



**Assessment of Diverse Control Measure Effectiveness During
Successive PM_{2.5} Pollution Episodes in Central China:
Implications for Regional Heavy Pollution Mitigation Strategies**

Yibing Zhou^a, Xiaohui Du^a, Yusheng Shi^b, Haoran Zhou^b, Lingling Wang^{c,d},
Shuangliang Ma^{c,d}, Nan Wang^{c,d}, Xiyuan Chi^e, Dongting Wei^a, Kaile Zhang^a, Jingnan
Hu^a, Yangxi Chu^{a*}

^a State Key Laboratory of Environmental Criteria and Risk Assessment, Chinese
Research Academy of Environmental Sciences, Beijing 100012, China

^b State Key Laboratory of Remote Sensing and Digital Earth, Aerospace Information
Research Institute, Chinese Academy of Sciences, Beijing 100094, China

^c Henan Ecological Environment Monitoring and Safety Center, Henan, 450046,
China

^d Henan Key Laboratory of Environmental Monitoring Technology, Henan, 450046,
China

^e National Meteorological Center, China Meteorological Administration, Beijing
100081, China

To whom correspondence should be addressed: Yangxi Chu (chuyx@craes.org.cn)

Abstract

Henan Province in Central China frequently experiences heavy winter PM_{2.5} pollution. Previous studies have revealed the important roles of meteorology and anthropogenic emissions in regional haze. However, how short-term changes in the intensity of control measures translate into changes in source emissions and PM_{2.5} chemical composition remains insufficiently understood. This study selected two successive province-wide PM_{2.5} heavy pollution episodes, one occurring from December 22, 2023, to January 3, 2024 (E1) and another one during January 8–14, 2024 (E2). We integrate air-quality and chemical-composition observations with continuous emission



29 monitoring and satellite data to reconstruct daily source-resolved emissions, and
30 further apply partial-correlation analysis and WRF-CAMx simulations to evaluate the
31 relationships between emission changes and atmospheric responses. During E1,
32 coordinated controls targeted industrial and mobile sources, together with enhanced
33 warnings in high-emission northwestern cities. During E2, the measures attenuated,
34 leading to a 13% increase in NO_x and primary PM emissions compared to E1.
35 Correspondingly, concentrations of $\text{PM}_{2.5}$, and its major components nitrate (NO_3^-)
36 and organic matter (OM) increased by 42%, 44%, and 25%, respectively. Partial
37 correlation analysis and WRF-CAMx simulation mutually verify that such
38 incremental emissions were the key driver of rapid NO_3^- and OM accumulation,
39 forming a closed-loop in diagnosing the fundamental driver of heavy $\text{PM}_{2.5}$ pollution
40 episodes in Central China. Therefore, in order to eliminate $\text{PM}_{2.5}$ heavy pollution in
41 the future, on top of necessary regulation for the industry sector, more efforts should
42 be devoted to reducing emissions from diesel vehicles and residential combustion.

43 **Keywords:** Henan Province; Regional $\text{PM}_{2.5}$ pollution episodes; Joint prevention and
44 control; Particulate nitrate; Organic matter

45 1. Introduction

46 Henan Province, located in Central China, has received considerable attention in
47 regional air pollution prevention and control due to its air quality conditions. The
48 annual average $\text{PM}_{2.5}$ concentration, and heavily polluted days during fall and winter
49 (daily $\text{PM}_{2.5}$ concentration $> 150 \mu\text{g}/\text{m}^3$) in Henan during 2021–2025 have been
50 among the highest provinces in China, posing significant challenges to public health
51 and sustainable development (Shen et al., 2017; Chuai et al., 2019; L. Zhang et al.,
52 2017; Ministry of Ecology and Environment of the People’s Republic of China, 2025).
53 Although the air pollution characteristics, formation mechanisms, and mitigation
54 pathways have been extensively investigated in the North China Plain (Y. Zhang et al.,
55 2017; Sulaymon et al., 2023; Lv et al., 2022; Wu et al., 2026), these atmospheric
56 dynamics remain insufficiently understood in the Central Plains.

57



58 The heavy PM_{2.5} pollution in Henan Province is induced by a synergy of unfavorable
59 topography, stagnant weather, and intense regional transport (Liu et al., 2018; Y.
60 Wang et al., 2023; He et al., 2021; Yan et al., 2021; Yang et al., 2025). Superimposed
61 on these external factors are the intense emissions from anthropogenic activities.
62 Particularly, area sources associated with residential heating contribute to nearly half
63 of the local PM_{2.5} mass (Du et al., 2021; Du et al., 2022). Meanwhile, mobile sources
64 are a major contributor to primary NO_x emissions, fueling the rapid formation of
65 inorganic nitrate aerosols during winter haze events (Liu et al., 2018). Furthermore,
66 the relative contributions of mobile and industrial sources notably surge during air
67 pollution episodes. Effectively mitigating these events requires a precise
68 understanding of how the atmospheric environment responds to targeted, sector-level
69 emission controls.

