



1 Anthropogenic-biogenic interactions and regional transport
2 drive summer ozone formation in an agricultural-urban
3 interface of Northeast China

4 Xinpeng Ye^{1,a}, Qian Jiang^{2,3,a}, Jin Ban¹, Mengyu Xie⁴, Qianyi Xu¹, Zeyu Wang¹, Jian
5 Sun^{1*}, Hongai Zhang⁵, Xinyi Niu⁶, Hongmei Xu¹, Zhenxing Shen¹, Guohui Li³

6

7 ¹Department of Environmental Science and Engineering, Xi'an Jiaotong University, Xi'an
8 710049, China

9 ²School of Environmental Science and Engineering, Southwest Jiaotong University, Chengdu,
10 611756, Sichuan, China.

11 ³Key Lab of Aerosol Chemistry & Physics, SKLLQG, Institute of Earth Environment, Chinese
12 Academy of Sciences, Xi'an 710049, China

13 ⁴East China University of Science and Technology, Shanghai 200237, China

14 ⁵Department of Neonatology, Shanghai General Hospital Affiliated to Shanghai Jiao Tong
15 University School of Medicine, 650 Xinsongjiang Rd, Songjiang District, Shanghai 201620, China

16 ⁶Department of Occupational and Environmental Health, School of Public Health, Xi'an Jiaotong
17 University Health Science Center, Xi'an 710049, China

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19 ^aThese authors contributed equally to this work and should be considered as co-first authors.

20 ^{*}Author to whom correspondence should be addressed. E-mail: sunjian0306@mail.xjtu.edu.cn
21 (Jian Sun).

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23 Abstract

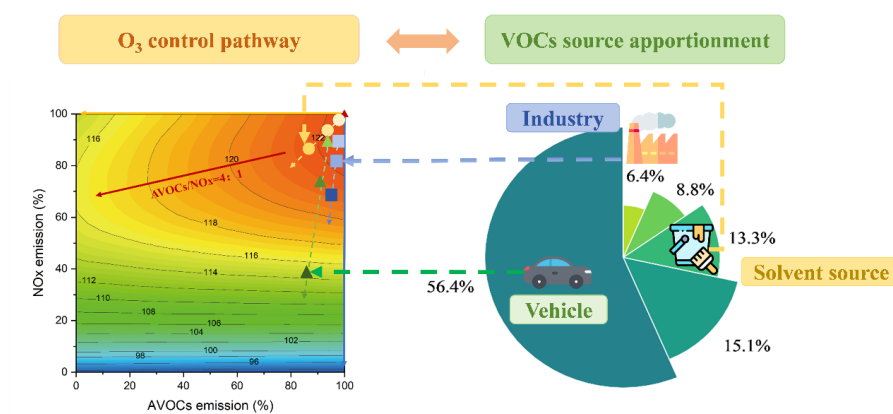
24 Agricultural-urban interfaces (AUIs) present distinct photochemical environments
25 shaped by the intense mixing of anthropogenic and biogenic precursors. To elucidate
26 the mechanisms driving summer ozone (O_3) formation in these regions, we conducted
27 an integrated study in Siping, a representative AUI in Northeast China, utilizing
28 high-time-resolution volatile organic compound (VOC) observations (2021-2022),
29 positive matrix factorization (PMF), and Weather Research and Forecasting model
30 coupled with Chemistry (WRF-Chem) simulations. Observational data indicated that
31 while alkanes and oxygenated VOCs dictate atmospheric abundances, the O_3 formation
32 potential is primarily governed by reactive alkenes and biogenic isoprene. PMF source
33 apportionment identified vehicle exhaust (56.4%) and biogenic emissions from crops
34 and vegetation as critical VOC sources. However, WRF-Chem modeling revealed a
35 pronounced decoupling between local VOC source contributions and actual O_3
36 production. Regional transport and background concentrations collectively account for
37 nearly 90% of the ambient O_3 burden, significantly dwarfing local photochemical
38 production. Empirical kinetic modeling approach (EKMA) analysis showed that local
39 O_3 formation operates within a transition regime sensitive to both VOCs and NO_x .
40 Although regional transport dominates the overall O_3 inventory, scenario simulations
41 demonstrate that mitigating biogenic emissions is unfeasible as a natural source, and
42 industrial emission controls yield negligible benefits due to suboptimal VOC/ NO_x
43 emission ratios. Consequently, controlling local transportation emissions emerges as
44 the most viable and practically effective pathway to alleviate O_3 pollution in AUIs. This
45 study provides a quantitative basis for formulating O_3 mitigation strategies in complex
46 agricultural-urban environments, emphasizing the necessity of integrating regional
47 joint control with targeted local vehicle emission reductions.

48 Keywords: Agricultural-urban interface, ozone formation sensitivity, VOC source
49 apportionment, regional transportation, ozone formulation

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51 Graphic abstract



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54 **1 Introduction**

55 In recent years, despite continued reductions in primary pollutant emissions
56 worldwide, summertime surface ozone (O_3) pollution has shown an increasing trend
57 across many regions of the world (Wang et al., 2025). As a highly oxidative secondary
58 pollutant, ozone not only poses a serious threat to human respiratory health but also
59 substantially suppresses crop growth, making it a critical risk factor that constrains
60 global food security and ecosystem services (Zhang et al., 2019; Manisalidis et al.,
61 2020). While integrated air pollution control has begun to achieve measurable success
62 in traditional industrialized metropolitan clusters, such as the Beijing-Tianjin-Hebei
63 and Yangtze River Delta regions, the Agricultural-Urban Interface (AUI) is emerging
64 as new hotspots of regional ozone pollution worldwide. This shift is largely driven by
65 rapid urbanization and intensive agricultural activities in these widely distributed
66 transitional regions (Benka-Coker et al., 2020).

67 Ozone formation is inherently nonlinear and is jointly governed by multiple factors,
68 including volatile organic compounds (VOCs) composition, precursor concentrations
69 (e.g., VOCs and NO_x), meteorological conditions, and regional transport (Zhao et al.,
70 2025; Tao et al., 2024; Wang et al., 2023a). Unlike heavily industrialized or highly
71 urbanized regions, AUIs exhibit a unique physicochemical environment shaped by
72 their distinctive precursor emission profiles. During summer, vigorous crop growth
73 and emissions from agricultural shelterbelts release substantial amounts of highly
74 reactive biogenic volatile organic compounds (BVOCs), particularly isoprene (Cao et
75 al., 2022); At the same time, seasonal agricultural machinery operations, which
76 generate high NO_x emissions, together with potential biomass burning, dispersed
77 agro-industrial activities, and transit traffic, create a highly complex mixture of
78 anthropogenic and natural emission sources. The strong interaction between highly
79 reactive BVOCs and diverse anthropogenic precursors profoundly alters the local RO_x
80 radical cycling, leading to pronounced nonlinearities in ozone production efficiency
81 and precursor sensitivity across the region (Masui et al., 2023; Liu et al., 2026).

