



1 **Insights into the abnormal increase of ozone during COVID-19**
2 **in a typical urban city of China**

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17

18 **Abstract**

19 The outbreak of COVID-19 promoted strict restrictions to human activities in China, which led to
20 dramatic decrease in most air pollutant concentrations (e.g., PM_{2.5}, PM₁₀, NO_x, SO₂, and CO). However,
21 abnormal increase of ozone (O₃) concentrations was found during the lockdown period in most urban
22 areas of China. In this study, we conducted a field measurement targeting ozone and its key precursors
23 by utilizing a novel proton transfer reaction time-of-flight mass spectrometer (PTR-TOF-MS) in
24 Changzhou, which is representative for the Yangtze River Delta (YRD) city cluster of China. We further
25 applied the integrated methodology including machine learning, observation-based model (OBM), and
26 sensitivity analysis to get insights into the reasons causing the abnormal increase of ozone. Major



27 findings include: (1) By deweathered calculation, we found changes in precursor emissions contributed
28 5.1 ppbv to the observed O₃ during the Full-lockdown period, while meteorological conditions only
29 contributed 0.5 ppbv to the O₃ changes. (2) By using an OBM model, we found that although significant
30 reduction of O₃ precursors was observed during Full-lockdown period, the photochemical formation of
31 O₃ was stronger than that during the Pre-lockdown period. (3) The NO_x/VOCs ratio dropped
32 dramatically from 1.84 during Pre-lockdown to 0.79 in Full-lockdown period, which switched O₃
33 formation from VOCs-limited regime to the conjunction of NO_x- and VOC-limited regime. Additionally,
34 the decrease in NO_x/VOCs ratio during Full-lockdown period was supposed to increase the MeanO₃ by
35 2.4 ppbv. Results of this study investigate insights into the relationship between O₃ and its precursors in
36 urban area, demonstrating reasons causing the abnormal increase of O₃ in most urban areas of China
37 during the COVID-19 lock-down period. This study also underlines the necessity of controlling
38 anthropogenic OVOCS, alkenes, and aromatics in the sustained campaign of reducing O₃ pollution in
39 China.

40 **Keywords:** Ozone; VOCs; PTR-TOF-MS; COVID-19

41 **1. Introduction**

42 At the end of 2019, a tragic coronavirus (COVID-19) occurred, which has caused over 184 million
43 global infection and over 3.99 million deaths as of this writing (5 Jun 2021). To protect people's health,
44 China adopted strict measures to control the spread of this pandemic. Thirty provinces, autonomous
45 regions and municipalities have launched Full-lockdown response (also known as Level I response,
46 roughly from 24 Jan to 25 Feb 2020) as early as 24 Jan 2020 (Shen et al., 2021; Li et al., 2020; Huang
47 et al., 2020). With the effective control of COVID-19 in China, the emergency response level in most
48 provinces (except Hubei province, the hardest-hit region) gradually downgraded to Partial-lockdown
49 (Level II and Level III response, roughly after 25 Jan 2020) (Li et al., 2020), and work resumption
50 started. During Full-lockdown period, all the social events that may cause crowds (excluding
51 transportation and industries that maintained the basic operation of society) were severely restricted.
52 Affected by the pandemic, many factories were shut down, and the on-road traffic volume and



53 construction activities have been reduced significantly (Zheng et al., 2020). During Full-lockdown
54 period, dramatic decrease of air pollutants (e.g., $PM_{2.5}$, NO_2 , BC) were found in China, especially in
55 urban areas (Fan et al., 2021; Gao et al., 2021; Li et al., 2020; Xu et al., 2020). Surprisingly, marginal
56 increases of O_3 were observed during the lockdown period in YRD region, and this seems to be
57 contradictory to the decrease of most air pollutants (Li et al., 2020). However, as suggested by previous
58 studies, the formation of O_3 is significantly influenced by $NO_x/VOCs$ ratio and meteorological
59 conditions (temperature and relative humidity) (Zhang et al., 2020a; Zhang et al., 2020b). Therefore, it
60 is essential to investigate the changes of meteorological and emissions conditions to figure out reasons
61 causing the abnormal increase of O_3 during this pandemic.

62 Previous studies on the O_3 pollution in the YRD region have often focused on the more populated
63 metropolitan areas, such as Shanghai and Nanjing, which are considerably far away from the industrial
64 zones that are essentially responsible for the sources of O_3 precursors (Li et al., 2019; Zhang et al.,
65 2020b). Changzhou, located in the center of the Yangtze River Delta (YRD) region, is a typical city with
66 fast urbanization, heavy industrial structure, huge energy consumption, increasing vehicle stocks and
67 frequent air pollution. Therefore, it provides a more representative environment to fully elucidate the
68 mechanism underlying the O_3 pollution in the YRD region (Shi et al., 2020). In a companion paper
69 (Jensen et al., 2021), we also demonstrated that Changzhou is representative for the region by analyzing
70 both surface observations and satellite data. According to previous studies, the anthropogenic VOCs
71 emission in Changzhou was around $9\sim 12.6\times 10^4$ tons/year, among which industries was the dominant
72 source, accounting for 27~47% of the total VOC emissions (Cheng et al., 2016; Fu et al., 2013). It is
73 notable that industrial sources together contributed over 80% of anthropogenic VOC emissions (Sun et
74 al., 2019). Apart from industrial sources, vehicle exhaust accounted for 9%~14% of total VOC
75 emissions (Sun et al., 2019). However, rare observation regarding VOCs characteristics during COVID-
76 19 in Changzhou has been conducted.

77 Highly time-resolved measurements of VOCs are generally much sparser and could not be easily
78 expanded during the lockdowns. This limits our understanding of how VOCs changed and how the
79 formation of ozone was affected. Here, we used a novel proton transfer reaction time-of-flight mass

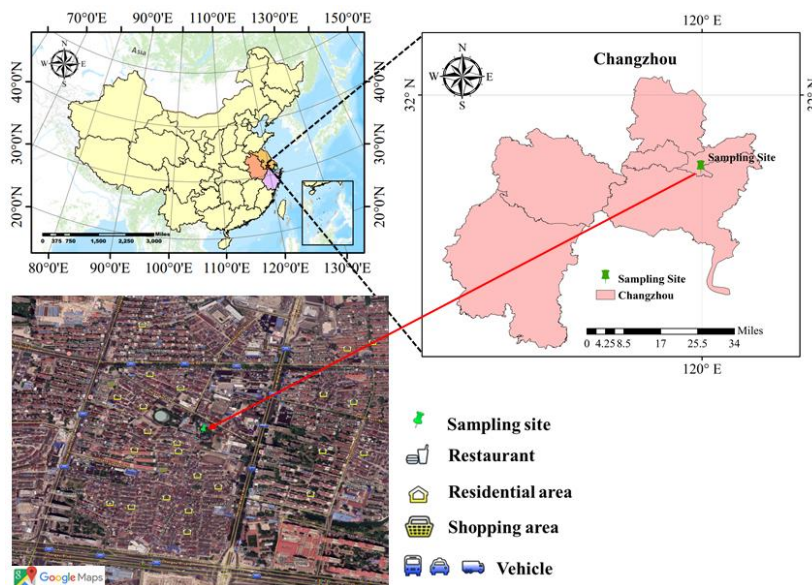


80 spectrometer (PTR-TOF-MS, ToFwerk, Model Vocus Elf, CHE) to conduct online observation of VOCs
81 in Changzhou. The characteristics of VOCs and the variations of general air pollutants in each
82 emergency response period were analyzed. Additionally, ozone formation during each period was
83 investigated by an OBM model. Although terrifying impact has been caused by the COVID-19, it
84 provided a rare experiment to analyze the variations of VOCs and NO_x due to changes of anthropogenic
85 activities in a typical city of China. Furthermore, results of this study offer theoretical support for
86 formulating refined ozone management policy in China.

