concentrations are underestimated by 26.19%-36.36% when UGS-BVOCs
 247 are excluded. Specifically, this range represents the proportion of ISOP originating from UGS-BVOCs.
 248 Moreover, numerous studies highlight the significant role of ISOP in ozone formation within the Pearl River
 249 Delta (PRD) region, including Guangzhou. For instance, Zheng et al., (2009) demonstrated that ISOP has the
 250 highest ozone formation potential among all VOCs. Therefore, incorporating UGS-BVOCs into ISOP
 251 concentration estimates is crucial for accurately modeling regional ozone levels.

252

253 **Table 2 Evaluation of ISOP concentrations.**

Location	Observed period	observed concentration (ppb)	Gdef_N (ppb)	Gdef_Y (ppb)	Ghr_N (ppb)	Ghr_Y (ppb)	Reference
Modiesha (urban) 23.11N, 113.33E	20 Sep. 2017 – 20 Nov. 2017	0.33	0.24	0.31	0.21	0.28	Meng et al., (2022)
Wanqinsha (suburban) 22.43N, 113.33E	20 Sep. 2017 – 20 Nov. 2017	0.42	0.31	0.38	0.27	0.35	Meng et al., (2022)

254

255 Additionally, various statistical metrics were utilized to assess the performance of NO₂ and O₃ concentrations
 256 from CMAQ simulation (Emery et al. 2017). These metrics comprise the correlation coefficient (R),
 257 normalized mean bias (NMB), and normalized mean error (NME). The formulas for these metrics are listed
 258 in Table S3. Emery et al. (2017) propose that the model performs acceptably when NMB and NME of hourly
 259 O₃ concentrations are less than 15% and 25%, respectively, and the correlation coefficient (R) is greater than
 260 0.5. As illustrated in Table 3, it is evident that all the scenarios exceed the specified requirement, albeit with
 261 some degree of underestimation. Despite these discrepancies, the model demonstrates sufficient reliability and
 262 can be effectively utilized in subsequent research. In addition, we also evaluate the simulation performance
 263 for NO₂ in each scenario and the results suggest that all models have R above 0.63, and while there is some
 264 overestimation, the NMB is 15.0%, 15.2%, 13.0%, and 13.2% for Gdef_N, Gdef_Y, Ghr_N, and Ghr_Y,
 265 respectively. It should be emphasized that integrating UGS-BVOC into the modeling process can slightly
 266 improve the accuracy of NO₂ predictions, reducing the MB from 7.01 µg/m³ to 6.94 µg/m³, and from 6.09
 267 µg/m³ to 6.03 µg/m³ for Gdef and Ghr scenarios, respectively.



268 **Table 3: The evaluation results for each scenario.**

Pollutant		Sim ($\mu\text{g}/\text{m}^3$)	Obs($\mu\text{g}/\text{m}^3$)	MB($\mu\text{g}/\text{m}^3$)	NMB	NME	R
O ₃	Gdef_N	60.49	65.33	-4.84	-6.7%	23.6%	0.82
	Gdef_Y	61.43	65.33	-3.90	-5.3%	23.6%	0.82
	Ghr_N	61.91	65.33	-3.42	-4.8%	22.5%	0.83
	Ghr_Y	62.86	65.33	-2.47	-3.4%	22.4%	0.83
NO ₂	Gdef_N	53.09	46.07	7.01	15.2%	45.7%	0.63
	Gdef_Y	53.02	46.07	6.94	15.0%	45.5%	0.63
	Ghr_N	52.17	46.07	6.09	13.2%	43.8%	0.63
	Ghr_Y	52.11	46.07	6.03	13.0%	43.6%	0.63

269

270 In terms of O₃, the UGS-BVOC, UGS-LUCC, and combined effects have various performances in different
 271 regions (Table 4). These results indicate that the inclusion of UGS-BVOC emissions significantly influences
 272 MDA8 O₃ concentrations in urban regions and this effect, primarily observed when comparing the Gdef_Y
 273 with Gdef_N and Ghr_Y with Ghr_N scenarios, is largely due to the VOC-limited areas prevalent in
 274 Guangzhou (He et al., 2024). By integrating the UGS-BVOC emissions into the models (comparing Gdef_Y
 275 and Gdef_N scenarios), the bias in all regions, including a notable improvement in the urban region from -
 276 7.77 $\mu\text{g}/\text{m}^3$ to -1.60 $\mu\text{g}/\text{m}^3$, is reduced. Additionally, the UGS-BVOC emissions slightly enhance R values in
 277 the urban and suburban regions, indicating a more accurate MDA8 O₃ trend representation. The UGS-LUCC
 278 (land use and land cover change) effects, as seen when comparing Ghr_N and Gdef_N scenarios, also
 279 significantly improve model biases and the combined effects of both UGS-BVOC and UGS-LUCC
 280 (comparing Ghr_Y and Gdef_N scenarios) substantially ameliorate model biases in the urban and suburban
 281 regions.

282 **Table 4 The evaluation results for O₃ in various regions.**

Regions	MB ($\mu\text{g}/\text{m}^3$)				R			
	Gdef_N	Gdef_Y	Ghr_N	Ghr_Y	Gdef_N	Gdef_Y	Ghr_N	Ghr_Y
Urban	-7.773	-4.803	-4.523	-1.600	0.805	0.810	0.810	0.813
Suburban	-8.737	-6.967	-6.880	-5.093	0.737	0.743	0.717	0.727
Rural	-10.950	-10.195	-10.430	-9.705	0.665	0.655	0.695	0.690

283 3.2 Estimation of UGS-BVOC emissions under different land use cover

284 This study comprehensively summarizes the UGS-BVOC emissions across various species for all regions in
 285 Guangzhou City in September. Given that the variances in the UGS-BVOC emissions due to different land
 286 use covers are relatively minor, the primary Table 5 presents emissions driven by the default land use cover.
 287 For a detailed breakdown of emissions attributable to varied land use covers, refer to Table S4. A review of
 288 the data reveals that monoethylene (TERP) and isoprene (ISOP) rank as the highest emitting species with
 289 proportions are 20.46% and 31.91% in this study, respectively, aligning with the findings of previous studies



290 (Cao et al., 2022; Guenther et al., 2012b). Furthermore, Table 5 reveals that in September, the suburban region
 291 registered the highest UGS-BVOC emissions in Guangzhou, peaking at 367.31 Gg. This is followed closely
 292 by the rural and urban regions, recording emissions of 173.65 Gg and 125.53 Gg, respectively.