82 Accurately characterizing ozone formation under such a complex emission
83 environment remains a major challenge in atmospheric chemistry. Receptor models



84 based on high-frequency observations, such as positive matrix factorization (PMF),
85 can effectively identify local VOC sources and quantify their contributions. However,
86 they cannot disentangle the influences of evolving meteorological conditions and
87 large-scale regional transport (Ye et al., 2025); In contrast, three-dimensional
88 chemical transport models, such as Weather Research and Forecasting model coupled
89 with Chemistry (WRF-Chem), can explicitly represent meteorology-chemistry
90 interactions and transport processes. Their performance in agriculturally dominated
91 regions, however, is often constrained by substantial uncertainties in localized
92 emission inventories (Zhang et al., 2026; Gupta et al., 2024).

93 As one of the world's three major black soil regions and a globally important
94 agricultural hub, the Northeast China Plain provides an ideal natural laboratory for
95 investigating the photochemical mechanisms of O₃ formation in AUI. During summer,
96 the region is characterized by intense solar radiation, open plain wind fields, and a
97 distinctive landscape in which urban areas are embedded within vast agricultural
98 lands. Nevertheless, studies integrating high-resolution field observations with
99 three-dimensional chemical transport modeling remain scarce in this representative
100 region. In particular, quantitative understanding of the coupled effects of local
101 anthropogenic-natural interactions and large-scale regional transport on O₃ formation
102 is still lacking.

103 To address these knowledge gaps, this study selected Siping, a representative
104 agricultural hub in Northeast China, as the receptor site and established an integrated
105 analytical framework combining high-time-resolution VOC observations, PMF source
106 apportionment, high-resolution WRF-Chem simulations, and empirical kinetic
107 modeling approach (EKMA). The study aims to address three key scientific questions.
108 First, it identifies the key reactive species within the complex precursor mixture of
109 AUI and quantifies the relative contributions of anthropogenic and biogenic emissions
110 to photochemical processes. Second, it quantitatively disentangles the individual and
111 synergistic contributions of local multi-source emissions and large-scale regional
112 transport to summertime O₃ pollution. Third, it explores potential O₃ control pathways
113 by constructing nonlinear O₃-precursor response surfaces specific to agricultural cities.



114 The findings provide a scientific basis for mitigating complex air pollution in
115 Northeast China. More importantly, the identified mechanisms linking
116 anthropogenic-natural interactions with regional transport offer broader insights into
117 the management of photochemical air pollution in agricultural-urban regions with
118 similar characteristics worldwide.

119 **2 Method**

120 2.1 Study area, sampling, and analytical methods

121 Sipong city (42°31'-44°09' N, 123°17'-125°49' E) is located in Northeast China and
122 represents a typical AUI. In 2024, the city had a grain cultivation area of 589,000 ha
123 and a total grain production of 4.901 million tons, reflecting the intensive agricultural
124 activities surrounding the urban area (Statistics Bureau of Jilin, <https://tjj.jl.gov.cn/>).
125 Ambient measurements were conducted at the Yishangchang National Ambient Air
126 Quality Monitoring Station in central Sipong (Fig. S1). No major industrial point
127 sources are located in the immediate vicinity of the site.

128 VOC measurements were conducted during the high-O₃ season in 2021 and 2022.
129 Ambient air was collected into 3.2 L SUMMA canisters with passivated inner surfaces.
130 Each canister was connected to a 3 h integrated sampler, which served as the sampling
131 inlet and controlled the transfer of ambient air into the canister. Field measurements
132 were carried out primarily under clear or partly cloudy conditions on 14
133 non-consecutive days from 17 July to 30 August 2021 and on another 14
134 non-consecutive days from 8 June to 22 July 2022.

135 To characterize VOC variations under different emission and photochemical
136 conditions, samples were collected during three periods: 08:00-09:00, when
137 anthropogenic emissions were enhanced but photochemical activity remained
138 relatively weak; 14:00-15:00, corresponding to stronger anthropogenic emissions and
139 photochemical activity; and 19:00-20:00, representing relatively low anthropogenic
140 emissions with negligible photochemical activity. In total, 85 samples were obtained,
141 including one field blank. A total of 106 VOC species were quantified and grouped
142 into alkanes, alkenes, alkynes, aromatics, halocarbons, and oxygenated volatile



143 organic compounds (OVOCs). Further information on chemical analysis and the
 144 complete list of measured species is provided in Text S1 and Table S1.

145 2.2 Ozone formation potential

146 The photochemical importance of individual VOC species was evaluated using the
 147 ozone formation potential (OFP), based on their measured concentrations and
 148 corresponding maximum incremental reactivity (MIR) coefficients (Carter, 1994;
 149 Zhang et al., 2021; Sha et al., 2021):

$$150 \quad OFP_i = VOC_i \times MIR_i$$

151 where OFP_i is the ozone formation potential of VOC species i , VOC_i is its
 152 measured concentration, and MIR_i is the corresponding maximum incremental
 153 reactivity coefficient. The fractional contribution of individual species or VOC groups
 154 was determined relative to the summed OFP of all species included in the calculation.
 155 Species for which MIR coefficients were unavailable were excluded.

156 2.3 PMF source apportionment

157 The sources of ambient VOCs were resolved using U.S. EPA PMF 5.0. The observed
 158 concentration matrix is expressed as:

$$159 \quad x_{ij} = \sum_{k=1}^p g_{ik} f_{kj} + e_{ij}$$

160 where x_{ij} is the measured concentration of species j in sample i , g_{ik} represents the
 161 contribution of factor k to sample i , f_{kj} is the profile of species j in factor k , and e_{ij} is
 162 the model residual. PMF constrains both factor contributions and factor profiles to
 163 non-negative values (Liu et al., 2023a; Gu et al., 2022).

164 Concentration and uncertainty matrices constructed from representative VOC species
 165 measured during the 2021-2022 campaigns were used as model inputs. Twenty runs
 166 were performed, and the final five-factor solution was selected according to model
 167 performance and solution stability.

168 2.4 WRF-Chem simulations

169 The WRF-Chem modeling framework followed that used in our previous study (Ye et
 170 al., 2025), with the model domain, emission inputs, simulation period, and sensitivity



settings adapted specifically for the summertime O₃ episode in Siping. A 6 km horizontal-resolution domain comprising 150 × 150 grid cells was established over Northeast China and centered at 43.5° N, 124.5° E (Fig. S2). Atmospheric chemistry was represented using the SAPRC-99 mechanism.

Anthropogenic emissions combined the localized Siping emission inventory with the Multi-resolution Emission Inventory for China (MEIC) and were separated into agriculture, industry, power plants, residential combustion, and transportation. Biogenic emissions were calculated online using the Model of Emissions of Gases and Aerosols from Nature (MEGAN). Additional information on the meteorological and chemical configurations is provided in Text S2 and Table S2.