70

71 Recent studies in India and South Korea conducted during lockdowns and high-PM
72 management periods have shown that short-term emission controls can substantially
73 alter PM_{2.5} pollution evolution, although their effectiveness is strongly modulated by
74 meteorological conditions, secondary aerosol formation, and regional transport
75 (Ravish, 2026; Kim et al., 2020; Panda et al., 2025). Studies in China have
76 demonstrated that emergency control measures implemented during PM_{2.5} pollution
77 episodes can reduce anthropogenic emissions and suppress PM_{2.5} peak concentrations
78 (Liang et al., 2017; G. Wang et al., 2023; Wen et al., 2024). However, because
79 meteorology strongly modulates how PM_{2.5} responds to emission cuts (Y. Zhang et al.,
80 2021; Huang et al., 2021), robustly evaluating control effectiveness and identifying
81 the dominant drivers of pollution changes remain challenging. This challenge is
82 further complicated by the contrasting responses of individual PM_{2.5} components to
83 emission controls (Dao et al., 2026; Wang et al., 2016; Han et al., 2023). While
84 primary organic matter (OM) typically exhibits a strong linear relationship with
85 residential heating and biomass burning (Lee et al., 2025; Oh et al., 2023; Cui et al.,
86 2025; Nirmalkar et al., 2024; Tobler et al., 2020), nitrate (NO₃⁻) undergoes rapid



87 growth that may not respond in direct proportion to NO_x emission changes (Yang et
88 al., 2022; Du et al., 2026; Fu et al., 2023; Song et al., 2026).

89

90 Literature has extensively reported the effectiveness of emission controls during
91 individual air pollution episodes, but comparative studies from multiple episodes
92 remains limited. In particular, it remains unclear how short-term differences in
93 regulatory stringency alter actual emissions and the accumulation of major PM_{2.5}
94 components under a relatively consistent background (e.g. identical energy, industrial
95 and cargo transport structure). To address this gap, we investigated two consecutive
96 winter pollution episodes in Henan Province: December 22, 2023–January 3, 2024
97 (E1), and January 8–14, 2024 (E2). The two episodes occurred only several days apart
98 within the same heating season but with contrasting regulatory stringencies. This
99 comparison constitutes a quasi-natural experiment, enabling the effects of short-term
100 control intensity to be evaluated.

101

102 In this study, we integrated Continuous Emission Monitoring System (CEMS), traffic
103 flow and satellite data to construct a daily-resolved anthropogenic emission inventory.
104 By pairing partial correlation analysis with WRF-CAMx chemical transport modeling,
105 we developed a closed-loop analytical framework that links emission changes directly
106 to atmospheric responses and pollution evolution. These complementary statistical
107 and physical approaches cross-validate each other, providing convergent evidence of
108 how variations in control stringency altered PM_{2.5} pollution and offering a scientific
109 foundation for targeted wintertime air quality management in Central China.

110 **2. Data and Methods**

111 **2.1 Research Data**

112 Hourly Air quality monitoring data for Henan Province, including concentrations of
113 six criteria pollutants (such as PM_{2.5}, PM₁₀, NO₂, SO₂, O₃ and CO) and PM_{2.5} major
114 components (SO₄²⁻, NO₃⁻, Cl⁻, F⁻, NH₄⁺, Na⁺, K⁺, Mg²⁺, Ca²⁺, OC, EC) are obtained
115 from Henan Ecological Environment Monitoring and Safety Center



116 (<http://1.192.88.18:18065>). Air quality monitoring data from all prefecture-level cities
117 in Henan Province were used to characterize the evolution of the two pollution
118 episodes. For PM_{2.5} chemical composition analysis, five representative sites located in
119 the urban area of Anyang, Zhengzhou, Zhoukou, Xinyang and Sanmenxia cities were
120 selected based on data completeness and regional representativeness, and the regional
121 mean of PM_{2.5} component concentration was calculated as the average across these
122 sites. Detailed information is provided in Table S1 of the supplementary information
123 (SI).

124

125 To characterize residential-combustion activity in rural areas and urban–rural fringe
126 zones, daily seamless gridded ground-level concentrations of PM_{2.5}, SO₂, and CO at a
127 spatial resolution of 0.01° × 0.01° (approximately 1 km) were additionally used. PM_{2.5},
128 concentrations were obtained from version 2 of the GlobalHighPM_{2.5} dataset within
129 the Global High Air Pollutants (GHAP) framework, whereas SO₂ and CO
130 concentrations were obtained from version 2 of the ChinaHighSO₂ and ChinaHighCO
131 datasets under the China High Air Pollutants (CHAP) framework (data repository:
132 <https://weijing-rs.github.io/product.html>) (Wei et al., 2021; Wei et al., 2023). These
133 machine-learning-based products integrate ground-based observations with
134 multisource environmental and geographical predictors. The data were used to derive
135 the daily activity coefficient for residential combustion, as detailed in Section 2.2.