293 **Table 5** The summarized table of UGS-BVOC emissions in Guangzhou city in September via default land use cover (units: Gg).

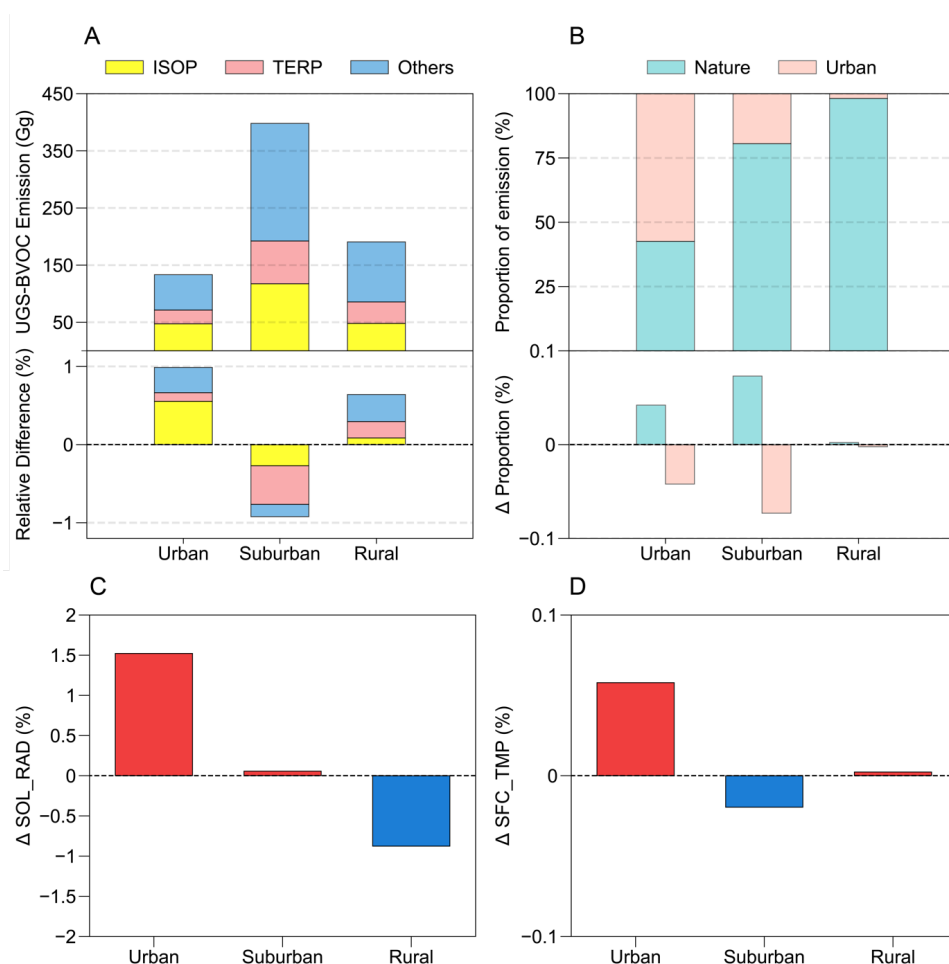
Species	Abbreviations	Urban (Gg)	Suburban (Gg)	Rural (Gg)	Total (Gg)
Acetic acid	AACD	0.86	2.44	1.18	4.48
Acetaldehyde	ALD2	3.46	11.57	5.83	20.86
Formaldehyde	FORM	0.95	3.90	2.17	7.02
Methanol	MEOH	12.47	41.31	20.36	74.14
Formic acid	FACD	2.79	7.84	3.79	14.42
Ethane	ETHA	2.12	8.40	4.64	15.16
Ethanol	ETOH	3.63	12.13	6.11	21.87
Acetone	ACET	6.22	21.52	11.63	39.37
Propane	PRPA	2.08	8.21	4.54	14.83
Ethene	ETH	3.97	15.64	8.64	28.25
Isoprene	ISOP	47.30	117.32	48.06	212.68
Monoterpenes	TERP	24.07	74.85	37.51	136.43
Alpha pinene	APIN	11.26	30.07	13.16	54.49
Methane	ECH4	0.04	0.14	0.08	0.26
Sesquiterpenes	SESQ	4.31	11.97	5.95	22.23
Total	Total	125.53	367.31	173.65	666.49

294

295 Figure 2 (A) provides a detailed illustration of the UGS-BVOC emissions across various regions in Guangzhou
 296 City, driven by default land use cover data, and compares these with the estimates derived from high-resolution
 297 land use cover data, which presents that the suburban region exhibits the highest UGS-BVOC emissions
 298 among the three studied regions, totaling 413.47 Gg. This predominance is linked to the larger extent of UGS
 299 in the suburban region, as depicted in Figure 5(A), while the emissions in urban and rural regions are reported
 300 at 137.69 Gg and 198.64 Gg, respectively. Moreover, UGS-LUCC is instrumental in modulating BVOC
 301 emissions, leading to an uptick in urban and rural regions while precipitating a decline in the suburban region.
 302 Notably, a slight increase in solar radiation (SOL_RAD) by 0.05% (Figure 2 (C)), attributable to a reduced
 303 urban fraction in the Ghr dataset, results in augmented solar exposure. Concurrently, a marginal reduction in
 304 surface temperature (SFC_TMP) by 0.02% (Figure 2 (D)), facilitated by increased vegetation albedo cooling
 305 effects, underpins the decrease in UGS-BVOC emissions within suburban regions. This phenomenon
 306 underscores the critical role of lowered SFC_TMP—driven by vegetation's higher albedo—in curtailing
 307 emissions stemming from UGS-LUCC. Moreover, in urban contexts, the diminished urban fraction enhances
 308 SOL_RAD and SFC_TMP, promoting higher emissions, a trend mirrored to a lesser extent in the rural region
 309 following the update of land use cover data to Ghr. Figure 2 (B) offers a clear depiction of the proportion of



310 UGS-BVOC emissions relative to natural area BVOC emissions in each region of Guangzhou City, which
 311 presents that the UGS-BVOC emissions in urban regions constitute 57.34% of the total BVOC emissions in
 312 this region because of the larger urban proportions in the urban region (Figure 5), while the UGS-BVOC
 313 emission proportion in suburban and rural are 19.44% and 1.86% respectively. This indicates a significant
 314 contribution of the UGS-BVOC emissions in the urban region. Furthermore, when examining the relative
 315 differences in the BVOC emissions resulting from various land use covers across the city, the changes are
 316 found to be minimal, which suggests that meteorological alterations from land use cover do not majorly
 317 influence the proportion of the UGS-BVOC emissions emanating in Guangzhou. Thus, factors other than land
 318 use changes might be more critical in shaping the distribution and intensity of the UGS-BVOC emissions in
 319 urban settings.