Model performance was assessed using hourly PM_{2.5}, O₃, NO₂, SO₂, and CO observations from the National Ambient Air Quality Monitoring Station in Siping. Three statistical metrics were used: mean bias (MB), root mean square error (RMSE), and index of agreement (IOA):

$$MB = \frac{\sum_{i=1}^N (P_i - O_i)}{\sum_{i=1}^N O_i}$$

$$RMSE = \left[\frac{1}{N} \sum_{i=1}^N (P_i - O_i)^2 \right]^{\frac{1}{2}}$$

$$IOA = 1 - \frac{\sum_{i=1}^N (P_i - O_i)^2}{\sum_{i=1}^N (|P_i - \bar{O}| + |O_i - \bar{O}|)^2}$$

where P_i and O_i denote simulated and observed values, respectively, N is the number of paired observations, and $\bar{O}$ represents the mean observed value.

2.5 Sensitivity analysis and EKMA

The factor separation approach (FSA) used to distinguish emission and transport effects followed the modeling framework established in our previous work (Ye et al., 2025), with scenario settings redesigned for summertime O₃ in Siping. The analysis covered 11-18 June 2021. Three sensitivity experiments, together with the baseline simulation, were used to separate the contributions associated with local emissions and regional transport and to quantify their interactions. The corresponding anthropogenic emission configurations are provided in Table S3, while the mathematical formulation of the FSA is described in Text S3.



200 A second set of sensitivity simulations was conducted to determine the contributions
201 of individual emission sectors. Emissions from agriculture, industry, power plants,
202 residential combustion, transportation, and biogenic sources were modified separately
203 relative to the baseline simulation. The settings for these source-specific experiments
204 are summarized in Table S4.

205 The EKMA analysis followed the emission-response framework developed in our
206 previous study(Ye et al., 2026b), but used the Siping-specific emission inventory and
207 chemical conditions. Because the analysis was intended to evaluate controllable
208 anthropogenic precursor reductions, BVOC emissions were maintained at their
209 baseline values. anthropogenic VOC (AVOC) and NO_x emissions were independently
210 varied from 0% to 100% of the baseline inventory at intervals of 10%, forming an 11
211 × 11 matrix of 121 sensitivity simulations. The resulting O₃ response surface was used
212 to identify precursor-sensitivity regimes and the coordinated AVOC-NO_x reduction
213 pathway.

214 **3 Result & Discussion**

215 **3.1 VOC composition, temporal characteristics, and OFP in Siping**

216 During the sampling period, the mean ambient VOC concentration in Siping was
217 42.33 ± 3.12 ppbv, which was higher than those reported for several other northern
218 Chinese cities, including Qingdao (18.8 ppbv, 2021), Shijiazhuang (29.3 ppbv, 2022),
219 and Zhumadian (17.7 ppbv, 2020) (Wu et al., 2024). The six VOC groups ranked, in
220 descending order of concentration, as follows: alkane (15.65 ppbv), OVOC (13.32
221 ppbv), halocarbons (5.64 ppbv), alkene (4.50 ppbv), aromatics (2.80 ppbv), and
222 alkyne (1.02 ppbv). Alkanes were the dominant group, accounting for 36.98% of total
223 VOCs, followed by OVOCs, which contributed 31.48%. Alkenes and halocarbons
224 exhibited comparable abundances, whereas aromatics and alkynes contributed
225 relatively little to the total VOC burden.

226 The concentrations of individual VOC species are summarized in Table S6.
227 Isopentane was the most abundant species, with a concentration of 29.14 ppbv,
228 followed by acetone, n-pentane, isobutane, n-butane, propane, ethane, ethylene, and
229 acetylene. A comparison of key VOC species between the summer of 2021 and 2022
230 is presented in Table S7. The dominant VOC species and their rankings showed little



interannual variation, with C₄-C₅ alkanes, acetone, and short-chain alkanes consistently accounting for the largest fractions. This consistency suggests that the major emission sources and their relative contributions remained broadly stable during the study period. However, the overall VOC concentration was substantially higher in the summer of 2022 than in 2021. Notably, the concentration of isopentane increased to approximately seven times that measured during the same period in the previous year, indicating that this species warrants particular attention. Figure 1 illustrates the diurnal variations in VOC composition in Siping. The VOC concentrations consistently exhibited distinct morning and evening peaks, a pattern that agrees well with observations reported for other Chinese cities, such as Jinan in Shandong Province during summer (Liu et al., 2023b) and Weinan in Shaanxi Province (Li et al., 2022a). This consistency suggests that the diurnal variation of VOCs in AUI remains primarily controlled by vehicular emissions, reflecting a common emission and photochemistry-driven pattern across regions. Analysis of individual VOC groups further showed that alkane, alkene, and alkyne concentrations during the evening peak were substantially higher than those observed at other times of the day. This increase was likely associated with emission sources exhibiting pronounced temporal patterns, particularly vehicle exhaust and residential biomass combustion (Fuchs et al., 2017).

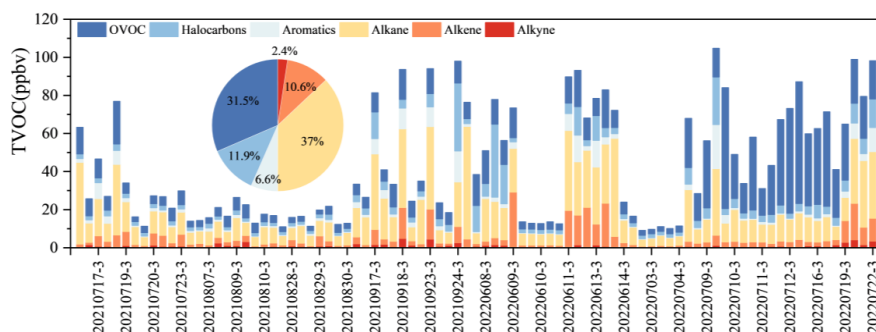


Figure 1: Temporal variations and chemical composition of VOCs in Siping during the summers of 2021-2022. Building on these results, the OFP of ambient VOCs in Siping was evaluated using the MIR method and compared with the observed O₃ concentrations (Fig. 2). Alkenes



255 contributed the largest fraction of OFP (51.96%), followed by alkanes (25.02%),
256 OVOCs (11.69%), and aromatics (10.78%), whereas halocarbons (0.55%) and
257 alkynes (0.0009%) made only minor contributions. This distribution differs
258 substantially from the VOC composition, indicating that OFP is determined not only
259 by VOC abundance but also by the intrinsic reactivity of individual species. Further
260 analysis of the major contributors to OFP (Table S8) showed that ethylene, propylene,
261 and isoprene were the dominant alkene species driving O_3 formation. These
262 compounds consistently ranked among the largest contributors to OFP across different
263 sampling months in both 2021 and 2022. Consequently, alkenes became the largest
264 contributor to OFP despite their relatively low ambient concentrations. Notably,
265 during the warmer months (August 2021 and July 2022), isoprene ranked among the
266 top three contributors to OFP across all VOC species, highlighting the critical role of
267 BVOCs in summertime O_3 formation. Among alkanes, isopentane, n-butane, propane,
268 and ethane contributed most to OFP, primarily because of their relatively high
269 ambient concentrations.