87 **2. Methodology**

88 **2.1 Field measurement**

89 The field campaign was conducted from 8 Jan to 31 Mar 2020 at a sampling site located on the
90 rooftop of a building at Changzhou Environmental Monitoring Center (CEMC, 31.76° N, 119.96° E),
91 which was approximately 15 m above ground level. As a typical urban monitoring station, this site is in
92 the center of Changzhou city, surrounded by residential and commercial area, which is also adjacent to
93 the main transportation junction in Changzhou (Figure 1). According to local epidemic prevention
94 policies, we roughly classified the measurement periods into three stages: Pre-lockdown (8th January to
95 23rd January 2020), Full-lockdown (25th January to 24th February 2020), Partial-lockdown (25th
96 February to 28th March 2020) as defined in a study of the Yangtze River Delta (Li Li et al., 2020).



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Figure 1. Location of the sampling site in Changzhou (© Google Maps).

99

From Jan 8 to Mar 27, 2020, the concentrations of traditional air pollutants ($PM_{2.5}$, PM_{10} , NO_x , SO_2 , CO, O_3) as well as meteorological parameters were monitored by a series of analyzers (Table 1). In particular, 87 VOCs species were quantified, 59 of which were identified, by a PTR-TOF-MS with time resolution of 1 min. Detailed measurement techniques and quality assurance and control has been documented in detail in our companion paper (Jensen et al., 2021). Here, we just briefly introduce the measurement. The air samples were directly inhaled into the 3 m-long tube connected to the instrument. A priming pump, with flow rate of 4 L/min, was used to reduce the retention time of the gas sample in the tube. To avoid blocking of inlet tube caused by particles, a particulate filter was assembled at the front of the inlet tube. The pressure of the ion source was set as 2 mbar and the temperature of the reaction chamber was set to 90 °C during the observation. The PTR-TOF-MS can detect most unsaturated hydrocarbons and VOCs with functional groups but cannot detect species with proton affinities lower than that of water, namely alkanes and small alkenes. Eighteen standard gases (including acetonitrile, acetaldehyde, acrolein, acetone, isoprene, butanone, 2-butanone, benzene, 2-pentanone, ethyl acetate, toluene, methyl isobutyl ketone, styrene, xylene, trimethylbenzene, naphthalene, α -pinene, and 1,3-dichlorobenzene) with concentrations of 1 ppmv were used for the calibration of the PTR-TOF-

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114 MS. In addition, a built-in calibration system was used to control the zero and standard gases.

115 **Table 1 Measurements performed during the field campaign.**

Species/Parameter	Experimental Technique
T, RH, WS, WD and P	2000WX, Airmax, USA
O ₃	400E, API, USA
NO _x (NO and NO ₂)	T200, API, USA
SO ₂	T100, API, USA
CO	T300, API, USA
PM _{2.5}	5030, Thermo Fisher, USA
PM ₁₀	5030, Thermo Fisher, USA
VOCs	Vocus Elf, Tofwerk, CHE

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117 2.2 Observation-based model

118 An OBM model coupled with MCM v3.3.1 was utilized to investigate the atmospheric oxidation
119 capability and the radical chemistry. Detailed information about the chemistry mechanism is available
120 on MCM website (<http://mcm.leeds.ac.uk/MCM/>, last access 8 Jul 2021). More than 5800 chemical
121 species and 17000 reactions are included in this mechanism. The photolysis frequencies (J values) were
122 calculated based on the trigonometric parameterization provided by MCM (Wolfe et al., 2016). Dilution
123 mixing within the boundary layer is considered. However, as a 0-zero model, vertical or horizontal
124 transport of airmasses are not involved. The observed meteorological parameters (T, RH, P), trace gases
125 (NO, NO₂, CO, SO₂, and VOCs) were used to constrain the model. Before each simulation, the model
126 was run 3 days as spin-up to reach a stable state. According to the definition of atmospheric oxidation
127 capability (AOC), AOC is quantified by Eq (1) (Zhu et al., 2020).

$$AOC = \sum_i k_{Y_i} [Y_i] [X] \quad (1)$$

128 where Y_i are the primary pollutants (e.g., VOCs, CH₄, and CO); X are atmospheric oxidants (OH, O₃,
129 NO₃); k_{Y_i} are the bimolecular rate constants for the reactions of Y_i and X . A high value of AOC indicates
130 fast scavenge of primary air pollutants. Additionally, OH reactivity (k_{OH}), defined as the reaction rate



131 coefficients multiplied by the concentrations of the reactants with OH, is also widely used as an indicator
132 of AOC. The value of k_{OH} depends on both the abundances and compositions of primary pollutants and
133 can be calculated by Eq (2).

$$k_{OH} = \sum_i k_{(OH+X_i)} \times [X_i] \quad (2)$$

134 where $k_{(OH+X_i)}$ are the reaction rate coefficients of reaction $OH+X_i$; X_i are the concentrations of pollutants
135 (VOC, NO_2 , CO, OVOC etc.) (Zhu et al., 2020).

136 2.3 Trend Analysis

137 Mann-Kendall (MK) trend test is a widely used non-parametric test method (Pathakoti et al., 2021;
138 Zhang et al., 2013), which is recommended by the World Meteorological Organization. It is applicable
139 to all distributions (that is, the data does not need to meet the assumption of normal distribution), but
140 the data should have no serial correlation. If the data has serial correlation, it will have an impact on the
141 significance level (p value). In this study, the MK trend analysis was performed for individual VOC
142 concentrations during Pre-lockdown and Full-lockdown period. Detailed description of this method
143 could be found in the study of Pathakoti et al. (2021) and Alhathloul et al. (2021). A positive z value
144 from the MK test indicates increasing trend of the target compound. On the contrary, a negative z value
145 suggests the target compound was decreasing.