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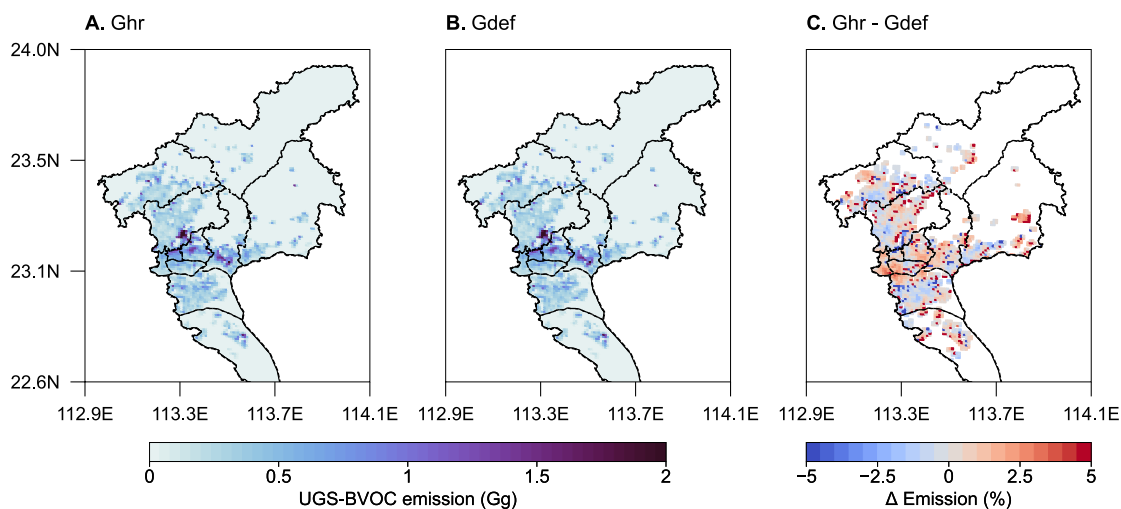
323

Figure 2 The UGS-BVOC emissions of each species and relative difference (Ghr - Gdef) from various land use cover (a), the proportion of emissions from urban and nature and the relative proportion difference (Ghr - Gdef) from various land use cover (b), the relative difference of solar radiation (C), and surface temperature (D) driven via various land use cover datasets.



324

325 Figure 3 (A) and (B) collectively highlight the patterns of the UGS-BVOC emissions across different land use
 326 covers, pinpointing the emission hotspots in urban and suburban regions, which effectively illustrate how land
 327 use cover influences the UGS-BVOC emissions in various parts of the city. Additionally, Figure 3 (C) delves
 328 into the disparities in the UGS-BVOC emissions attributed to different land use cover datasets. It reveals that
 329 the variations in emissions are predominantly concentrated in the identified hotspots. Moreover, Figure 3 (C)
 330 indicates that employing high-resolution land cover data typically results in marginally higher estimates of the
 331 UGS-BVOC emissions, with an increase ranging between 0.8% to 2.9%. Figure 5 (E) and (F) illustrate that
 332 despite a marginal reduction in solar radiation within urban locales, a corresponding minor temperature
 333 elevation modestly boosts UGS-BVOC emissions, which presents that the increase in temperature from UGS-
 334 LUCC causes the rise of the UGS-BVOC emissions.



335

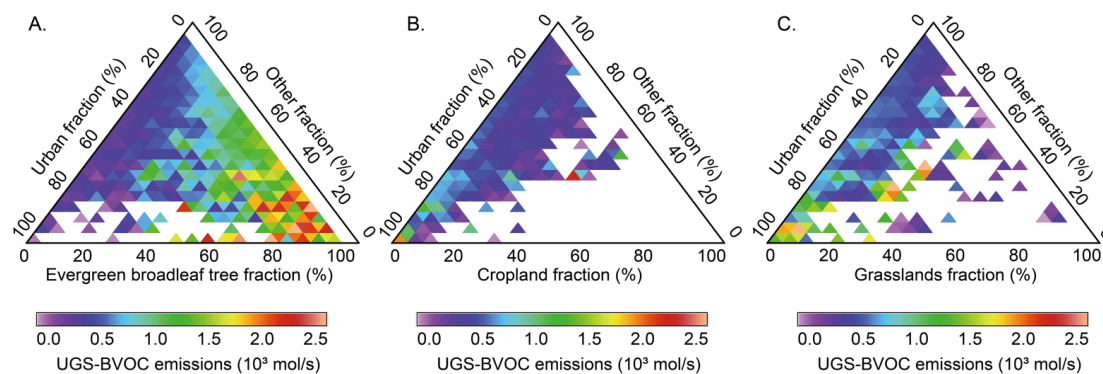
336 **Figure 3** The UGS-BVOC emission maps from default (A) and high-resolution (B) land use cover, and the differences of various UGS-
 337 BVOC emissions (C).

338

339 As illustrated in Figure S1, UGS in Guangzhou comprises three primary types of vegetation: evergreen
 340 broadleaf forests, which are composed of Evergreen Broadleaf Trees (EBTs), cropland, and grasslands. This
 341 classification has enabled a more nuanced understanding of how different types of UGS vegetation influence
 342 UGS-BVOC emissions. Figure 4 reveals that EBTs predominate the urban vegetation landscape in Guangzhou
 343 and are associated with higher rates of UGS-BVOC emissions as their coverage increases. Conversely, an
 344 increase in the proportion of cropland correlates with reduced UGS-BVOC emissions, highlighting its minimal
 345 contribution to the overall UGS-BVOC emissions of Guangzhou. Grasslands exhibit a variable impact on
 346 BVOC emissions; when they constitute over 80% of the UGS, the emission rates are relatively low. However,



347 when grassland coverage ranges between 60-80%, its BVOC emissions surpass those from cropland within
 348 the same percentage range. Overall, EBTs emerge as the primary contributors to UGS-BVOC emissions, with
 349 grasslands and croplands making lesser contributions.