270 The diurnal variation in OFP closely followed that of VOC concentrations, with
271 pronounced morning and evening peaks. Table S9 lists the top 10 VOC species
272 contributing to OFP during the morning, afternoon, and evening periods. During the
273 morning peak, isopentane, isobutane, n-pentane, and acetone were the largest
274 contributors to OFP. The dominant contribution of alkanes indicates that vehicular
275 emissions during the morning rush hour were an important driver of O_3 formation
276 (Yang et al., 2019). During the afternoon, ethylene and acetone became the major
277 contributors to OFP. As an important secondary oxidation product, the elevated
278 contribution of acetone suggests that atmospheric oxidation had reached its maximum
279 intensity. At this stage, substantial consumption of VOCs by photochemical reactions
280 led to an overall decline in OFP (Li et al., 2022a; Sha et al., 2021). Notably, as a
281 representative AUI, Siping experiences substantial BVOC emissions from intensive
282 crop growth and agricultural shelterbelts during summer. The diurnal variation in
283 isoprene OFP first decreased and then increased, reaching its maximum in the evening.
284 This pattern suggests that elevated daytime temperatures suppress plant isoprene



emissions, followed by compensatory emissions later in the day (Li et al., 2025); Despite the reduction in absolute emissions, isoprene remained one of the leading contributors to OFP during the afternoon because of its high chemical reactivity and the concurrent depletion of anthropogenic VOCs by photochemical oxidation (Tan et al., 2021). These findings further confirm the important role of BVOCs, particularly isoprene, in O_3 formation in Siping and underscore the necessity of jointly considering natural and anthropogenic emissions when developing O_3 control strategies for agricultural regions. During the evening, the contributions of C_4 - C_5 alkenes to OFP increased markedly, particularly those of trans-2-pentene and trans-2-butene. These species are strongly associated with natural gas, coal gas, and solid fuel combustion, suggesting that residential emissions from the surrounding areas substantially influenced ambient VOC levels (Li et al., 2022b; Gao et al., 2021). It is worth noting that the temporal trend of OFP did not correspond to the observed variation in O_3 concentrations (Fig. 2), further demonstrating the complex nonlinear relationship between VOCs and O_3 formation in Siping. Therefore, source apportionment and numerical modeling are required to further elucidate the underlying mechanisms.

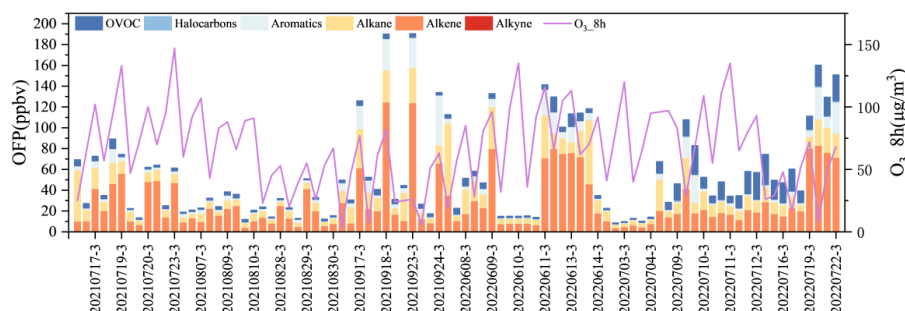


Figure 2: Temporal variations in OFP of VOCs and observed O_3 concentrations in Siping during the summers of 2021-2022.

3.2 Source apportionment of VOCs

To identify the sources of ambient VOCs in Siping, PMF analysis was performed using representative VOC species collected during the 2021-2022 sampling



308 campaigns. The identified source profiles and their relative contributions are
309 presented in Fig. 3. Based on the monitoring data, together with the local emission
310 inventory and PMF source profiles, VOC emissions in Siping were classified into five
311 major source categories: vehicle emission, industrial combustion, solvent source,
312 gaseous fuel combustion, and biogenic source.

313 A detailed interpretation of the PMF factors is provided in Text S4. Factor 1 was
314 characterized by high loadings of aromatic compounds and several halocarbons,
315 including styrene, ethylbenzene, xylenes, ethyl acetate, and chloroform. This factor
316 was therefore identified as solvent source (Li et al., 2024; Sha et al., 2021; Wang et al.,
317 2023b). Factor 2 was dominated by light hydrocarbons, together with
318 chlorofluorocarbons and methyl tert-butyl ether (MTBE), indicating a mixed source
319 associated with gaseous fuel use, combustion processes, and refrigerant emissions.
320 Accordingly, this factor was attributed to gaseous fuel combustion, including natural
321 gas and liquefied petroleum gas (LPG) (Zhu et al., 2025; Man et al., 2020; Wu et al.,
322 2023a). Factor 3 exhibited exceptionally high isoprene together with abundant
323 oxygenated VOCs, indicating a secondary/biogenic source dominated by biogenic
324 emissions (Wang et al., 2024; Vestenius et al., 2021; Wu et al., 2023b). Factor 4 was
325 characterized by substantial contributions from C₄-C₆ alkanes and alkenes, including
326 isopentane, n-pentane, n-butane, ethylene, and cis-2-butene, as well as elevated
327 toluene, which are typical tracers of vehicle emissions (Zhou et al., 2020; Man et al.,
328 2020; Sun et al., 2021; Zi et al., 2023). Factor 5 was enriched in heavier aromatic
329 compounds, such as trimethylbenzene and diethyl benzene, together with long-chain
330 alkanes, and was therefore identified as industrial combustion, primarily associated
331 with diesel-related heavy-oil combustion (Frischmon and Hannigan, 2024; Liang et al.,
332 2020; Lyu et al., 2021).

333 Fig. 3(b) presents the relative contributions of different VOC emission sources in
334 Siping during the 2021-2022 sampling period based on the PMF results. Vehicle
335 emissions were the dominant source, accounting for 56.4% of total VOCs. Gaseous
336 fuel combustion and solvent source contributed 15.1% and 13.3%, respectively.
337 Biogenic sources accounted for 8.8%, likely reflecting the strong influence of