146 Sen's slope, a non-parametric test proposed by Sen (1968), is also used in this study to assess the
147 rate of change in individual VOC concentrations. Sen's slope (Q) is mathematically represented by the
148 following equations.

$$Q = \text{median}(SS_{ij}) \quad (3)$$

$$SS_{ij} = \frac{x_j - x_i}{j - i}, 1 \leq i \leq j \leq n \quad (4)$$

149 where x_j and x_i are concentrations of VOC specie x at time j and i ($1 \leq i \leq j \leq n$), respectively. SS_{ij} is the
150 linear slope between time i and j , and Q is the median of SS_{ij} . Positive and negative Q values indicating
151 increasing or decreasing trend of VOC specie x, respectively.

152 2.4 Deweathered model



153 The observed concentrations of O₃ could be influenced by meteorological conditions,
154 emissions/chemistry. To quantitatively assess the contribution of meteorological conditions and
155 emissions/chemistry, the deweathered O₃ concentrations was calculated based on the random forest (RF)
156 approach. The number of trees in the RF model was set as 300, the minimal node size was five, and the
157 number of samples was 300. Hourly data of Unix date (number of seconds since 1970-01-01), Julian
158 day, weekday, hour of day, wind speed (WS), wind direction (WD), temperature (T), relative humidity
159 (RH), and pressure (P) were used for the deweathered calculation of O₃. More details of this model
160 could be found in the study of Grange and David (2019).

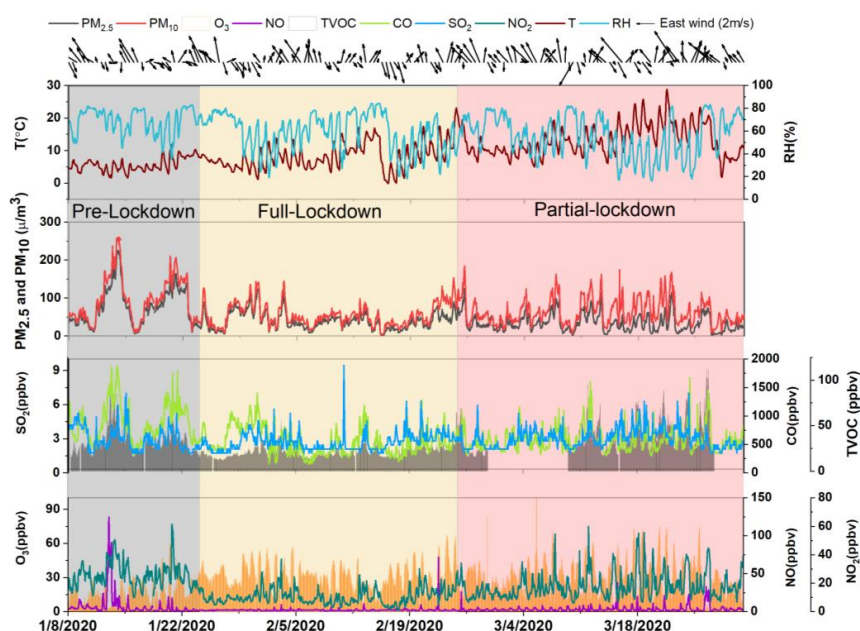
161 **3. Results and discussion**

162 **3.1 Overview of the field campaign**

163 Figure 2 shows the meteorological conditions during the observation. During the whole experiment,
164 the prevailing WD was southeast. The average T and RH was $9.9 \pm 5.1^\circ\text{C}$ and $58.9 \pm 17.1\%$, respectively.
165 Compared to Pre-lockdown period, the concentrations of PM_{2.5}, PM₁₀, SO₂, NO, NO₂, TVOC and CO
166 during Full-lockdown period decreased by 48%, 42%, 11%, 65%, 58%, 33% and 39%, respectively. It
167 is interesting to note that the decreasing ratio of VOC : NO_x is around 1:2. Meanwhile, the average O₃
168 concentrations in Full-lockdown period was 67% higher than that during Pre-lockdown period. To
169 estimate whether the increase of O₃ during Full-lockdown period is abnormal, we summarized the
170 meteorological conditions and O₃ concentrations during the same period in 2020 and 2019 (Table 2 and
171 Figure 3). It should be noted that, considering the influence of Chinese New Year, the corresponding
172 period in 2019 was decided according to lunar calendar. Compared to Full-lockdown period in 2019,
173 the mean O₃ concentration in 2020 was 5.5 ppbv higher (Figure 2). The T and RH in Full-lockdown
174 period in 2020 was $\sim 1.6^\circ\text{C}$ higher and 6.1% lower than that in the same period in 2019, while the P and
175 WS were comparable during the same period in 2020 and 2019. The relatively higher T and lower RH
176 condition was supposed to be in favor of O₃ formation during the Full-lockdown period in 2020.
177 Additionally, we compared the hours of adverse weather conditions (with RH >70% and WS <1m/s)
178 and found that the meteorological condition during Full-lockdown period in 2020 restrained the dilution



179 of air pollutants (Table 2). Therefore, the meteorological conditions during Full-lockdown period in
 180 2020 seemed to favor O₃ formation. However, changes in O₃ concentrations could be a result of the joint
 181 effect of meteorological conditions and emissions/chemistry, the following sections would discuss the
 182 influences respectively.



183

184 **Figure 2** Time series of meteorological parameters and air pollutants during the whole observation.

184

185 **Table 2** Comparison of average meteorological conditions during Pre-lockdown, Full-lockdown, and Partial-

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186 **lockdown period in 2020 and the same period in 2019.**

186

Periods	Date	P (hPa)	RH (%)	T (°C)	Precipitation (mm)	WS (m/s)	Adverse weather conditions*	
							Number of hours (h)	Proportion (%)
Pre-lockdown	(2020.1.8-1.24)	1025.4	84.9	4.8	0.13	1.8	54	17.5%
Same period in 2019	(2019.1.19-2.4)	1025.6	72.7	5.2	0.05	1.9	70	18.5%
Full-lockdown	(2020.1.25-2.24)	1025.6	73.0	7.3	0.09	2.1	103	15.6%
Same period in 2019	(2019.2.5-3.7)	1024.1	79.1	5.7	0.15	2.1	82	13.7%
Partial-lockdown	(2020.2.25-3.31)	1018.9	69.5	12.1	0.11	2.4	106	12.3%
Same period in 2019	(2019.3.8-4.12)	1017.6	64.	13.8	0.02	2.	72	8.3%

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* The non-rainfall periods with RH less than 70% and WS below 1m/s were defined as adverse weather condition.