350

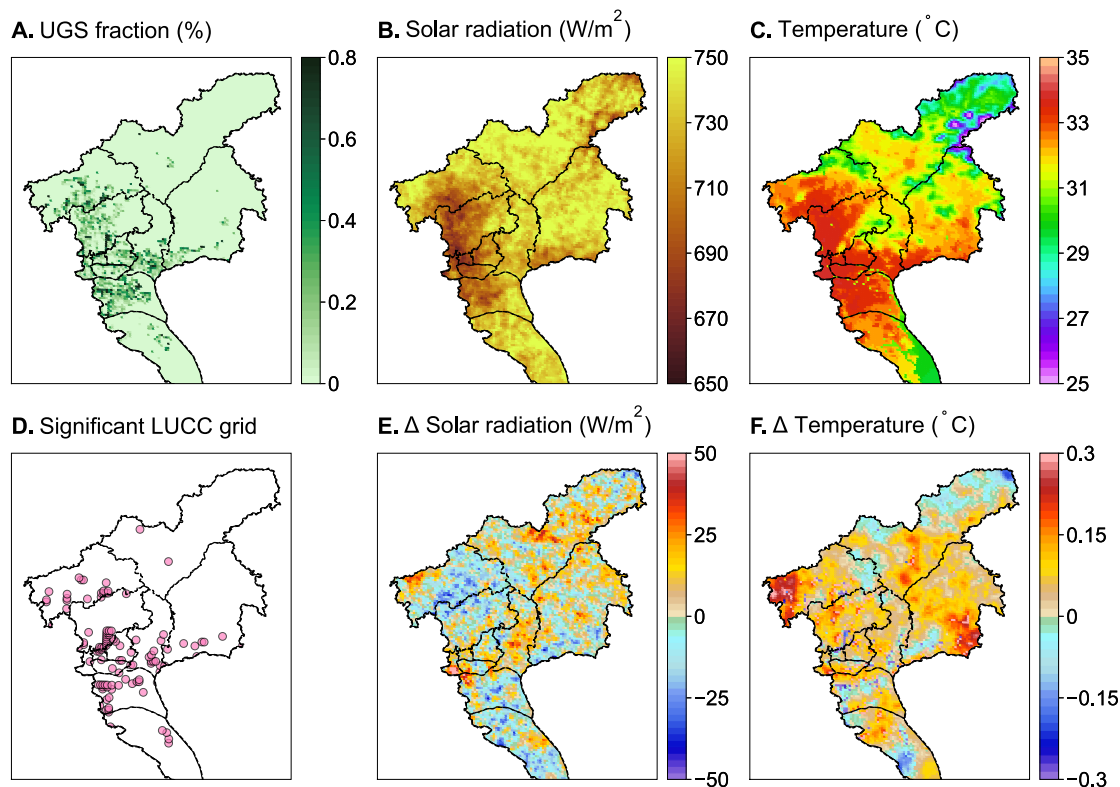
351 **Figure 4 Ternary heat map for various vegetation in UGS with the UGS-BVOC emission rate and the invalid value in this figure represents**
 352 **no UGS-BVOC emission.**

353

354 In addition to the proportion of UGS, the UGS-BVOC emissions in Guangzhou city are significantly
 355 influenced by meteorological factors such as surface temperature and solar radiation (Guenther et al., 2020b).
 356 To elucidate the spatial heterogeneity of the UGS-BVOC emissions, this study analyzes variations in these
 357 key factors. The simulation results depicted in Figure 5 (A) show the distribution pattern of UGS, which are
 358 predominantly located in the urban region, which account for a higher percentage of the UGS-BVOC
 359 emissions compared to others. Interestingly, as indicated in Figure 5 (B), the urban region receives less solar
 360 radiation than other regions likely due to the shading effect of urban canopies. Conversely, the urban region
 361 exhibits elevated temperatures attributable to the urban heat island effect, leading to an increase in UGS-
 362 BVOC emissions. Thus, while the distribution of UGS contributes to the variation in the UGS-BVOC
 363 emissions across different regions, the more significant factor is the enhanced UGS-BVOC emission due to
 364 higher temperatures in densely urbanized areas. The spatial dynamics of the UGS-BVOC emissions are
 365 significantly shaped by two key meteorological factors: solar radiation and surface temperature. These
 366 elements independently play a crucial role in determining both the spatial pattern and the intensity of the UGS-
 367 BVOC emissions. Solar radiation directly influences the rate of photosynthesis and, consequently, the
 368 production of BVOCs, while temperature affects not only the physiological processes of vegetation but also
 369 the volatilization rate of these compounds (Fuhrer et al., 1997; Lombardozzi et al., 2014). The intricate
 370 interplay between these factors leads to spatial variations in the UGS-BVOC emissions, with areas receiving
 371 higher solar radiation and experiencing warmer temperatures typically exhibiting more intense BVOC



372 emissions.



373

374

375 **Figure 5** The UGS map (A) and the meteorological fields from the Ghr_N scenario (B and C). (D) is the grid locations where the land use
 376 experienced significant changes, (E) and (F) are the differences in solar radiation and temperature in various land use cover data (Ghr -
 377 Gdef).

377

378

379 This section has conclusively demonstrated that during the high O_3 season (September) in Guangzhou, the
 380 contribution of UGS-BVOC is substantial and cannot be overlooked and a notable finding is the strong spatial
 381 heterogeneity in these emissions across the city. The analysis also highlights high-resolution land use cover
 data increase the estimation of the UGS-BVOC emissions in the urban and suburban regions.