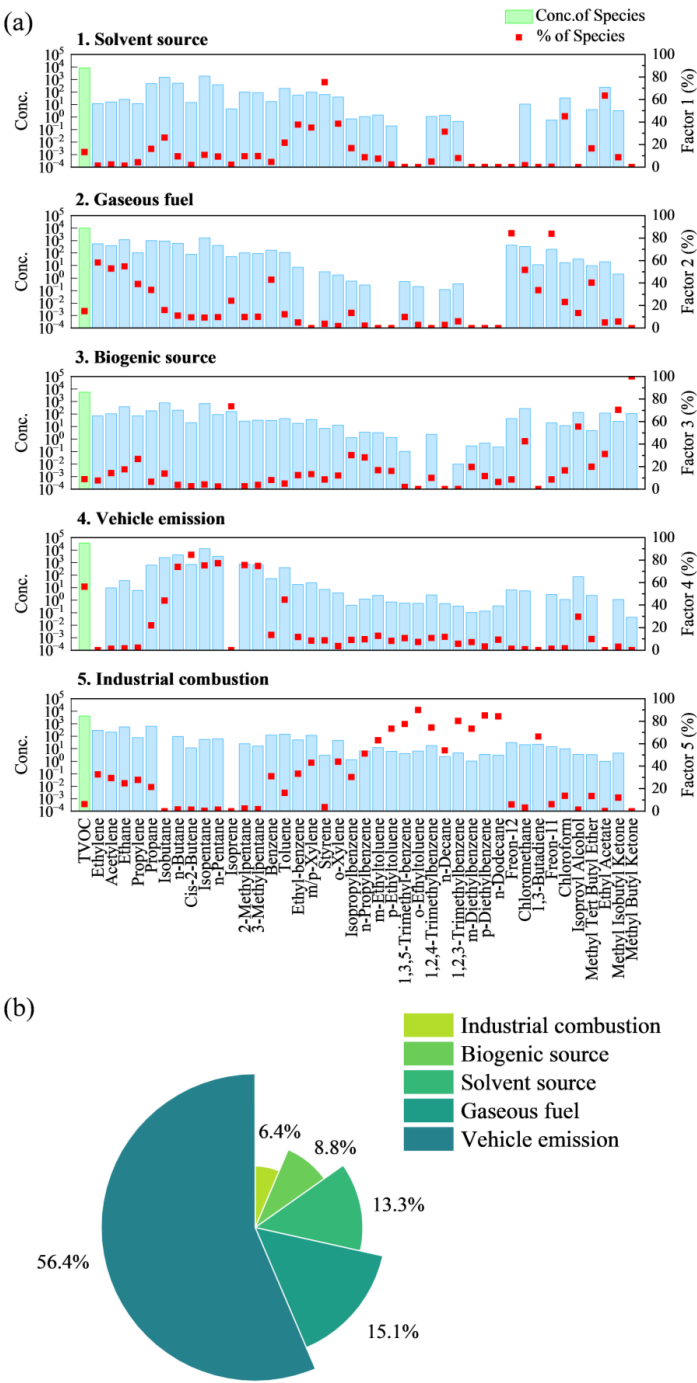


338 agricultural activities in Siping, whereas industrial combustion contributed only 6.4%.
339 Notably, the contribution of vehicle emissions in Siping was substantially higher than
340 those reported for other cities and background sites, including Qingdao (17.1%) (Wu
341 et al., 2023a), Deqing, Zhejiang (11.8%) (Wang et al., 2026), the Shangdianzi regional
342 background station (23.4%; 40.65°N, 117.12°E), which is located at a similar latitude
343 and is part of the Global Atmosphere Watch (GAW) network (Han et al., 2021), and
344 Harbin (28.9%; 45°45'N, 126°41'E), another city at a comparable latitude (Xuan et al.,
345 2021). The exceptionally high contribution of vehicle emissions suggests that, in AUI,
346 where industrial sources are relatively limited, seasonal BVOC emissions together
347 with urban and transit traffic constitute the dominant local precursor sources. This
348 unique emission structure likely leads to O₃ formation efficiency and precursor
349 sensitivity that differ fundamentally from those observed in large industrialized cities,
350 highlighting the need for integrated analyses combining receptor models and chemical
351 transport modeling to elucidate the mechanisms.

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356 Figure 3: PMF-resolved factor contribution characteristics and source contributions



357 3.3 WRF-Chem model evaluation

358 3.3.1 Evaluation of summertime O₃ simulations

359 The WRF-Chem simulations covered the period from 11 to 18 June 2021. Fig.S3
 360 compares the observed and simulated hourly O₃ concentrations at the National
 361 Ambient Air Quality Monitoring Stations in Jilin Province and Siping during the
 362 simulation period. Relative to the observations, the model slightly overestimated O₃
 363 concentrations across Jilin Province. Nevertheless, the simulated O₃ exhibited good
 364 agreement with the observations, with IOA values of 0.84 and 0.87 for Jilin Province
 365 and Siping, respectively. More importantly, the model successfully reproduced the
 366 overall diurnal variation in O₃ concentrations. For Siping, the MB of the simulated
 367 hourly O₃ concentration was -4.2 µg/m³, these results indicate that the model
 368 reasonably captured the temporal evolution of hourly O₃ concentrations during the
 369 study period.

370 Fig.S4 presents the spatial distributions of the simulated and observed mean
 371 near-surface concentrations of the maximum daily 8 h average (MDA8) O₃ and other
 372 major air pollutants during 11-18 June 2021. The model successfully reproduced the
 373 spatial distribution of major air pollutants over Siping and the surrounding region.
 374 The simulated mean MDA8 O₃ concentrations ranged from 125 to 175 µg/m³,
 375 corresponding to a slight pollution level. Meanwhile, the observed mean MDA8 O₃
 376 concentration at the monitoring site was 162.63 µg/m³, while the simulated values
 377 exhibited a slight underestimation compared to the observation.

378 Overall, the WRF-Chem model satisfactorily reproduced both the temporal variations
 379 and spatial distributions of major air pollutants over Jilin Province and Siping.
 380 However, discrepancies between the simulations and observations remained. In
 381 addition to uncertainties associated with meteorological simulations, such as planetary
 382 boundary layer development and horizontal wind fields, uncertainties in
 383 anthropogenic emission inventories are considered a major source of model bias (Ye
 384 et al., 2025).

385 3.3.2 Contributions of background concentrations, local emissions, and regional 386 transport to MDA8 O₃

387 Figure S5 illustrates the spatial distributions of background MDA8 O₃ concentrations,
 388 locally produced MDA8 O₃, and MDA8 O₃ associated with regional transport in
 389 Siping and the surrounding areas during 11-18 June 2021. Background concentrations



390 accounted for more than 50% of the total MDA8 O₃ burden, contributing
 391 approximately 80-100 µg/m³. In contrast, the contribution from local emissions was
 392 relatively small, averaging about 15 µg/m³ (approximately 10% of total MDA8 O₃)
 393 and was primarily concentrated in the Tiedong and Tiexi districts. Regional transport
 394 also made a substantial contribution, ranging from 40 to 50 µg/m³ (approximately
 395 30-40% of total MDA8 O₃). As shown by the wind field in Fig. S5(c), southwesterly
 396 winds prevailed over Northeast China during summer. On a broader regional scale,
 397 the southwestern upwind region is characterized by higher total column O₃.
 398 Consequently, atmospheric disturbances originating from the southwest can reshape
 399 regional circulation patterns, causing O₃ pollution in Siping to be strongly influenced
 400 by elevated background O₃ transported from this direction (Du et al., 2026; Shi et al.,
 401 2024).

402 The quantitative contributions of background concentrations, local emissions, and
 403 regional transport to MDA8 O₃ in Siping are summarized in Table S10. The mean
 404 MDA8 O₃ concentration was 155.04 µg/m³, of which the background concentration
 405 contributed 88.79 µg/m³ (57.27%) in Siping. Regional transport represented the
 406 second largest contributor, accounting for 49.89 µg/m³ (32.18%). By comparison,
 407 MDA8 O₃ produced from local emissions contributed only 15.71 µg/m³ (10.13%).
 408 Interactions among atmospheric pollutants slightly increased the O₃ concentration by
 409 0.65 µg/m³ (0.42%), indicating a weak net chemical production. These results are
 410 generally consistent with the observed pollution characteristics.