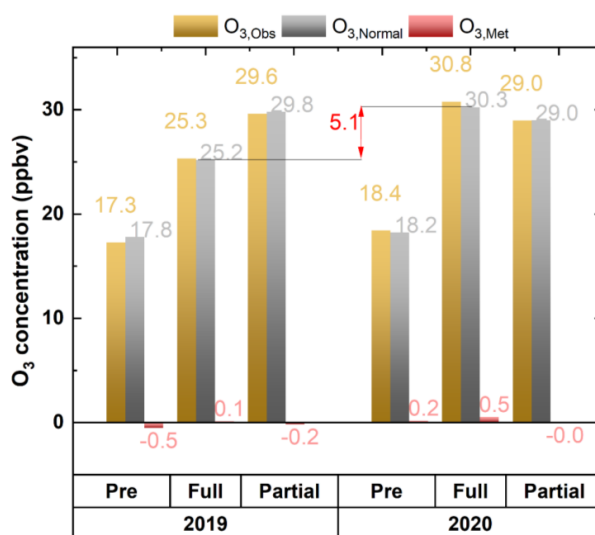
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189 **3.2 Mechanism affecting the abnormal O₃ increase**



190 **3.2.1 Meteorological perspective**

191 Deweathered O₃ concentrations were calculated based on the model described in Section 2.4. The
 192 random forest model grown for O₃ at the sampling site had R² values of 0.84, therefore, the model shows
 193 good performance for O₃ predictions. The difference between observed (O_{3,Obs}) and weather-normalized
 194 O₃ (O_{3,Normal}) can be regarded as the meteorological influence (O_{3,Met}). In addition, the difference
 195 between O_{3,Obs} concentrations in different years could be considered as the influence of emissions
 196 (O_{3,Emi}). Figure 3 exhibited the average O_{3,Obs}, O_{3,Normal}, O_{3,Met} during the same periods in 2019 and 2020,
 197 respectively. The mean O_{3,Normal} during Pre-lockdown and Partial-lockdown periods in 2019 and 2020
 198 were close, suggesting the similar emission condition during these periods in 2019 and 2020. During
 199 Full-lockdown period in 2020, O_{3,Met} contributed +0.5 ppbv to O_{3,Obs}, which is consistent with the rough
 200 summary of meteorological conditions in Table 2, confirming that the weather conditions during the
 201 Full-lockdown period in 2020 favored O₃ formation. However, the average O_{3,Normal} during Full-
 202 lockdown period in 2020 was 5.1 ppbv higher than that in 2019, indicating that improper decline of
 203 precursor emissions was possibly the key reason for the abnormal increase of O₃ during Full-lockdown
 204 period in 2020.



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Figure 3. Comparison of observed (Obs), weather-normalized (Normal), and meteorological-factors-infected

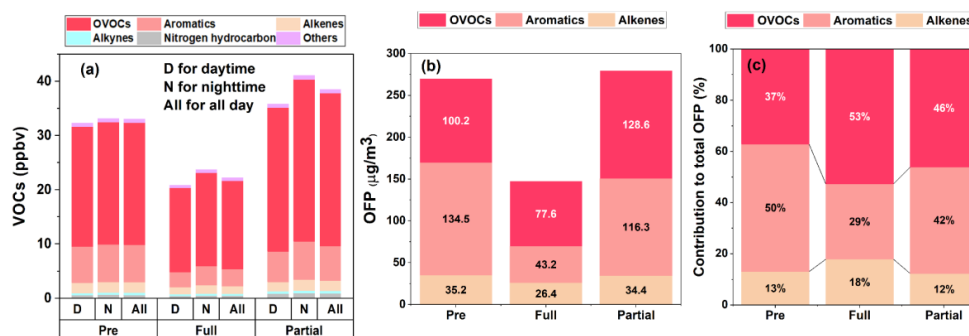
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(Met) O₃ concentrations during the same period in 2019 and 2020.



208 3.2.2 Ambient VOCs

209 As mentioned above, the changes in O_3 precursor emissions strongly affected the $O_{3,Obs}$, and the
210 changes in VOCs and NO_x emissions would eventually be reflected by the observed concentrations of
211 individual VOCs and NO_x . Therefore, the concentrations of each VOC group in different periods were
212 summarized (Figure 4). OVOCs dominated the total VOCs (TVOC) concentrations during the whole
213 observation, with a daily average concentration of 21.44 ± 10.27 ppbv. During Full-lockdown period,
214 the TVOC dropped to 22.19 ± 7.9 ppbv, which was mainly affected by the decrease in industrial activities
215 and traffic volume. The most obvious drop was found in aromatics (~54%), followed by OVOCs (~27%),
216 alkenes (~26%), nitrogen hydrocarbon (~25%), and other VOCs (~21%). Additionally, the discrepancy
217 of daytime and nighttime VOCs concentrations during different periods were compared (Figure 4 (A)).
218 Interestingly, the concentration of each VOCs group exhibited higher values during nighttime, which
219 was caused by the low atmospheric oxidation condition and the low atmospheric boundary layer height
220 (Maji et al., 2020; Valach et al., 2015).



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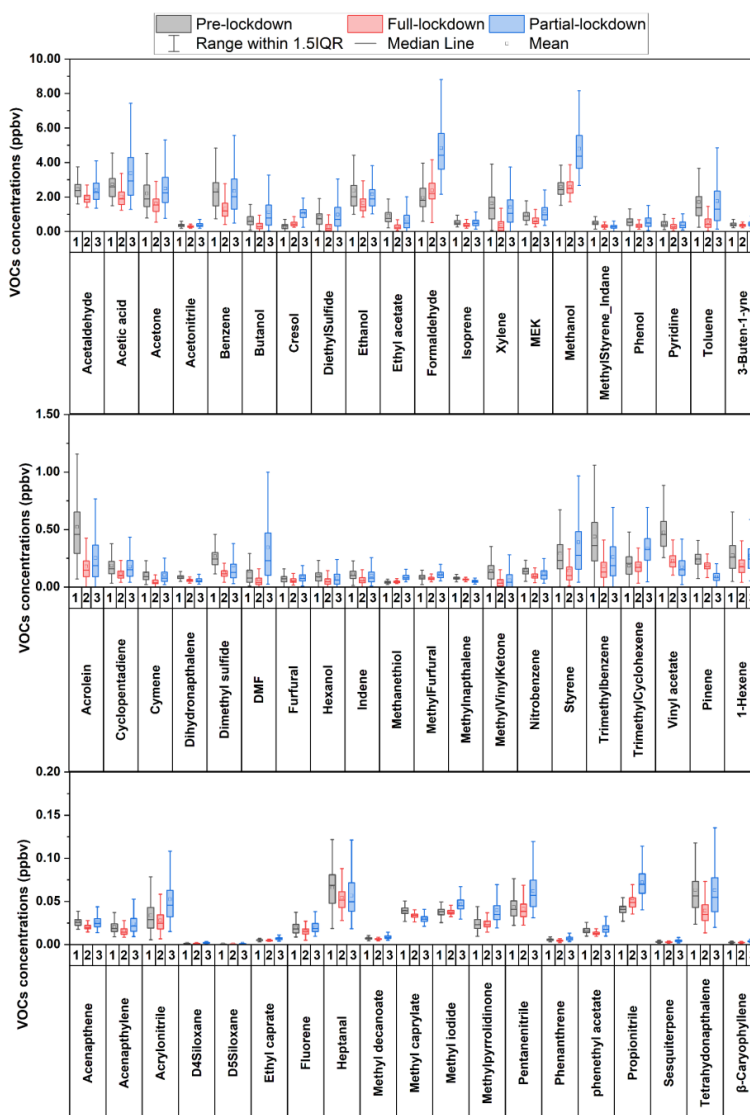
222 **Figure 4. Comparison of daytime and nighttime VOCs concentrations (A), average OFP (B), and contribution**
223 **to total OFP (C) during different periods.**

224 Furthermore, the average concentrations of individual VOCs during different periods were
225 summarized in Figure 5. Most VOC species exhibited an ‘U’ shape trend during the whole observation,
226 except for several VOCs (such as formaldehyde (HCHO) and methanol), which showed an increasing
227 pattern. It should be noted that the measurement of HCHO could be strongly influenced by humidity.
228 Since within the drift tube, the back reaction, which convert the protonated HCHO back into HCHO,



229 is highly humidity dependent (Inomata et al., 2008; Warneke et al., 2011). To quantitatively evaluate the
230 changes of individual VOC concentrations from Pre-lockdown to Full-lockdown period, when the
231 variations of each VOCs are obvious, we applied MK trend test and Sen's slope analysis based on the
232 hourly average VOCs concentration data.