136

137 Hourly meteorological variables, including wind speed, relative humidity,
138 temperature, and surface downward shortwave radiation (SSRD), were obtained from
139 the ERA5 reanalysis data provided by the European Centre for Medium-Range
140 Weather Forecasts (ECMWF). The Environmental Meteorology Index (EMI) is
141 obtained from the China Meteorological Data Service Centre
142 (<http://idata.cma/cmadaas/>) (Gong et al., 2021). The topographic characteristics of
143 Henan Province and the locations of representative monitoring cities are shown in Fig
144 S1.

145



2.2 Dynamic Characterization of Air Pollutants Emissions

The emission inventory compiled by Zhi et al (Zhi et al., 2024) is adopted. By integrating continuous emission monitoring system (CEMS) data from industrial sources, traffic flow of vehicles, operating hours of non-road machinery, and satellite remote sensing data, daily activity coefficients (A_d) for industrial, mobile and area sources are allocated in order to achieve a day-to-day characterization of air pollutants emissions across the whole society:

$$E_{d,i,p} = E_{m,i,p} \times \frac{A_{d,i}}{\sum_i A_{d,i}} \quad (1)$$

where $E_{d,i,p}$ is the emission of air pollutant p from pollution source i on day d ; $E_{m,i,p}$ represents the emission of air pollutant p from pollution source i in month m . $A_{d,i}$ represents the dynamic coefficient of pollution source i over d days. Derivation of A_d is given below.

2.2.1 Industrial sources

The oxygen content of the exhaust plume from CEMS is used to determine whether a production facility is operating on a given day:

$$AE_{d,i,j} = \begin{cases} 1, & c_{O_2,d,i,j} < cr_{O_2,i} \\ 0, & c_{O_2,d,i,j} \geq cr_{O_2,i} \end{cases} \quad (2)$$

$$A_{d,i} = \frac{\sum_j AE_{d,i,j}}{n_i} \quad (3)$$

where $AE_{d,i,j}$ indicates whether a facility j in industry i is working on day d ; $c_{O_2,d,i,j}$ represents the monitored daily average oxygen content; $cr_{O_2,i}$ represents the reference oxygen content, below which the facilities of industry i are considered in operation; n_i represents the number of facilities in industry i . Typical cr_{O_2} values for individual industries are given in Table S2.



167 2.2.2 Mobile sources

168 The normalized daily traffic flow of vehicles, or the normalized daily operation hours
169 of non-road machinery is directly taken as the $A_{d,i}$ value.

$$A_{d,i} = \frac{M_{d,i}}{\sum_d M_{d,i}} \quad (4)$$

170 Here, $M_{d,i}$ represents the traffic flow of vehicles, or the operation hours of non-road
171 machinery on day d . $M_{d,i}$ data were obtained from the Transport Planning and
172 Research Institute of Ministry of Transport and from major non-road machinery
173 manufacturers (e.g., SANY, Zoomlion, etc.), respectively.

174

175 2.2.3 Area sources

176 Residential combustion, mainly consisting of coal and biomass burning in households,
177 is characterized by substantial emissions of primary $PM_{2.5}$, particularly carbonaceous
178 particles dominated by organic matter, as well as SO_2 generated from
179 sulfur-containing fuels. According to the emission inventory adopted in this study,
180 residential combustion contributed >80% of total area-source primary $PM_{2.5}$
181 emissions, making it the dominant area-source contributor to winter primary
182 particulate emissions. Therefore, the daily dynamic characterization of area sources in
183 this study focused on residential combustion. Emission from residential combustion
184 were estimated using satellite-derived data. First, daily satellite-derived data
185 (tropospheric column concentrations of $PM_{2.5}$, SO_2 , and CO) during E1 and E2 were
186 utilized. Through manual interpretation, isolated or clustered high-concentration
187 zones where both $PM_{2.5}$ and SO_2 concentrations were significantly higher than
188 surrounding areas were identified. The center coordinates of these high-concentration
189 zones are extracted and overlaid with vector data of rural settlements or
190 township/village boundaries in Henan Province. Locations situated in rural areas or
191 urban-rural fringe zones are then selected as representative sites for estimating
192 residential combustion emissions. For each site, an initial daily emission intensity
193 index ($R_{d,s}$) is constructed:



$$R_{d,s} = \frac{C_{PM_{2.5}}}{C_{CO}} \quad (5)$$

194 where $C_{PM_{2.5}}$ and C_{CO} are the tropospheric column concentrations of $PM_{2.5}$ and CO at
195 the particular site s on day d , respectively. This ratio partially eliminates the effect of
196 meteorological dispersion conditions on absolute concentrations due to a relatively
197 long atmospheric lifetime of CO, thereby reflecting relative changes in emission
198 intensity more directly.