382

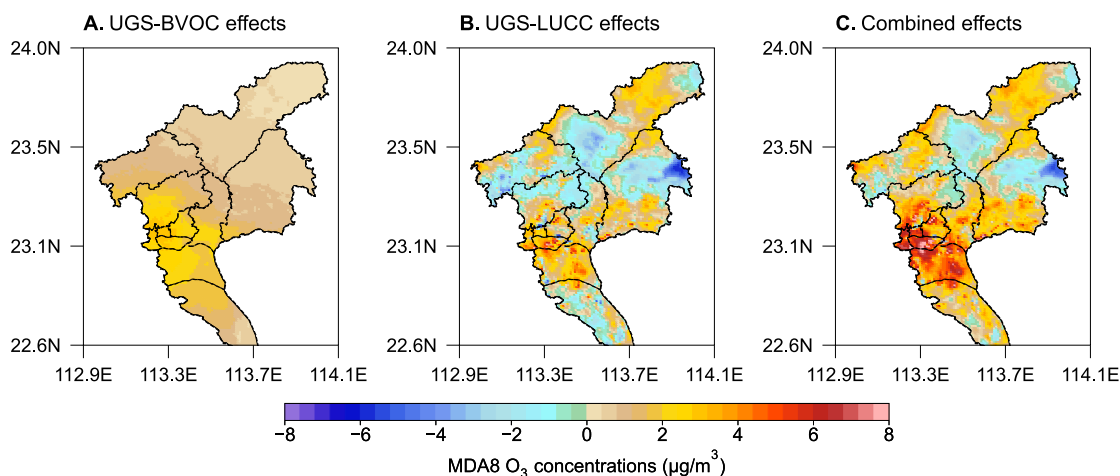
3.3 Impact of UGS-LUCC and UGS-BVOC on Ozone Concentrations

383

384 The study evaluates the effects of UGS-BVOC and UGS-LUCC on MDA8 O_3 concentrations in Guangzhou,
 385 both individually and in combination. The analysis reveals that the UGS-BVOC emissions alone (Figure 6 A)
 386 primarily affect urban areas, significantly increasing MDA8 O_3 concentrations by 2.2-3.0 $\mu g/m^3$ (+2.3-3.2%),
 387 which increment aligns with findings from Los Angeles, where Schlaerth et al., (2023) reported a contribution
 of 2.5 $\mu g/m^3$ from UGS-BVOC to urban MDA8 O_3 levels. In contrast, the sole impact of the UGS-LUCC



388 effects (Figure 6 B) is more extensive, influencing both urban and suburban regions and resulting in a general
 389 increase of approximately 2.3-4.2 $\mu\text{g}/\text{m}^3$ (+2.3-4.3%) in MDA8 O_3 levels, which can be attributed to the higher
 390 temperature and solar radiation (Figure 5 (E)-(F)). In Guangzhou, the transformation of urban surfaces to
 391 natural vegetation due to UGS-LUCC results in lower albedo and consequently lower temperatures. However,
 392 this change also reduces the height of the urban canopy, diminishing its shading effects on solar radiation and
 393 paradoxically leading to higher temperatures in some regions. Therefore, considering the UGS-LUCC effect,
 394 the decreased urban canopy height could lead to elevated temperatures, thereby potentially increasing ozone
 395 production. However, the most significant results emerge under the combined effect of UGS-BVOC and UGS-
 396 LUCC (Figure 6 C), where a substantial increase in O_3 concentration, ranging from 3.6-8.0 $\mu\text{g}/\text{m}^3$ (+3.8-8.5%),
 397 is observed across both urban and suburban areas. The observed increase highlights the critical influence of
 398 UGS-BVOC emissions and UGS-LUCC on ozone levels, underlining the impossibility of overlooking these
 399 factors in ozone concentration research. This revelation points to the essential role that integrated urban
 400 planning and environmental management play in controlling ozone pollution within metropolitan regions.



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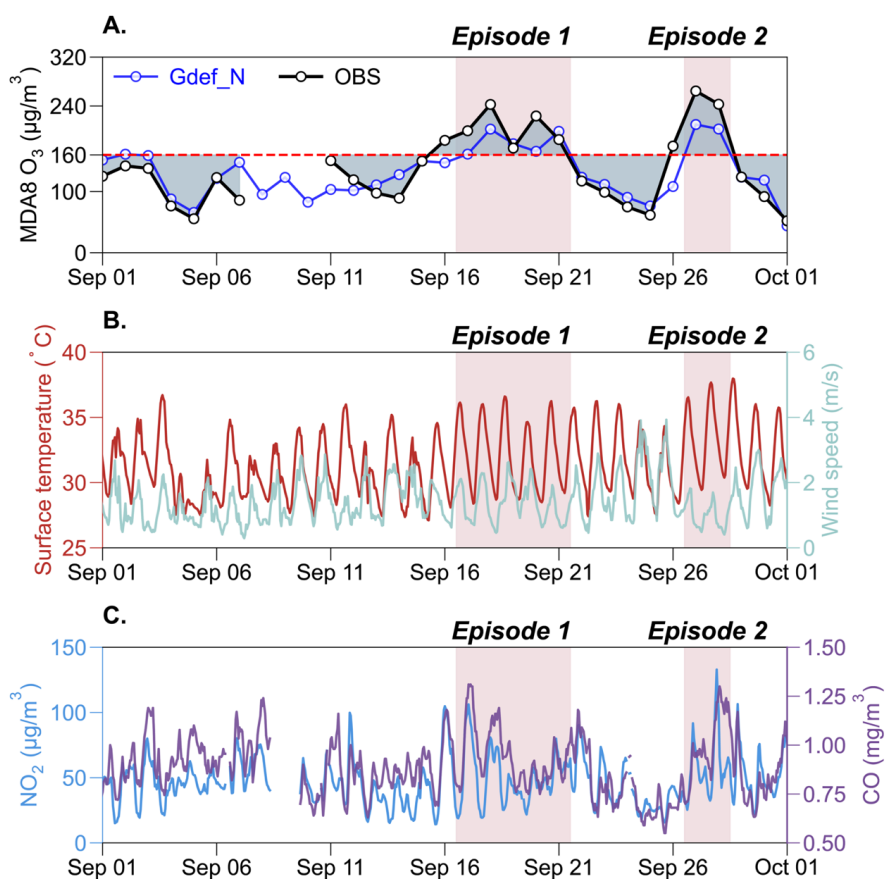
402 **Figure 6** The map of UGS-BVOC effects (a), LUCC effects (b), and combined effects (c) in MDA8 O_3 .