233 Table 3 lists the top 10 VOCs species with decreasing pattern from Pre-lockdown to Full-lockdown
234 period. Interestingly, toluene, benzene and xylene exhibited the most significant decreasing pattern, with
235 a slope of 7.73×10^{-4} , 7.36×10^{-4} , and 7.20×10^{-4} ppbv h⁻¹, respectively. As for NO_x and TVOC, the slope
236 was -1.62×10^{-2} and 5.48×10^{-3} ppb h⁻¹. This result corresponds with the drastic drop of industrial
237 activities and traffic volumes, which are key sources of aromatics and NO_x, from Pre-lockdown to Full-
238 lockdown period. Other VOCs, such as ethyl-acetate, acetic acid, acetaldehyde, diethyl sulfide, ethanol,
239 butanol and acrolein are also tightly associated with industrial processes, thereby showed decreasing
240 trend from Pre-lockdown to Full-lockdown period. Additionally, the average diurnal variations of
241 acetonitrile, dimethyl formamide (DMF), and styrene, which are tracers of biomass burning and
242 industrial emission, respectively, exhibited significant reduction during Full-lockdown period (Figure
243 S1), also indicating strong decrease in these emissions. However, formaldehyde and methanol exhibited
244 increasing trend, with a slope of 12.78×10^{-4} and 6.35×10^{-4} ppbv h⁻¹, respectively. This could be
245 explained by the secondary formation of HCHO and methanol, which was promoted under better
246 oxidation condition in Full-lockdown period.



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Figure 5. Concentrations of individual VOC species during different period.

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*MEK, DMF, are abbreviation of Methyl ethyl ketone and dimethylformamide, respectively.

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Table 3. Top 10 VOCs with decreasing trend from Pre-lockdown to Full-lockdown

VOC	Z value	Q *10000 (ppbv h ⁻¹)	VOC	Z value	Q *10000 (ppbv h ⁻¹)
Toluene	-14.02	-7.73	Acetaldehyde	-10.31	-3.95
Benzene	-9.65	-7.36	Diethyl sulfide	-9.15	-3.16
xylene	-12.38	-7.20	Ethanol	-5.48	-3.09
Ethyl-acetate	-18.53	-5.20	Butanol	-10.42	-2.83
Acetic acid	-6.79	-4.12	Acrolein	-15.48	-2.76

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3.2.3 Chemistry perspective

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The reactivities of different VOCs varies significantly, hence, ozone formation potential (OFP) is used in this study to assess the potential contribution of active VOCs (including alkenes, aromatics and OVOCs) to O₃ formation on the same basis, and it can be calculated by formula (5):

$$OFP_i = MIR_i \times [VOC_i] \quad (5)$$

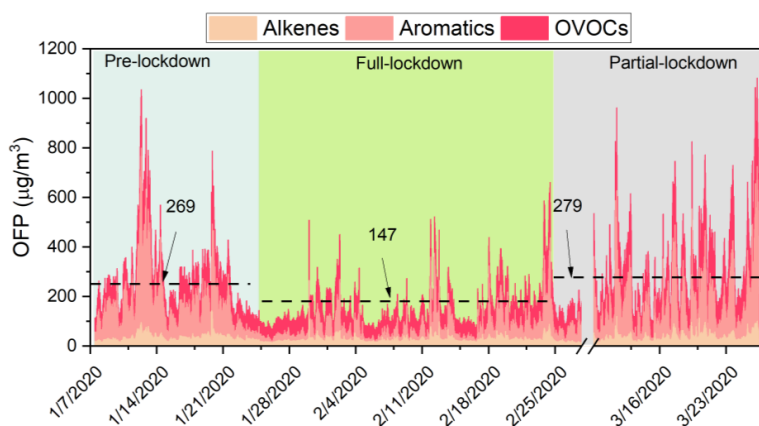
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where MIR_i is the ozone formation potential coefficient for a given VOC specie i in the maximum increment reaction of O₃, acquired from Carter (2009); $[VOC_i]$ is the concentration of VOC species i (in $\mu\text{g}/\text{m}^3$). The time series of total OFP is shown in Figure 6. The average OFP in Pre-lockdown, Full-lockdown, and Partial-lockdown period was 269.4 ± 146.0 , 147.2 ± 72.4 , $279.3 \pm 168.6 \mu\text{g}/\text{m}^3$, respectively. The trend of the total OFP indicates the drastic decrease of VOCs reactivities from Pre-lockdown to Full-lockdown period. During Pre-lockdown period, aromatics were the dominant OFP contributor (49%), followed by OVOCs (38%) and alkenes (13%) (Figure 4). Among aromatics, xylene exhibited the maximum OFP value ($68.6 \pm 59.3 \mu\text{g}/\text{m}^3$), followed by acetaldehyde ($28.8 \pm 6.4 \mu\text{g}/\text{m}^3$), toluene ($25.7 \pm 20.1 \mu\text{g}/\text{m}^3$), trimethylbenzene ($25.4 \pm 15.8 \mu\text{g}/\text{m}^3$), and formaldehyde ($22.7 \pm 9.1 \mu\text{g}/\text{m}^3$) (Figure S2), suggesting that anthropogenic emissions could be the main source of secondary formation of O₃ during Pre-lockdown period. Compared to Pre-lockdown period, the OFP of aromatics decreased dramatically ($-91.2 \mu\text{g}/\text{m}^3$) during Full-lockdown period (Figure 4 (B)), which was mainly attributed to the rapid decline of human activities (e.g., transportation and industry). However, the OFP of alkenes and OVOCs only decreased by 8.9 and 22.5 $\mu\text{g}/\text{m}^3$, respectively. As for alkene, this could be explained by their chemical reactivities, which led to the fast degradation after emission. As for OVOCs, the secondary formation could compensate the decrease in primary emissions. The OFP values of aromatics