199 The values of $R_{d,s}$ from all representative sites are averaged to obtain the provincial
200 index (R_d). Then, the daily emission of residential combustion ($E_{d,res}$) is allocated:

$$A_{d,res} = \frac{R_d}{\sum_{d \in m} R_d} \quad (6)$$

$$E_{d,res} = E_{m,res} \times A_{d,res} \quad (7)$$

201 $E_{m,res}$ stands for the monthly emissions from residential combustion from Zhi et al
202 (Zhi et al., 2024).

203

204 Following previous quantitative uncertainty assessments of temporally resolved
205 emission inventories, uncertainty in the daily temporal allocation was quantified using
206 10,000 Monte Carlo realizations (Zheng et al., 2010). In each realization,
207 source-specific daily activity coefficients were perturbed using mean-one lognormal
208 multiplicative factors, with coefficients of variation assigned according to the
209 reliability-based classification of An et al (An et al., 2021), and subsequently
210 renormalized within each calendar month to preserve the corresponding monthly
211 source-specific emissions. Detailed procedures are provided in Text S1.

212

213 **2.3 Partial Correlation Analysis**

214 Partial correlation analysis is employed to quantify the relationships between pollutant
215 emissions and ambient concentrations while controlling for meteorological factors
216 (i.e., temperature, relative humidity, and wind speed). This approach has been widely



217 applied in environmental and atmospheric studies to distinguish emission-driven
218 effects from meteorological influences (X. Zhang et al., 2021; Yin et al., 2026; Li et
219 al., 2021). The partial correlation coefficients ($r_{xy,z}$) are derived as follows:

$$r_{xy,z} = \frac{r_{xy} - r_{xz}r_{yz}}{\sqrt{(1 - r_{xz}^2)(1 - r_{yz}^2)}} \quad (8)$$

220 where x represents the hourly mass concentration ($\mu\text{g}/\text{m}^3$) of the target chemical
221 component (NO_3^- or OM); y represents the daily emission (t); z denotes the vector of
222 daily mean values composed of controlled meteorological covariates (such as relative
223 humidity, temperature, wind speed, etc.). By statistically accounting for these
224 covariates, the partial correlation analysis isolates the association between emissions
225 and pollutant concentrations from concurrent meteorological influences, thereby
226 providing a more robust assessment of emission-related variations in ambient
227 pollution levels. In addition, this study employs a threshold-based meteorological
228 screening method (Zhu et al., 2021) to extract sub-periods with highly consistent
229 meteorological backgrounds (E1_met and E2_met). The screening procedure and
230 threshold criteria are described in Text S2 and Table S3, while the resulting
231 meteorological consistency between E1_met and E2_met is documented in Table S4
232 and Fig. S2..

233

234 **2.4 WRF-CAMx model**

235 To investigate the response of $\text{PM}_{2.5}$ and its major chemical components to emission
236 changes during different control regimes, the Weather Research and Forecasting
237 model with the Advanced Research WRF dynamic core (WRF-ARW) was coupled
238 with the Comprehensive Air Quality Model with Extensions (CAMx, version 7.10).
239 WRF was configured with two-way nested domains at horizontal resolutions of 36
240 and 12 km using a Lambert conformal projection. The meteorological fields were
241 simulated with 35 vertical layers and were output at hourly intervals. Detailed WRF
242 configurations and physical parameterizations are summarized in Table S5.



243

244 CAMx was applied from December 12, 2023, to January 24, 2024, covering both
245 pollution episodes (E1 and E2) and the transition period. Two nested CAMx grids
246 with horizontal resolutions of 36 and 12 km were employed, with chemical processes
247 represented using the SAPRC07_CF2 mechanism. Initial and boundary conditions
248 were generated using the CAMx ICBCPREP processor. The daily resolved
249 anthropogenic emissions developed in Section 2.2 were spatially allocated to CAMx
250 emission inputs to characterize temporal variations in source strength. Simulated
251 PM_{2.5}, chemical components, and precursor gases were extracted from grid cells
252 corresponding to the chemical-composition monitoring sites for comparison with
253 observations. Other model configurations are provided in Table S5.

254

255 **3. Results**

256 **3.1 Distinct PM_{2.5} pollution characteristics between E1 and E2**

257 Both E1 and E2 exhibited a gradual progression from light to heavy or even severe
258 pollution. However, E2 featured a faster accumulation, higher PM_{2.5} peak
259 concentration, and a broader affected area. The provincial average PM_{2.5}
260 concentration was elevated from 104 µg/m³ during E1 to 142 µg/m³ during E2, and
261 the number of severely polluted cities (with daily PM_{2.5} concentration > 250 µg/m³)
262 increased from none to 12. Moreover, the onset of heavy pollution was significantly
263 more rapid in E2, taking only three days to transition from “good” air quality,
264 compared to six days during E1. (Table S6 and Fig. 1).