411 Overall, background concentrations and regional transport together accounted for
 412 nearly 90% of the total MDA8 O₃ concentration, highlighting the dominant influence
 413 of regional processes on summertime MDA8 O₃ pollution in Siping. This strong
 414 dependence on regional transport substantially limits the effectiveness of strategies
 415 based solely on local emission reductions. Therefore, optimizing O₃ mitigation in AUI
 416 requires integrating regional emission control with analyses of the nonlinear
 417 relationship between MDA8 O₃ and precursor response surface (e.g., EKMA) and
 418 detailed emission inventories to identify the most effective control pathways.

419 3.3.3 Contributions of major emission sources to summertime O₃ in Siping

420 Figure 4 and Fig. S6 present the spatial distributions of the mean contributions and
 421 percentage contributions of industrial, power plant, residential, transportation,
 422 agricultural, and biogenic sources to MDA8 O₃ concentrations in Siping during 11-18



June 2021. The quantitative contributions of these source categories are summarized in Table 1. Among all sources, biogenic emissions made the largest contribution to O_3 , accounting for 11.76% ($18.24 \mu\text{g}/\text{m}^3$) of the total concentration. Although biogenic emissions were one of the dominant contributors, their contribution was comparable to or lower than those reported for other AUI and temperate regions, including agricultural and forested areas in six U.S. cities (10–19%) (Zhang et al., 2017), the Yangtze River Delta (9.5–20%) (Li et al., 2019), the North China Plain (29.5%), the Pearl River Delta (24.7%), and India (15.0%) (Gao et al., 2020). This relatively modest contribution is primarily attributable to the land-use characteristics surrounding Siping. The region is dominated by cropland, where BVOC emissions are generally lower than those from forest ecosystems. Moreover, vegetation with high isoprene and monoterpene emission capacities occupies only a limited area, restricting the regional BVOC emission potential (Li et al., 2025). Therefore, despite being a representative AUI, Siping does not exhibit an exceptionally strong biogenic enhancement of O_3 formation compared with other regions.

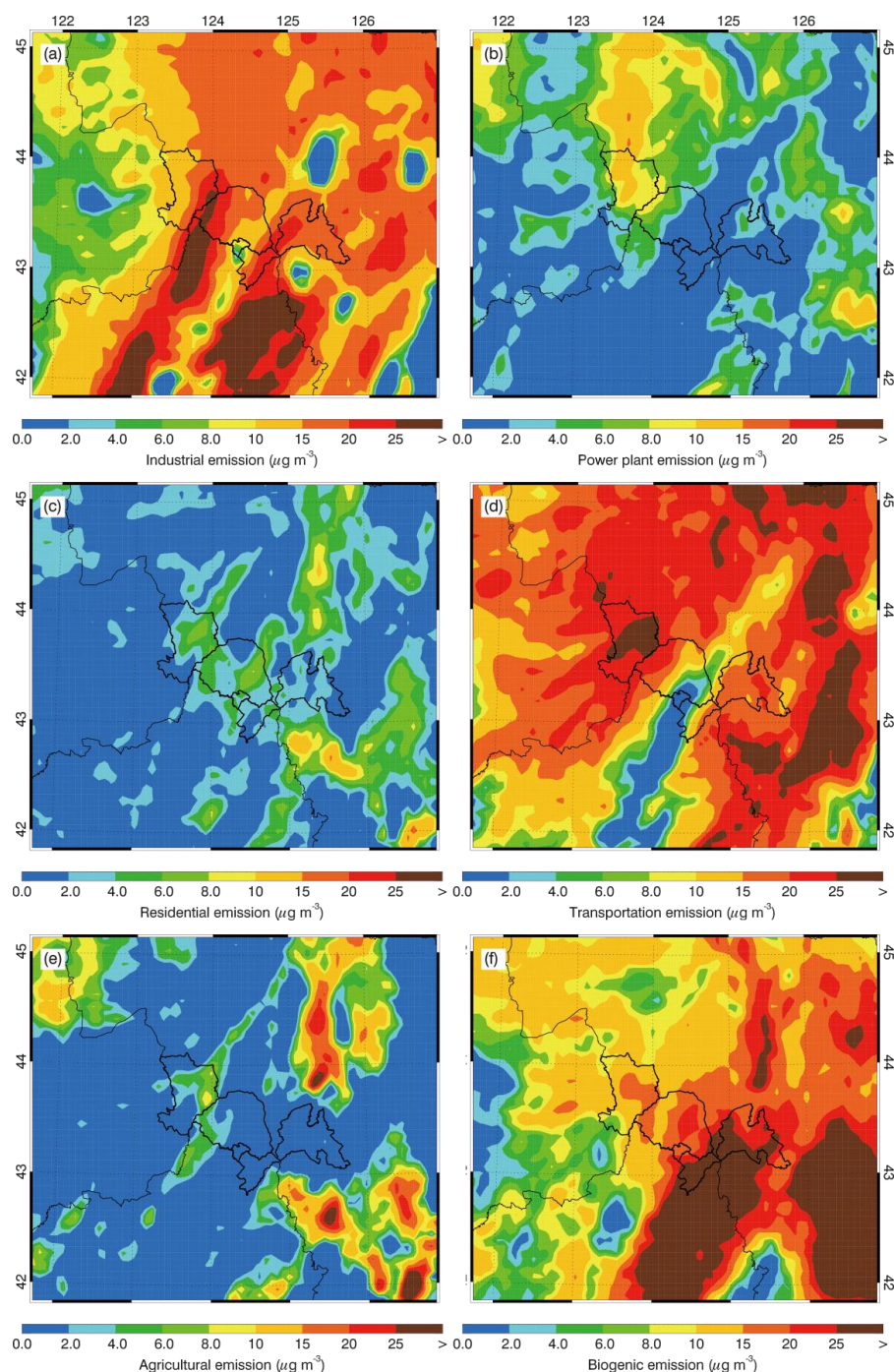
Industrial emissions and transportation were the second and third largest contributors, accounting for 11.19% ($17.35 \mu\text{g}/\text{m}^3$) and 10.87% ($16.85 \mu\text{g}/\text{m}^3$), respectively. In contrast, contributions from power plants, residential combustion, and agricultural emissions were relatively small, at 1.14%, 1.84%, and 0.92%, respectively. Notably, agricultural emissions contributed only 0.92% to MDA8 O_3 , substantially less than other anthropogenic sources. This result is mainly because agricultural emissions in the present emission inventory are dominated by NH_3 released from agricultural activities. NH_3 primarily promotes the formation of secondary inorganic aerosols through atmospheric acid-base reactions and has only a limited direct influence on O_3 photochemistry (Pan et al., 2024). Overall, these results indicate that industrial emissions, biogenic emissions, and transportation were the primary drivers of summertime MDA8 O_3 pollution in Siping.