403

404 Previous studies have established that O_3 episodes are often accompanied by high temperatures and intense
 405 solar radiation, conditions that can exacerbate the UGS-BVOC emissions, critically affecting air quality model
 406 performance (Shan et al., 2023; Soleimanian et al., 2023). In this study, an O_3 episode is defined as a period
 407 of two or more consecutive days with maximum daily average 8-hour (MDA8) O_3 concentrations exceeding
 408 160 $\mu\text{g}/\text{m}^3$ (Wu et al., 2020). Our analysis, as depicted in Figure 7 (A), identified two such episodes in
 409 Guangzhou City during September: the first from September 16 to 21 and the second from September 26 to
 410 28. The Gdef_N scenario successfully captures these episodes but tends to underestimate both MDA8 O_3



411 during these episodes. Figure 7 (B) and (C) highlight a notable reduction in wind speed during both episodes,
 412 particularly during the second episode. Despite some diffusion enhancement due to increased PBLH with
 413 rising surface temperatures (Figure S4), the surface temperature hike concurrently fosters O₃ production.
 414 Consequently, the episodes were dominated by a combination of temperature increases, which elevated O₃
 415 concentrations, and wind speed decreases. Furthermore, Figure 7 (C) illustrates that there was a significant
 416 spike in carbon monoxide (CO) concentrations during these episodes. CO, often used as a tracer in studies,
 417 indicates the worsening of diffusion conditions, leading to the accumulation of NO₂ - a primary O₃ precursor
 418 - thereby culminating in O₃ episodes in Guangzhou city.



419
 420 **Figure 7** The comparison between the average values from simulation results grids which have air quality stations produced by the
 421 Gdef_N scenario and the average observation values for MDA8 O₃ (A). (B) are the meteorological fields from the average values from
 422 the simulation result grids, which have the same locations as the air quality stations. (C) are the observed average values for NO₂ and
 423 CO concentrations from all air quality stations.

424

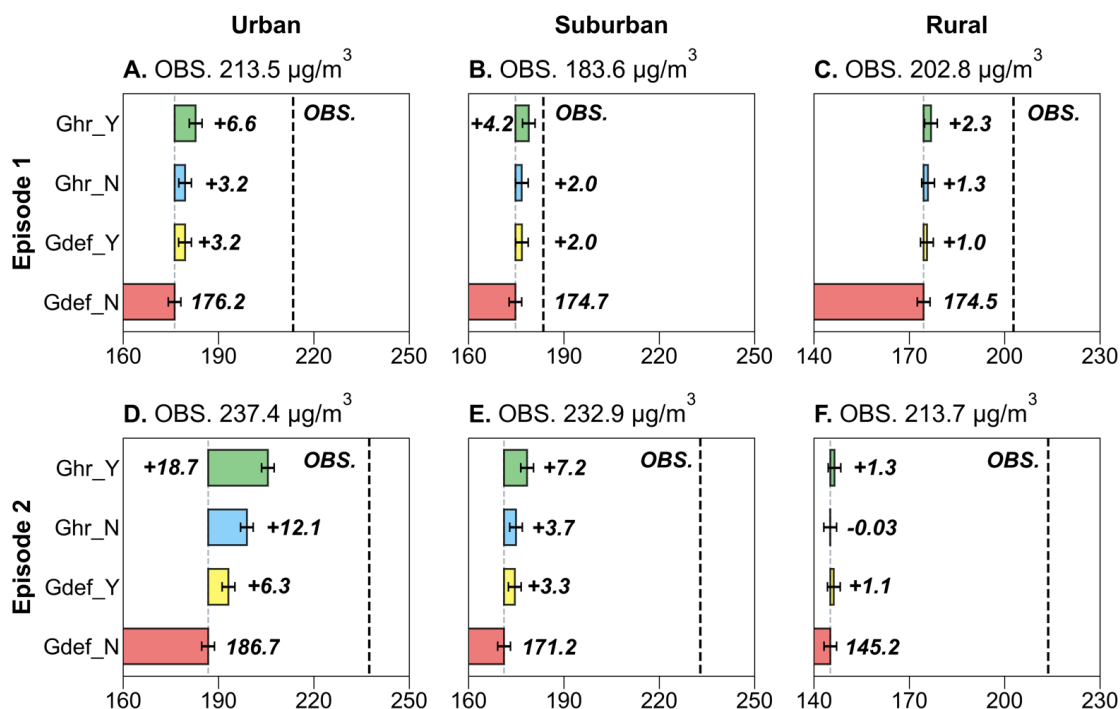
425 Figure 8 presents that in assessing the simulation of O₃ episodes, the Gdef_N scenario, which initially
 426 underestimated O₃ concentrations, prompted an evaluation of improvements using different scenarios: UGS-



427 LUCC (Ghr_N), UGS-BVOC emissions (Gdef_Y), and a combination of both (Ghr_Y). The analysis,
428 focusing on urban, suburban, and rural stations, reveals that all scenarios tend to underestimate O₃ levels
429 between both episodes. However, incorporating the UGS-BVOC emissions into the model results in a notable
430 increase in mean simulated MDA8 O₃ concentrations, particularly in urban and suburban areas. For urban
431 sites, the mean simulated MDA8 O₃ increased by +3.2 and +6.3 µg/m³ (+1.8% and +3.3%, respectively), while
432 for suburban sites, the increase was +2.0 µg/m³ (+1.1%) and +3.3 µg/m³ (+1.9%), with rural sites experiencing
433 a smaller increase of only +1.0 µg/m³ (+0.5%) and +1.1 µg/m³ (+0.7%). This trend indicates a more
434 pronounced impact in urban and suburban areas compared to rural. Notably, the influence of the UGS-BVOC
435 emissions on MDA8 O₃ in Episode 2 (+6.3 µg/m³) was significantly greater than in Episode 1 (+3.2 µg/m³),
436 suggesting that meteorological conditions in Episode 2 were more conducive to the UGS-BVOC emissions,
437 particularly in urban areas, which usually is VOC-limited areas.