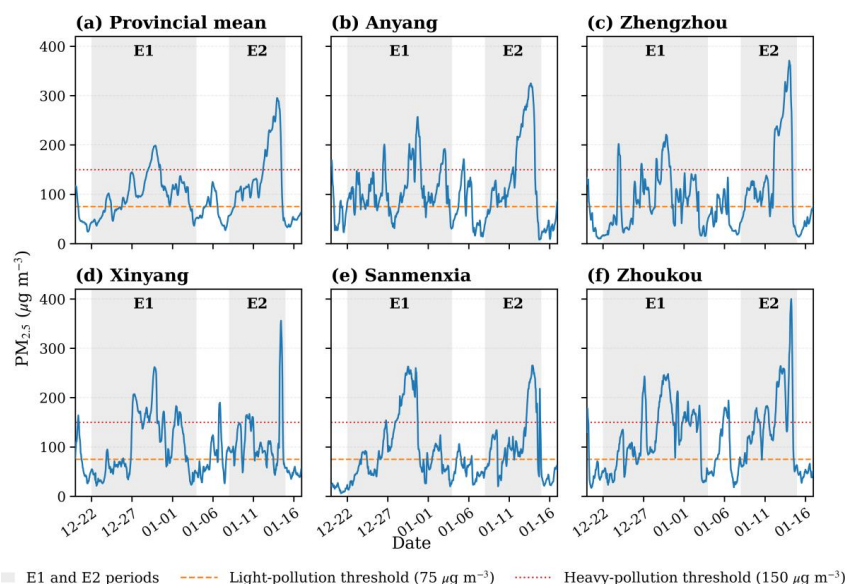


Figure 1. Hourly $PM_{2.5}$ concentrations for (a) provincial average and (b–f) representative cities in Henan Province as a function of time.

Regarding meteorological conditions (Fig. 2c), the episode-mean relative humidity was comparable between E1 and E2, decreasing slightly from 66.4% to 65.8%. The mean temperature increased from 1.1 to 4.3 °C, while the mean wind speed increased from 1.80 m/s to 2.26 m/s, corresponding to an increase of approximately 26.1%. EMI rose from 5.3 to 6.5, representing a 24% increase. Overall, from E1 to E2, the increase in $PM_{2.5}$ was twice the magnitude of the deterioration in meteorological conditions, indicating that non-meteorological factors played a more significant role in air quality deterioration.

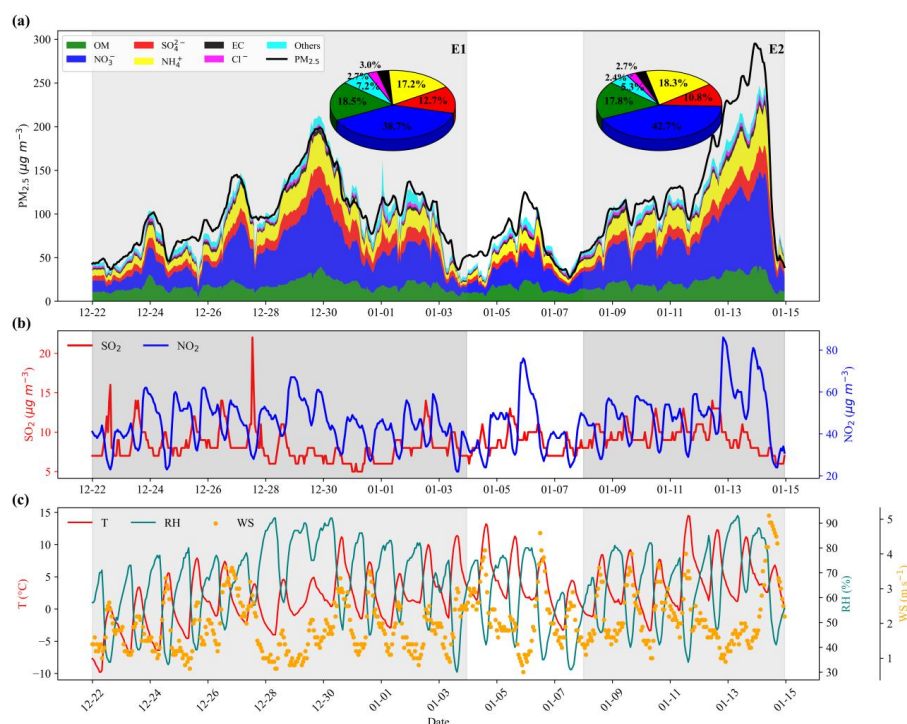


Figure 2. Changes in (a) PM_{2.5} and its components, (b) SO₂ and NO₂ concentrations, and (c) meteorological conditions as a function of time during E1 and E2.