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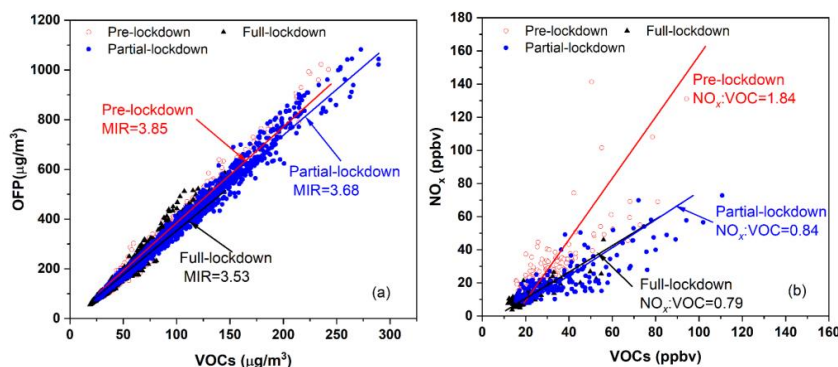


276 and alkenes during Pre-lockdown and Partial-lockdown period are comparable, but OVOCs exhibited
277 higher OFP contribution (~46%) in Partial-lockdown period, which could be attributed to the higher
278 AOC condition during Partial-lockdown period. To compare the average reactivity of VOCs during
279 different periods, we calculate the mean MIR in each period. As shown in Figure 7, the average MIR
280 during Pre-lockdown, Full-lockdown, and Partial-lockdown period was 3.85, 3.53 and 3.68 (g O₃/g
281 VOC), respectively. This result suggests that the VOCs in Partial-lockdown should produce less O₃ than
282 that in Pre-lockdown, and Partial-lockdown period. This is inconsistent with the observation, which
283 shows relatively higher O₃ concentration during Full-lockdown period. However, the formation of O₃
284 was sensitive to the ratio of NO_x/VOCs and meteorological conditions, which can be significantly
285 different in each period. As shown in Figure 7, the average NO_x/VOCs ratio in the three periods (shown
286 in) was 1.84, 0.79, and 0.84, respectively, suggesting more NO_x was eliminated during Full-lockdown
287 period, which could further influence the sensitivity of O₃ formation.



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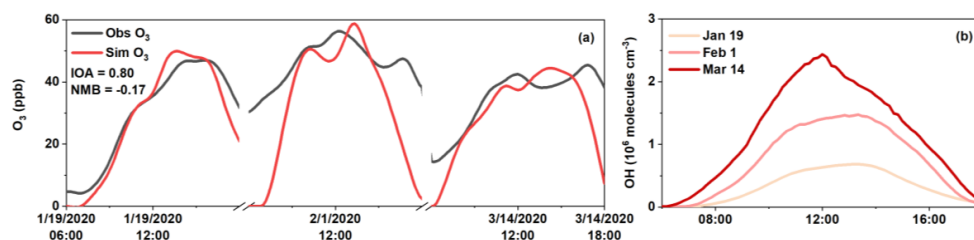
Figure 6. Time series of OFP during the whole observation period (dash lines represent the average OFP value during each period)



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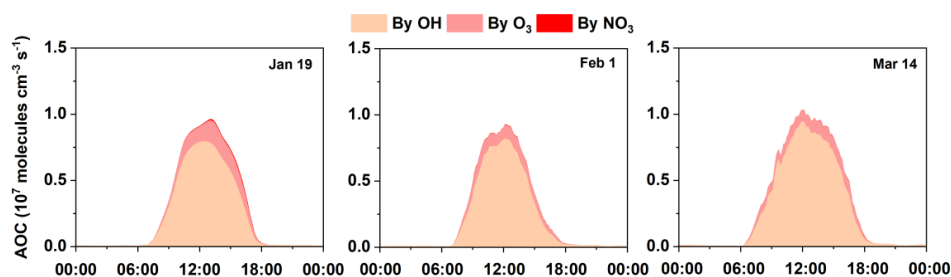
Figure 7. Plot of average MIR and NO_x vs VOCs during three periods.

293 To investigate the detailed formation mechanism of O_3 in each period, three cases (January 19th,
294 February 1st, March 14th) with stagnant meteorological conditions were chosen. The index of agreement
295 (IOA) of O_3 is 0.80, indicating that the model can capture the daytime variation of O_3 . The simulated
296 daytime OH concentrations exhibited an increasing trend from January 19 to March 14, with an average
297 value of $0.36 \pm 0.27 \times 10^6$, $0.75 \pm 0.54 \times 10^6$ and $1.18 \pm 0.78 \times 10^6$ molecules cm^{-3} , respectively. This
298 could be attributed to the increasing solar radiation and temperature from January to March. To analyze
299 the atmospheric oxidation, we calculated the AOC according to Eq(1). The average daytime AOC on
300 Jan 19th, Feb 1st, and Mar 14th was 0.26 ± 0.35 , 0.23 ± 0.33 , and 0.31 ± 0.38 molecules $\text{cm}^{-3} \text{ s}^{-1}$,
301 respectively (Figure 9). Comparatively, these values are much lower than those simulated for Shanghai
302 and Beijing (Liu et al., 2012; Zhu et al., 2020; Zhang et al., 2021) in summer, mainly due to the
303 meteorological conditions in winter season. It is notable that the simulated OH on Jan 19th was
304 significantly lower than that on Feb 14th, but the AOC on Jan 19th was comparable to that on Feb 1st.
305 This should be ascribed to the abundant primary pollutants, which efficiently react with OH, during Pre-
306 lockdown period.
307



308

309 **Figure 8. Comparison of simulated and observed O₃ (a) and simulated daytime OH concentrations (b) in three**
310 **cases.**



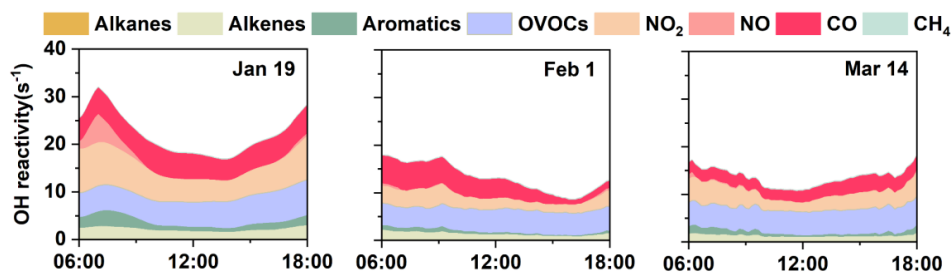
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312 **Figure 9. Diurnal variation of AOC in three cases**