A notable finding is the discrepancy between the PMF and WRF-Chem results. PMF analysis showed that vehicle emissions accounted for 56.4% of total VOC concentrations, making them the dominant VOC source. In contrast, WRF-Chem sensitivity simulations indicated that transportation contributed only 10.87% to summertime MDA8 O_3 . This contrast between a high contribution to VOCs and a relatively low contribution to MDA8 O_3 further highlights the strong nonlinearity between precursor emissions and O_3 formation in AUI.



457 Several factors explain this discrepancy. First, background concentrations and
458 regional transport together accounted for nearly 90% of the total O₃ concentration,
459 substantially diluting the incremental O₃ produced by local transportation emissions
460 and limiting their contribution to ambient O₃. Second, although transportation emits
461 large amounts of VOCs, these emissions are dominated by C₄-C₅ alkanes and some
462 aromatic compounds. In contrast, the OFP analysis demonstrated that O₃ formation in
463 Siping is more strongly controlled by highly reactive species, particularly alkenes
464 such as ethylene, propylene, and isoprene. Despite their relatively small contribution
465 to total VOC concentrations, BVOCs, especially isoprene, exhibit exceptionally high
466 chemical reactivity. Under strong summertime solar radiation, they efficiently
467 enhance RO_x radical cycling and substantially increase O₃ production efficiency.
468 These findings indicate that O₃ formation depends more strongly on the abundance of
469 highly reactive precursors than on total VOC concentrations alone. Therefore,
470 inferring O₃ formation directly from VOC concentrations or source contributions may
471 lead to substantial bias in AUI. Integrating high-resolution WRF-Chem simulations
472 with the EKMA provides a more robust framework for identifying effective O₃
473 control strategies.

474



475
 476 Figure 4. Spatial distributions of the mean contributions of industrial, power plant, residential,
 477 transportation, agricultural, and biogenic sources to MDA8 O₃ concentrations in Siping during
 478 11-18 June 2021.



479

480 Table 1: Contributions of major emission sources in Northeast China to MDA8 O₃ concentrations
 481 in Siping during the simulation period.

Case	MDA8 O ₃	
	Concentration (μg/m ³)	Contribution (%)
Baseline simulation	155.04	/
Industrial emissions	17.35	11.19
Power plant emissions	1.77	1.14
Residential emissions	2.85	1.84
Transportation emissions	16.85	10.87
Agricultural emissions	1.43	0.92
Biogenic emissions	18.24	11.76

482

483 3.3.4 Sensitivity analysis of summertime O₃ formation and control strategies

484 To further investigate the sensitivity of summertime O₃ formation in Siping, EKMA
 485 isopleths were constructed by varying AVOC and NO_x emissions (Fig. 5(a)). The
 486 inflection points of the O₃ isopleths were connected to derive the ridgeline, along
 487 which the AVOC/NO_x ratio was approximately 4:1, representing the most effective
 488 coordinated reduction pathway. The ridgeline separated the EKMA diagram into
 489 different sensitivity regimes, with the reference condition of Siping located close to
 490 this boundary. Given the relatively low AVOC emissions, no distinct VOC-limited
 491 regime was identified; instead, summertime O₃ formation occurred within a transition
 492 regime where both AVOCs and NO_x influenced ozone production. Under this
 493 condition, coordinated precursor controls are required to achieve effective O₃
 494 mitigation, while the actual reduction efficiency may further depend on the emission
 495 sources contributing to these precursors.

496 However, the relationship between precursor emissions and O₃ formation is more
 497 complex in an AUI than in conventional urban environments because anthropogenic
 498 emissions coexist with biogenic VOC inputs and substantial regional background
 499 ozone. Therefore, control strategies based solely on bulk VOC or NO_x reductions may
 500 not fully capture the ozone mitigation potential of individual emission sectors.

501 To identify the most effective controllable sources under this complex chemical



environment, combining the source apportionment and sensitivity simulations, this study identified biogenic, industrial, and transportation emissions as the major precursor sources of summertime O_3 in Siping. According to the 2021 local emission inventory, regional BVOCs are emitted predominantly by crops and natural vegetation and therefore represent an uncontrollable natural source. This characteristic is a common challenge for O_3 mitigation in AUI across northern China (Ye et al., 2025). Consequently, emission control efforts in Siping should focus primarily on anthropogenic sources, particularly industry and transportation.

Our previous studies have demonstrated that emission-inventory-based mitigation scenarios provide an effective framework for evaluating ozone reduction potential (Ye et al., 2026a). Therefore, we further combined EKMA analysis with emission inventory reductions to quantify the ozone mitigation effectiveness of the three major emission sources. Nine emission reduction scenarios were designed to evaluate the effectiveness of different control strategies (Fig. 5(b)-(d) and Table S11). The results reveal clear differences in O_3 mitigation efficiency between industrial and transportation emissions. For industrial process emissions (Industry 1), the VOC/ NO_x emission ratio was close to 1:1, placing the system near the NO_x -limited regime. However, because VOC emissions from this source were relatively low, reducing these emissions alone produced only a limited decrease in O_3 , with a maximum reduction of 0.9% even under a 100% emission reduction scenario. Industrial fossil fuel combustion (Industry 2) exhibited an even lower VOC/ NO_x ratio, deviating further from the optimal EKMA control pathway and resulting in relatively poor O_3 mitigation efficiency. These findings suggest that reducing emissions from individual industrial sectors alone is insufficient to effectively alleviate O_3 pollution in Siping, a limitation that may also apply to other AUI.

In contrast, transportation emissions exhibited substantially greater mitigation potential. As the dominant source of VOCs in Siping, transportation represents the most effective controllable target for O_3 reduction. Scenario simulations showed that reducing transportation emissions by 50% and 100% decreased the mean O_3 concentration from 125 $\mu g/m^3$ to 121 $\mu g/m^3$ and 114 $\mu g/m^3$, corresponding to reductions of 3.2% and 8.8%, respectively. These results are consistent with the source contribution analysis (Table 1), confirming that transportation emission control is the most effective and practically achievable strategy for mitigating summertime O_3 pollution in Siping.



From the perspective of O₃ control effectiveness, these findings also highlight the environmental benefits of transportation electrification. For AUI such as Siping, replacing conventional vehicles with electric vehicles can directly reduce emissions from the dominant controllable precursor source, providing an efficient and practical pathway for O₃ mitigation. These results provide scientific evidence to support coordinated O₃ management and green transportation policies in AUI and offer useful guidance for developing integrated precursor control strategies in agricultural-urban regions.