PM_{2.5} chemical composition monitoring data indicate that nitrate (NO₃⁻) and organic matter (OM) were the major components in both episodes (Fig. 2a). Among these, NO₃⁻ was consistently the most abundant, accounting for 38.7% and 42.7% of PM_{2.5} mass during E1 and E2, respectively. Its average concentration increased from 37.5 μg/m³ to 54.0 μg/m³, with an amplitude (43.9%) exceeding the overall PM_{2.5} increase. Concurrently, compared to E1, the average NO₂ concentrations during E2 increased by 12.0% (Fig. 2b). The rise suggests that enhanced precursor accumulation during E2 was likely a driver of the rapid increase in particulate nitrate. OM was the second largest component, with average concentration rising from 18.6 μg/m³ to 23.2 μg/m³, an increase of approximately 25%. Although the OM concentration increased, its mass fraction decreased from 18.5% to 17.8% due to the more evident increase in nitrate. Analysis for representative cities indicate that different parts across the



293 province exhibited consistent evolution (Fig. S3). These results indicate that the
294 worsening of air quality during E2 was primarily driven by nitrate.

295

296 To further assess whether enhanced secondary formation contributed to the greater
297 nitrate accumulation during E2, daytime and nighttime nitrate formation potentials
298 were approximately estimated using observation-constrained chemical expressions.
299 The detailed calculation procedures, assumptions, and parameterizations are provided
300 in Text S3. Fig. 3a compares the mean daytime and nighttime nitrate
301 formation-potential anomalies during E1 and E2. Overall, the daytime and nighttime
302 nitrate formation potentials in E2 were substantially higher than those in E1.
303 Specifically, the mean daytime and nighttime anomalies in E2 reached 0.24 and 0.18,
304 compared with -0.06 and 0.02 during E1. The results indicate that E2 possessed
305 more favorable environmental conditions for nitrate formation during both daytime
306 and nighttime. Fig. 3b and Fig. 3c show the hourly anomalies in nitrate formation
307 rates for E1 and E2, respectively. Overall, both episodes exhibited distinct diurnal
308 patterns: negative anomalies predominated at night and in the early morning,
309 gradually increased to positive values after sunrise, surged during the noon and the
310 afternoon, and then declined again, reflecting the significant influence of
311 photochemical processes driven by solar radiation on nitrate formation. Compared to
312 E1, both the magnitude and duration of positive anomalies were significantly greater
313 during E2. E2 reached a maximum positive anomaly of 4.6 in the evening of Jan. 12th,
314 whereas E1 reached a maximum positive anomaly of only 2.8 in the evening of Dec.
315 26th. The larger and more persistent positive anomalies during E2 suggest stronger
316 oxidative conditions conducive to the conversion of NO_2 to HNO_3 and subsequent
317 particulate nitrate formation.

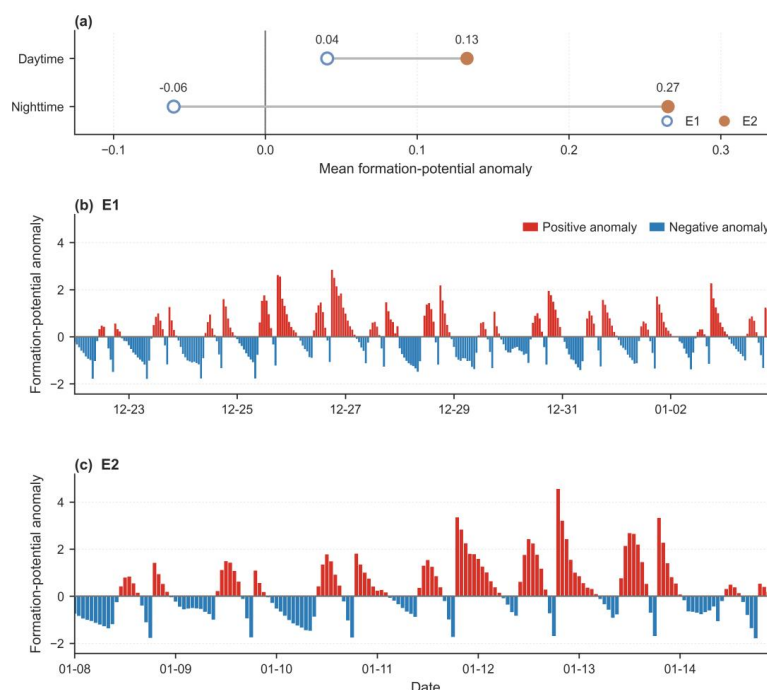


Figure 3. Mean daytime and nighttime nitrate formation-potential anomalies during E1 and E2 (a), and hourly variations in nitrate formation-potential anomalies during E1 (b) and E2 (c).

3.2 Dynamic Assessment of Major Air Pollutant Emissions

3.2.1 Activity Levels of Anthropogenic Sources

As shown in Fig. S4, there were significant differences in the intensity of regional emergency response measures between E1 and E2. Specifically, heavy air pollution red and orange warnings were issued in 4 and 13 cities during E1, respectively, with emergency measures activated approximately 2-3 days before the substantial $PM_{2.5}$ buildup. On the other hand, the heavy air pollution warnings were issued in 17 cities until the third day after the onset of E2, with no red alerts activated. The downgrading of alert levels and the delayed response indicated a relaxation of control measures in the latter episode.