313 The daytime variations of OH reactivity calculated by OBM model are exhibited in Figure 10,
314 including the contribution from measured pollutants (e.g., VOCs, NO_x, and CO) and model-simulated
315 species (OVOCs). Generally, the k_{OH} assessed at Changzhou was in the range of 9–32 s⁻¹, which was
316 comparable to that calculated for other cities in China (e.g., Shanghai (4.6–25 s⁻¹, (Zhu et al., 2020)),
317 Chongqing (15–25 s⁻¹, (Tan et al., 2019)) and Beijing (15–25 s⁻¹, (Tan et al., 2019))). It is obvious that
318 OH reactivity peaked in the morning, with maximum values of 31.76, 17.98, and 17.30 s⁻¹, respectively.
319 The OH reactivity from NO₂ exhibited obvious daytime variation, especially during the morning rush
320 hour, which lead to the peak k_{OH} value during morning. The OH reactivity (k_{OH}) on Feb 1st was much
321 lower than that in the other two cases, which was mainly due to the abundance of emissions during Pre-
322 lockdown and Partial-lockdown period. Compared to Jan 19th, the k_{OH} from NO₂ on Feb 1st and Mar
323 14th showed lower levels, with an average value of 2.62 and 3.35 s⁻¹, respectively. This corresponds with
324 the dramatic drop of traffic volume during lockdown periods. Similarly, compared to Jan 19, the k_{OH}
325 from alkenes and aromatics were lower on Feb 1st and Mar 14th. It is notable that the OH reactivity from



326 OVOCs kept almost stable in the three cases, this was mainly attributed to the stable OVOC
327 concentrations during these cases.



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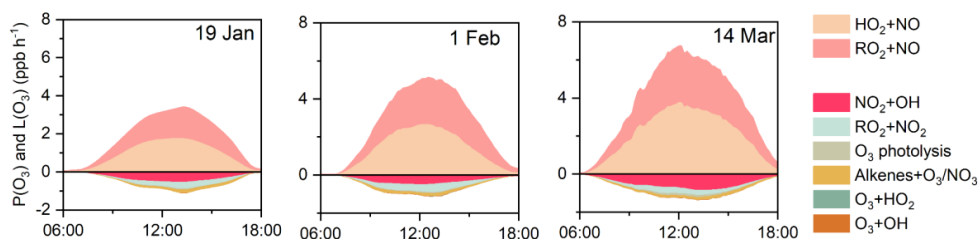
Figure 10. Daytime variation of OH reactivity in three cases

330

To investigate the variation of O_3 during different periods, the formation and loss pathways of O_3
331 were calculated (Figure 11). The formation of O_3 ($P(O_3)$) was dominated by HO_2+NO and RO_2+NO
332 pathways. Although the average MIR during Full-lockdown period was the minimum among the three
333 periods, the $P(O_3)$ on Feb 1st was higher than that on Jan 19th. This could be attributed to the higher
334 AOC and better photochemical conditions during Full-lockdown period. Similarly, much higher $P(O_3)$
335 was found on March 14th. To avoid the influence of meteorological conditions and test the potential
336 mean O_3 (Mean O_3) concentrations under different $NO_x/VOCs$ ratios, a series of scenario analyses were
337 performed based on the average condition during the whole observation, and the isopleths of Mean O_3
338 concentrations are exhibited in Figure. 12. Note that the value of temperature and photolysis frequencies
339 (J values) in the scenario analyses could be higher than the actual value during Pre-lockdown period
340 and could further lead to overestimation of simulated Mean O_3 during Per-lockdown period. Additionally,
341 the VOCs concentrations mentioned in this section only represent the VOC species in the MCM
342 mechanism. By connecting the inflection points in each O_3 isopleth, we get the ridge line, which divides
343 the whole regime into NO_x -sensitive and VOCs-sensitive regimes (Figure. 12). During Pre-lockdown
344 period, the O_3 formation was in VOC-limited regime (triangles in Figure. 12), with an average
345 NO_x/VOC ratio of 1.84. As for Full-lockdown period, significant decrease of NO_x and VOC emissions
346 was observed, and the $NO_x/VOCs$ ratio dropped to 0.79, which gradually switched the O_3 formation to
347 the junction of VOCs-limited and NO_x -limited regimes, especially on Feb 16th and Feb 17th (circles in
348 the red rectangle in Figure. 12), when the O_3 formation went into NO_x -limited regime. During Partial-



349 lockdown period, increasing of VOCs and NO_x emission again dragged the formation of O_3 back into
350 VOCs-limited regime (triangles in Figure. 12). Interestingly, although a great deal of NO_x and VOCs
351 emissions were diminished during Full-lockdown period, the average Mean O_3 in Full-lockdown was
352 supposed to be 2.4 ppbv higher than that in Pre-lockdown period. This result is consistent with the trend
353 of the observed MDA8 O_3 and the results of the deweathered calculation. Therefore, the improper
354 NO_x/VOCs reduction ratio and further influence on chemistry was the key reason for the abnormal
355 increase of O_3 during Full-lockdown period in Changzhou in 2020.



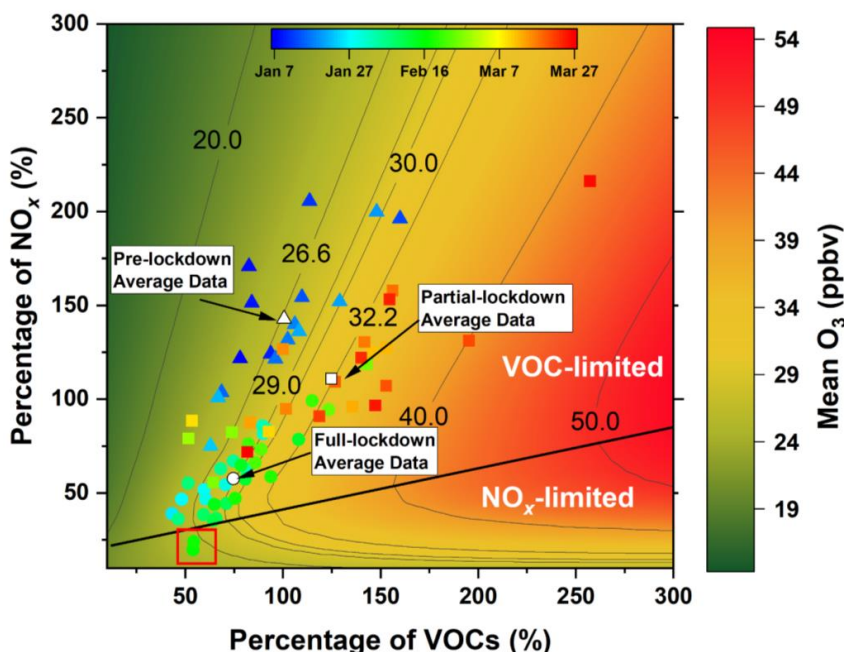
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Figure 11. Daytime variation of $\text{P}(\text{O}_3)$ and $\text{L}(\text{O}_3)$ in three cases