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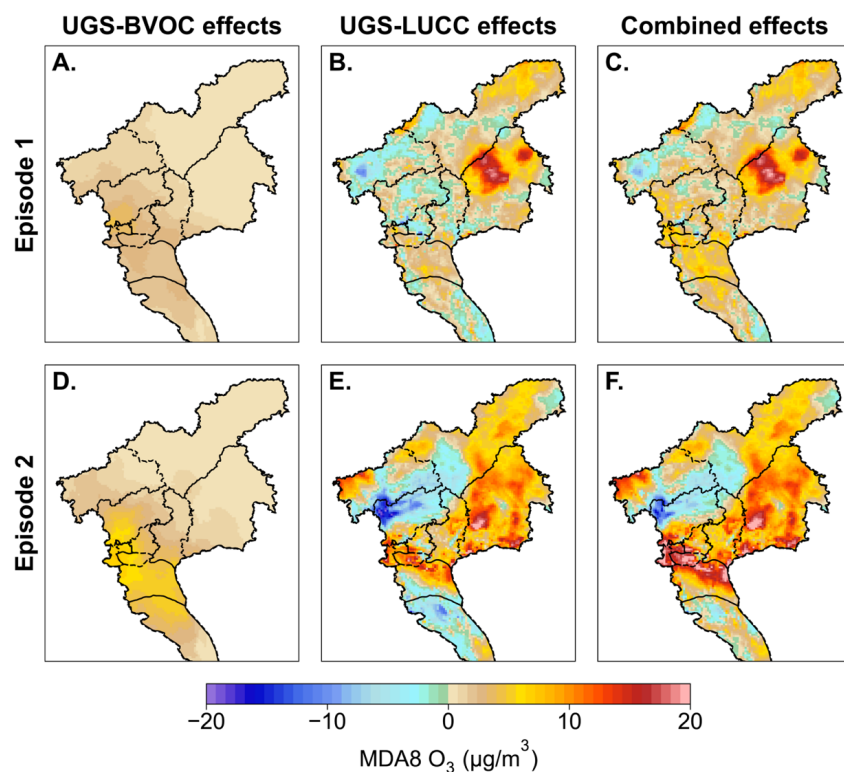
439 In Episode 1, the UGS-LUCC effects on O₃ concentrations were comparable to that of UGS-BVOC emissions,
440 but in Episode 2, the UGS-LUCC effects led to a near doubling of urban MDA8 O₃ increase by 12.1 µg/m³
441 (+6.48%) compared to the UGS-BVOC emissions. This indicates that the UGS-LUCC effects play a non-
442 negligible role in O₃ pollution studies, and the response to such changes under different meteorological
443 conditions varies significantly. Furthermore, due to the limited proportion of UGS in suburban and rural areas,
444 the increased effect of UGS on O₃ is less pronounced in these regions, and nearly negligible in Episode 2.
445 While the UGS-BVOC emissions alone have a modest effect on O₃ concentrations, their impact can become
446 significant when combined with the UGS-LUCC effects. For instance, the combined effects in the urban region
447 increased by 6.6 µg/m³ (+3.7%) and 18.7 µg/m³ (+10.0%) during Episode 1 and Episode 2, respectively.



448

449 **Figure 8** Comparison of simulated versus observed mean MDA8 O₃ concentrations across different scenarios for two episodes. The figure
 450 is organized into columns representing urban (4 sites), suburban (3 sites), and rural (2 sites) settings (columns 1-3, respectively) and rows
 451 indicating comparisons for episode 1 and episode 2 (rows 1 and 2, respectively).
 452

453 Figure 9 presents the map of each effect on MDA8 O₃ in both episodes and the influence of UGS-BVOC
 454 emissions (Figure 9 (A) and (D)) on the MDA8 O₃ concentration during Episode 1 and Episode 2 ranges from
 455 0 to 4.27 $\mu\text{g}/\text{m}^3$ and 0 to 7.43 $\mu\text{g}/\text{m}^3$, respectively, with urban areas witnessing the most significant impact.
 456 This variance can be primarily ascribed to the heightened temperatures during Episode 2 (Figure 7 (B)), which
 457 create conditions more conducive to ozone generation through UGS-BVOC emissions. Furthermore, the UGS-
 458 LUCC effect's maximal contribution to the urban MDA8 O₃ levels could escalate to 4.62 $\mu\text{g}/\text{m}^3$ in Episode 1
 459 and 50.90 $\mu\text{g}/\text{m}^3$ in Episode 2 while the cumulative effects of UGS-LUCC and UGS-BVOC emissions are
 460 projected to enhance MDA8 O₃ concentrations to 10.31 $\mu\text{g}/\text{m}^3$ and 53.93 $\mu\text{g}/\text{m}^3$ for the respective episodes.
 461 This marked increase in the episodes' contributions can be linked to the differential responsiveness of land use
 462 data under various meteorological conditions. Notably, while the contribution from the UGS-BVOC effect
 463 during Episode 2 substantially exceeds that of Episode 1, the incremental impact of UGS-LUCC on combined
 464 effects in Episode 2 is notably smaller than in Episode 1. This phenomenon indicates that the escalated UGS-
 465 BVOC emissions in Episode 2 may start to inhibit ozone production rates incrementally.



466

467 **Figure 9** The UGS-BVOC effects (A, D), the UGS-LUCC effects (B, E), and the combined effects (C, F) in Episode 1 and Episode 2,
468 respectively.

469

470 Figure 8 reveals that both observed O_3 episodes were primarily caused by reduced diffusion conditions.

471 Notably, the impact of the UGS-LUCC effects varied significantly between the two episodes. Analysis of

472 meteorological variables, specifically wind speed and PBLH, which are crucial for diffusion, demonstrate

473 distinct patterns. Figure 10 illustrates that during Episode 1, the UGS-LUCC effects led to a notable increase

474 in the frequency of wind speeds at 1.2-1.4 m/s, while simultaneously reducing the frequency at 0.9-1.1 m/s,

475 which indicates an overall increase in wind speed due to the UGS-LUCC effects during Episode 1. In contrast,