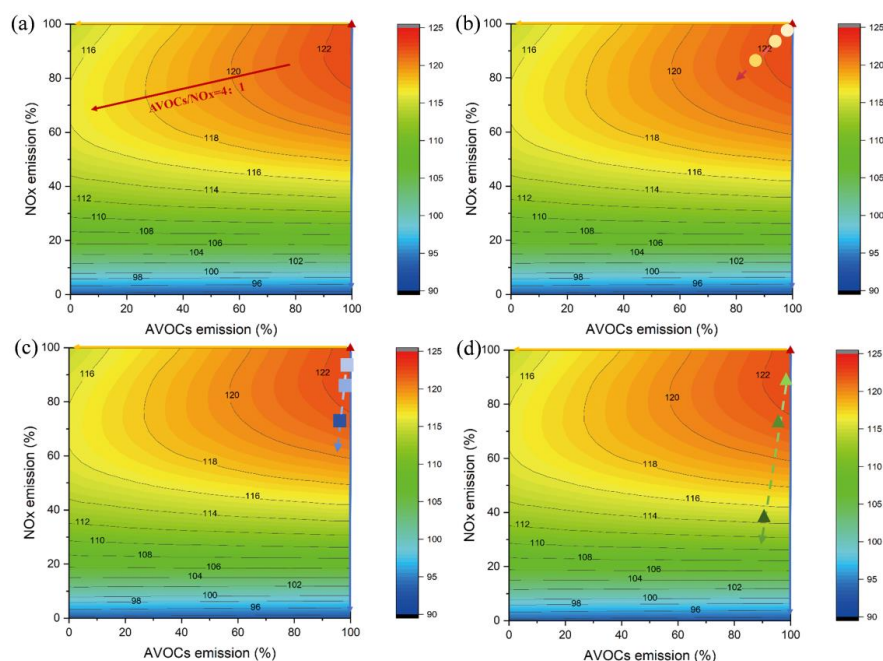


Figure 5: EKMA isopleths of summertime O₃ (MDA8 O₃) in Siping. (a) EKMA isopleths under the baseline emission scenario. (b) Emission reduction scenarios for industrial process emissions (Industry 1). (c) Emission reduction scenarios for industrial fossil fuel combustion (Industry 2). (d) Emission reduction scenarios for vehicle emissions. The x- and y-axes represent the fractions of remaining AVOC and NO_x emissions relative to the baseline emissions, respectively. The red triangle in the upper-right corner denotes the baseline emission scenario (100% AVOC and 100% NO_x emissions). The circles, squares, and triangles represent the emission reduction scenarios for Industry 1, Industry 2, and vehicle emissions, respectively. Marker colors from light to dark indicate emission reductions of 20%, 50%, and 100%, respectively.



555 **4 Conclusions**

556 This study investigated Siping, a representative AUI in Northeast China, by
557 integrating VOC observations, PMF source apportionment, WRF-Chem simulations,
558 and EKMA analysis to elucidate the interplay between local emissions and regional
559 processes in summertime O₃ pollution. PMF results showed that vehicle emissions
560 were the dominant local VOC source, accounting for 56.4% of total VOCs. In contrast,
561 WRF-Chem simulations indicated that background O₃ and regional transport together
562 contributed nearly 90% of ambient O₃, highlighting the strong influence of
563 regional-scale processes on O₃ levels in the AUI. Notably, despite this dominant
564 regional influence, reductions in transportation emissions still effectively decreased
565 O₃ concentrations. This finding demonstrates that the dominance of regional
566 processes does not imply that local emission control is ineffective, and that the
567 mitigation potential of a local source cannot be evaluated solely from its contribution
568 to the existing O₃ burden.

569 Several limitations should be acknowledged. VOC measurements were conducted at
570 only one urban site and were restricted to relatively short sampling periods during
571 summer, limiting the representation of spatial heterogeneity within the AUI and
572 seasonal variability in O₃ formation. In addition, the WRF-Chem source attribution
573 and emission-reduction analyses focused on a single representative summertime O₃
574 episode and were subject to uncertainties in meteorological fields and emission
575 inventories. In particular, the predicted O₃ responses to hypothetical
576 emission-reduction scenarios cannot be directly validated through equivalent emission
577 perturbations in the real atmosphere. Future studies combining multi-site,
578 multi-season, and long-term continuous observations are therefore needed to further
579 assess the robustness and broader applicability of the mechanisms identified here.

580 More importantly, this study provides broader atmospheric-chemistry implications for
581 understanding O₃ formation and control in AUIs. Many AUIs worldwide lack major
582 industrial point sources but are simultaneously influenced by anthropogenic emissions
583 such as traffic, agricultural and vegetation-related biogenic emissions, and substantial
584 regional O₃ background and transport. Despite its pronounced AUI characteristics, the
585 biogenic contribution remains lower than that reported for forest regions, indicating
586 that an agriculture-dominated landscape does not necessarily translate into a
587 disproportionately large biogenic O₃ contribution. Under such conditions, the largest



588 local precursor source does not necessarily correspond to the largest contributor to
589 ambient O₃, while a source making only a modest contribution to the existing O₃
590 burden may still have considerable mitigation potential. Our results show that
591 transportation emission reductions remain effective even when background O₃ and
592 regional transport account for nearly 90% of ambient O₃. This effectiveness arises
593 because transportation simultaneously emits both VOCs and NO_x, and their
594 coordinated reduction shifts the precursor mixture along a more favorable pathway for
595 O₃ mitigation identified by the EKMA response surface. In contrast, reductions in
596 some industrial sources produce only limited O₃ benefits because of their less
597 favorable VOC/NO_x emission ratios. Therefore, O₃ control in AUIs should not be
598 prioritized solely according to the source contributions to ambient O₃, but should also
599 consider precursor reactivity, source-specific VOC/NO_x emission structures, and
600 nonlinear photochemical sensitivity. This perspective links regional transport, local
601 emission characteristics, and nonlinear O₃ chemistry, and demonstrates that targeted
602 control of local anthropogenic sources with favorable precursor-reduction
603 characteristics can remain effective even when regional processes dominate the
604 overall O₃ burden. With the continuing electrification of the vehicle fleet, coordinated
605 reductions in traffic-related VOC and NO_x emissions are becoming an increasingly
606 feasible local intervention and may provide additional co-benefits for O₃ mitigation in
607 AUIs. Accordingly, for AUIs characterized by strong regional O₃ backgrounds,
608 intensive mixing of anthropogenic and biogenic precursors, and pronounced
609 agricultural-urban transitions, combining regional cooperative control with targeted
610 reductions in key local precursors may be more effective than control strategies based
611 solely on local source contributions.

612

613 **Data availability**

614 The data of this paper can be obtained from Zenodo ([https://doi.org/10.5281/ze](https://doi.org/10.5281/zenodo.21532281)
615 [nodo.21532281](https://doi.org/10.5281/zenodo.21532281))

616

617 **Author contributions**

618 **Xinpeng Ye:** Writing (Original draft preparation), Data curation. **Qian Jiang:**
619 Methodology. Validation. **Jin Ban:** Methodology. **Mengyu Xie:** Validation. **Qianyi**



620 **Xu:** Methodology. **Zeyu Wang:** Investigation. **Jian Sun:** Funding acquisition.
 621 Writing (Review & Editing), Supervision. **Hongai Zhang:** Methodology. **Xinyi Niu:**
 622 Funding acquisition. **Hongmei Xu:** Methodology. **Zhenxing Shen:** Conceptualization,
 623 Supervision. **Guohui Li:** Methodology. Supervision.
 624

625 **Competing interests**

626 The authors declare that none of the authors has any competing interests.
 627

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 632

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