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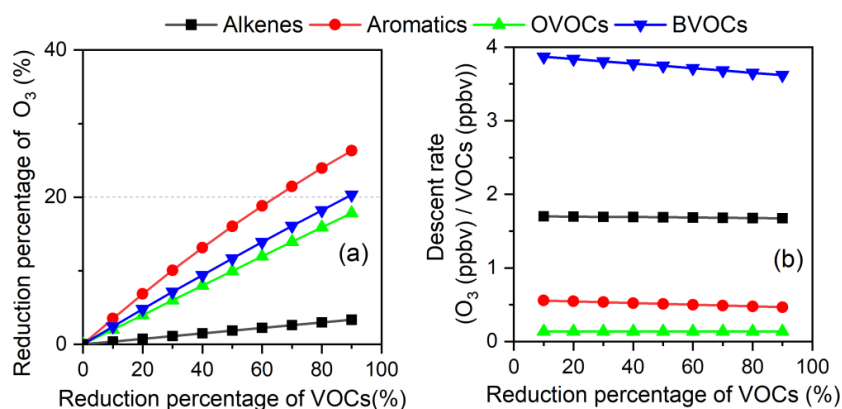
361 **Figure. 12 MeanO₃ isopleth.** The colored circles, triangles, and rectangles represent the daily average
362 concentrations of NO_x and VOCs during Pre lockdown, Full-lockdown, and Partial-lockdown period,
363 respectively. The white circle, triangle, and rectangle indicates the average NO_x and VOCs concentrations
364 during Pre lockdown, Full-lockdown, and Partial-lockdown period, respectively.

365 The scenario analyses raise a question: how much O₃ would change as a function of reduction of
366 NO_x and VOCs? Therefore, the reduction percentage of O₃ ($\Delta O_3/O_3$) during Pre-lockdown period as a
367 function of reduction of VOCs and NO_x were calculated, and the result could be regarded as a potential
368 to control O₃ pollution. Based on the VOCs species in MCM v3.3.1, we classified the measured VOCs
369 into four groups: alkenes (n-butene); aromatics (including benzene, toluene, phenol, xylene, styrene,
370 cresol, and trimethylbenzene); OVOCs (including methanol, ethanol, formaldehyde, aldehyde, acrolein,
371 methyl vinyl ketone, methyl ethyl ketone, ethyl acetate, methyl isobutyl ketone, hexanol, and heptanal);
372 and BVOCs (isoprene, pinene, and caryophyllene). The results in Figure 13(a) indicate that more
373 reduction potential of O₃ could be achieved by diminishing aromatics, followed by BVOCs, OVOCs,
374 and alkenes. It should be noted that many light alkanes and active alkenes, such as ethene and propene,



375 could not be measured by the PTR-TOF-MS and might further lead to the underestimation of ozone
376 sensitivity to alkanes and alkenes. Additionally, this comparison has a drawback of being influenced by
377 the concentrations of VOCs. To normalize the influence of concentrations of VOCs, the descent rate of
378 O_3 (ΔO_3 (ppbv) / Δ VOCs (ppbv)) as a function of reduction percentage of VOCs were calculated (Figure
379 13 (b)). O_3 exhibited the highest dependence on BVOCs, with an average descent rate of 3.74 ± 0.09
380 ppbv/ppbv. Differing from the result in Figure 13 (a), diminishing alkenes could lead to decreasing of
381 O_3 by an average descent rate of 1.69 ± 0.01 ppbv/ppbv. On the contrary, reduction of NO_x would lead
382 to increase of O_3 , with an average rate of 1.29 ± 0.21 ppbv/ppbv (Figure S3). Although the descent rate
383 of O_3 turned to decrease and the sensitive of O_3 formation get into NO_x -limited regime when over 70%
384 of NO_x were eliminated, it still causes net increase of O_3 .

385 Although diminishing BVOCs seems to be the most efficient way to restrain O_3 pollution, most of
386 BVOCs were emitted directly from plants and could not be easily controlled. Besides, huge number of
387 OVOCs (such as formaldehyde, aldehyde, methanol, ethanol, methyl vinyl ketone, methyl ethyl ketone,
388 etc.) could be directly emitted from anthropogenic processes or secondary formatted from the oxidation
389 of precursors (such as alkenes and aromatics), which complicates the control of OVOCs. Therefore,
390 considering the reduction potential and descent rate of O_3 , more efforts are needed on the control of
391 alkenes and aromatics.



392
393 **Figure 13. Reduction percentage of O_3 as a function of reduction percentage of VOCs (a); descent rate of O_3 as a**
394 **function of reduction percentage of VOCs (b).**



395 4. Conclusions

396 After the outbreak of COVID-19, strict epidemic prevention measures have been adopted
397 throughout China, leading to dramatic decrease in traffic volume and industrial activities. Affected by
398 the decrease of number of vehicles on the road, non-essential industrial productivity, and associated
399 pollutant emissions, most of the air pollutants (e.g., PM_{2.5}, PM₁₀, NO, NO₂, SO₂, and VOCs) dropped
400 to a lower level during lockdown period (especially during Full-lockdown period). However, O₃
401 increased compared to that during the same period in 2019 in many urban areas of China. To figure out
402 the reasons for this abnormal increase of O₃, the characteristics of O₃ precursors (NO_x, VOCs) during
403 Pre-lockdown, Full-lockdown, and Partial-lockdown periods in Changzhou were analyzed. Although
404 this study was conducted in single city of China, the representativeness of Changzhou guaranteed the
405 applicability of the results the YRD region. Results suggested that the decrease of human activities
406 during Full-lockdown period significantly suppressed the emissions of NO_x and VOCs, which further
407 lead to dramatic drop in the concentrations of most VOCs, especially aromatics. As a result, the
408 NO_x/VOCs ratios dropped from 1.84 at Pre-lockdown period to 0.79 during Full-lockdown period. By
409 deweathered calculation, we found that meteorology only contributed a minor positive (0.5 ppbv) value
410 to the increase of O₃, whereas changes in precursor emissions led to 5.1 ppbv increase in O₃
411 concentrations during Full-lockdown period. To verify this result, a box model was used to simulate the
412 formation of O₃. Results show that the AOC level during Full-lockdown was comparable to that during
413 Pre-lockdown period, but the formation rate of O₃ was much higher during Full-lockdown period. By
414 scenario analysis, we found the decrease of NO_x and VOCs in Full-lockdown period dragged the
415 formation of O₃ from VOC-sensitive regime to the junction of VOCs- and NO_x-limited regime, and the
416 average simulated MeanO₃ in Full lockdown period could be 2.4 ppbv higher than that in Pre-lockdown
417 period. Although the deweathered model and OBM model shows differences in the emission-derived
418 change of O₃, the results together point out that the improper reduction of NO_x and VOCs was the key
419 reason for the abnormal increase of O₃ during Full-lockdown period in 2020. Overall, the outbreak of
420 COVID-19 has caused devastation over the world. However, it provided an extreme experiment to



421 investigate the O₃ formation under strict emission control policies and provided insights into the policy
422 formulation for diminishing O₃ pollution in the YRD region. The data indicate that the concentrations
423 of VOCs and NO_x have changed dramatically during the pandemic, a common situation also found in
424 other Chinese cities, and led to the switch of O₃ formation sensitivity. These results have a clear
425 indication that, in the future, more efforts should be paid on the reduction ratio of anthropogenic VOCs
426 and NO_x.

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