334 Activity indicators derived from CEMS, traffic flow ,non-road machinery operation
335 data and satellite data showed an overall rebound in industrial and mobile-source
336 activities during E2 relative to E1 (Table S7). Except for non-interruptible industries
337 and iron and steel sintering, whose operating rates decreased by 3% and 32%,
338 respectively, the operating rates of major controllable industrial sectors increased by
339 23-65%. The largest increases occurred in lime kilns (65%), cement production (44%),
340 refractory materials (40%), and brick-and-tile production (25%). Meanwhile,
341 heavy-duty truck traffic, heavy-freight flow at provincial boundary checkpoints, and
342 the operating hours of non-road machinery increased by 20.0%, 16.4%, and 21.0%,
343 respectively. These concurrent increases were consistent with the delayed activation
344 and lower warning levels during E2, indicating weaker restrictions on industrial
345 production and mobile-source activities than during E1.

346

347 **3.2.2 Dynamic Changes in Air Pollutant Emissions**

348 Based on the dynamic emission characterization algorithm, the whole-societal
349 emissions of major air pollutants as a function of day, particularly NO_x and primary
350 particulate matter (PM), were reconstructed, as shown in Fig. 4 and Fig. 5. For NO_x,
351 the total emissions increased from 2,188 t d⁻¹ during E1 to 2,476 t d⁻¹ during E2,
352 corresponding to an increase of 13.2% (Fig 4). The increase was mainly due to mobile
353 source. NO_x emissions from heavy-duty trucks and non-road machinery increased
354 from 1,105 and 233 t d⁻¹ during E1 to 1,317 and 285 t d⁻¹ during E2, representing
355 increases of 19.2% and 22.3%, respectively. By comparison, emissions from
356 industrial process sources increased from 121 to 135 t d⁻¹ (+11.6%), whereas those
357 from stationary fossil-fuel combustion sources changed only slightly, from 729 to 740
358 t d⁻¹ (+1.5%). These results are consistent with the rebound in traffic flow and
359 machinery operating hours described above, indicating that mobile sources were the
360 principal contributor to the increase in NO_x emissions during E2.

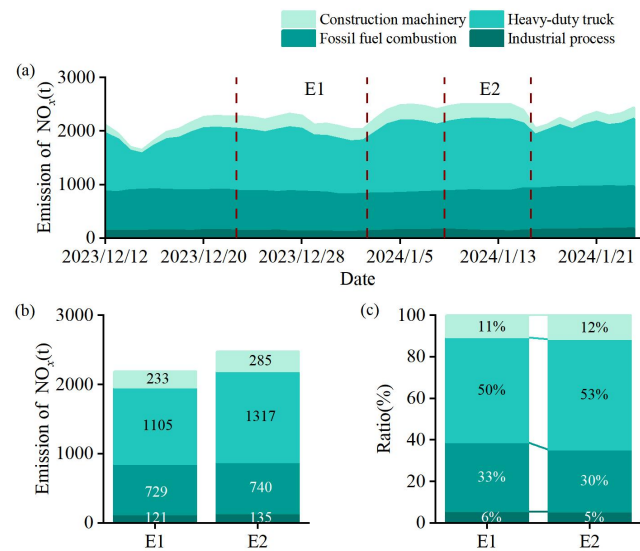


Figure 4. NO_x emission profiles (a), and the comparison of emission amount (b) and source contribution ratios (c) between E1 and E2.

For primary PM, the daily mean emissions increased from 653 t d⁻¹ during E1 to 742 t d⁻¹ during E2, corresponding to an increase of 13.6% (Fig 5). Residential combustion remained the dominant source, contributing approximately 60% of total primary PM emissions. Its emissions increased from 386 to 453 t d⁻¹ (+17.5%), accounting for approximately 75% of the total primary PM increment between the two episodes. Emissions from industrial process sources increased from 128 to 146 t d⁻¹ (+14.1%), while mobile-source emissions increased from 24 to 28 t d⁻¹ (+16.7%), although their absolute contribution remained relatively small.

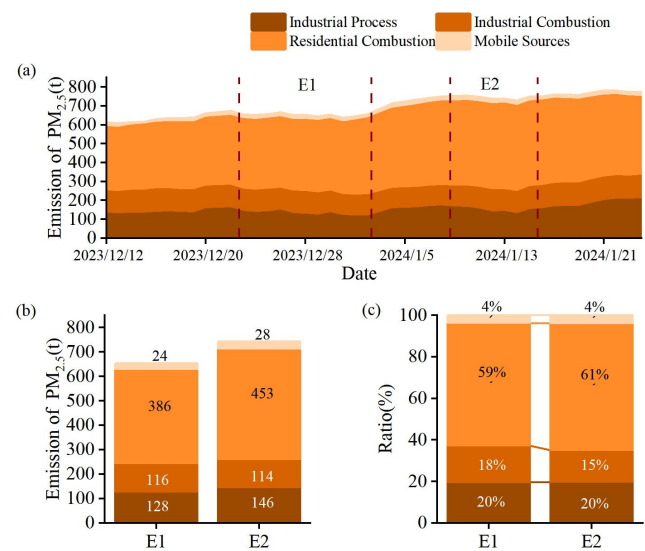


Figure 5. PM emission profiles (a), and the comparison of emission amount (b) and source contribution ratios (c) between E1 and E2.