476 Episode 2 experiences a significant decrease in wind speed frequency at 0.7-1.1 m/s, with an increase in the

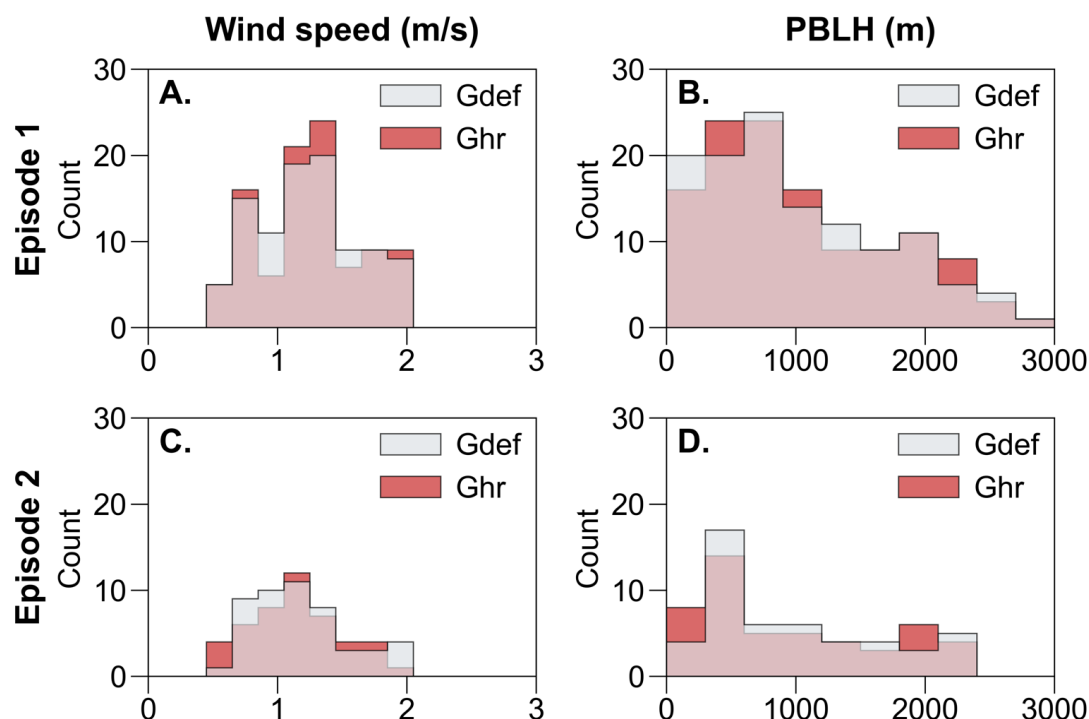
477 lower range of 0.5-0.7 m/s. This suggests that the UGS-LUCC effects further reduce the already low wind

478 speeds in Episode 2. Concerning PBLH, the UGS-LUCC effects are observed to elevate PBLH during Episode

479 1, which led to a decrease in PBLH during Episode 2. Therefore, the UGS-LUCC effects are markedly more

480 pronounced in Episode 2 than in Episode 1, contributing to a more substantial alteration of meteorological

481 conditions affecting air dispersion and, consequently, O_3 formation.



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Figure 10 The frequency of wind speed (column 1) and PBLH (column 2) in Episode 1 (row 1) and Episode 2 (row 2) driven by different land use cover datasets.

485

4. Conclusion

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1. In September 2017, the UGS-BVOC emissions in Guangzhou totaled 666.49 Gg, with ISOP and TERP as the primary species, emitting 212.68 and 136.43 Gg, respectively. Spatially, UGS-BVOC emissions



498 were predominantly located in urban areas, attributed to the more extensive distribution of UGS there.
499 The study also indicates that meteorological changes caused by UGS-LUCC do not significantly affect
500 UGS-BVOC emissions. Instead, the formation of emission spatial distribution and intensity is closely
501 related to local surface temperature and solar radiation. This understanding underscores the importance
502 of considering local solar radiation and temperature conditions when assessing and modeling the
503 distribution of the UGS-BVOC emissions, as they are pivotal in driving the spatial characteristics of
504 these emissions. Moreover, EBTs, which are the main vegetation type in the UGS of Guangzhou and
505 a significant source of UGS-BVOCs, provide a reference for future urban greening in the city to select
506 species with lower emission factors as the primary vegetation types.

507 2. Considering UGS-BVOC and UGS-LUCC can effectively mitigate the underestimation of surface
508 ozone concentrations by regional air quality models. For instance, incorporating UGS-BVOC
509 emissions results in an increase in ISOP concentration from 0.24 ppb to 0.31 ppb and from 0.21 ppb
510 to 0.28 ppb under different land use scenarios (Gdef and Ghr), compared to a baseline concentration
511 of 0.33 ppb. This significant enhancement in ISOP concentrations—the predominant component in
512 BVOCs and the most crucial VOC for O₃ formation in the PRD—highlights two key points. Firstly, it
513 indicates an improvement in the accuracy of BVOC concentration simulations. Secondly, this precise
514 estimation of BVOCs has notably shifted the MB of O₃ simulations from 7.77 µg/m³ to -1.60 µg/m³ in
515 urban areas. Additionally, the simulation of NO₂ concentrations also shows slight improvements, with
516 the MB decreasing from 7.01 µg/m³ to 6.03 µg/m³ upon accounting for UGS-BVOCs and UGS-LUCC.
517 Given that the UGS are often located in densely populated urban regions, their inclusion in air quality
518 simulations is crucial for accurately modeling urban air quality.

519 3. The UGS-BVOC emissions have a significant impact on ozone concentrations, with increases ranging
520 from 2.2-3.0 µg/m³ in urban regions, However, when considering the combined UGS-LUCC and UGS-
521 BVOC effects, the impact on MDA8 O₃ concentrations becomes significant, with values ranging from
522 3.6-8.0 µg/m³ in urban regions. This indicates the importance of considering both UGS-LUCC and
523 UGS-BVOC impacts when discussing the influence of UGS on air quality. Since UGS exhibits
524 different effects in various ozone episodes, it is found that the impact of UGS on ozone levels is related
525 to specific meteorological conditions. In the episodes of this study, the combined effects on MDA8 O₃
526 can reach up to 18.7 µg/m³ in urban regions.

527

528 This study on ozone pollution in Guangzhou provides key insights for other cities on integrating UGS with
529 air quality management. By including UGS-BVOC emissions and UGS-LUCC in the air quality model, the



530 study demonstrates improved accuracy in predicting surface ozone concentrations, which can aid urban
531 planners and environmental policymakers in refining their strategies to better address urban air pollution.
532 Moreover, these findings encourage cities to integrate urban forestry into their land use planning and air quality
533 frameworks, promoting environmental sustainability amid rapid urbanization.

534 **Data availability**

535 Model output data used for analysis and plotting, and the code used for simulations can be made available
536 upon request (Haofan Wang, wanghf58@mail2.sysu.edu.cn).

537 **Author contributions**

538 HFW conceived the study, carried out the model simulations, and drafted the manuscript. YJL and THZ
539 completed the data visualization. YML conceived and supervised this study, and reviewed and edited the paper.
540 XL and YZ provided useful comments on the paper. QF supervised and funded the study. CS provided the
541 meteorological data for model evaluation.

542 **Competing interests**

543 The contact author has declared that neither they nor their co-authors have any competing interests.

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