The concurrent increases in NO_x and primary PM emissions indicate that the control measures during E2 was less effective in reducing emissions than those during E1. In particular, the NO_x increase was primarily associated with mobile sources, whereas the primary PM increase was dominated by residential combustion. Monte Carlo analysis indicated that the estimated increase in NO_x emissions from E1 to E2 was robust to uncertainties in the daily activity indicators, with a median increase of 13.2% (95% uncertainty interval: 2.9-24.7%) and a 99.5% of the realizations yielded a positive change. The increase in primary PM_{2.5} emissions was also evident, with a median change of 13.3% and 92.7% of the realizations yielding a positive change (Fig. S5 and Table S8). These results indicate that the episode-to-episode emission rebound was not an artifact of uncertainties in daily temporal allocation, thereby supporting the conclusion that increased anthropogenic emissions accompanied weaker controls during E2.



391 **3.3 Causal Analysis Between Emission Control and Peak** 392 **Concentration Reduction**

393 To examine whether the contrasting emission levels under the two control regimes
394 contributed to the observed changes in $PM_{2.5}$ and its major components, partial
395 correlation analysis and WRF-CAMx simulations were jointly applied. The former
396 was used to isolate emission-concentration relationships from the effects of relative
397 humidity, temperature, and wind speed, whereas the latter evaluated whether the
398 observed component responses from E1 to E2 could be reproduced using the
399 dynamically resolved emissions.

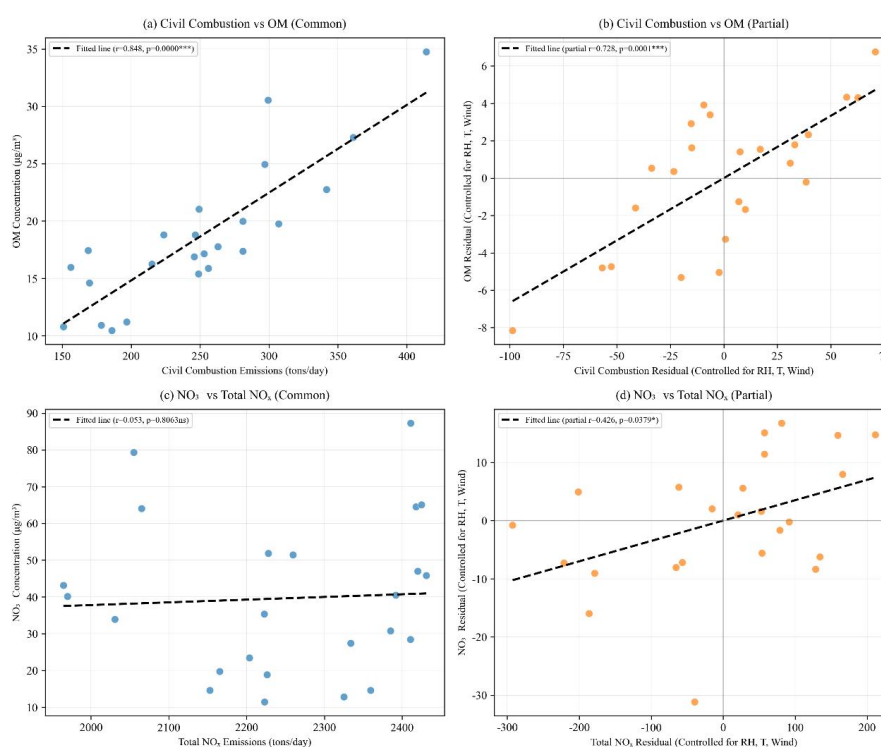
400

401 **3.3.1 Partial Correlation Analysis**

402 Fig. 6 examines the correlation between emissions and $PM_{2.5}$ composition. Organic
403 aerosols are the primary driver of $PM_{2.5}$'s oxidation potential, and their main source is
404 residential combustion (Bhattu et al., 2024). As shown in Fig. 6a, the correlation
405 coefficient r between primary particulate matter emissions from domestic combustion
406 sources and the OM (organic matter) component is 0.848, indicating a significant
407 positive correlation. After controlling for meteorological covariates, the partial
408 correlation coefficient r between the two is 0.728 (Fig. 6b), still indicating a
409 significant positive correlation. Meteorological conditions only slightly weaken the
410 correlation between the two but cannot alter their fundamental driving relationship;
411 the driving effect of domestic combustion sources on OM remains extremely strong.
412 As shown in Fig. 6c, the direct correlation coefficient r between NO_x emissions and
413 NO_3^- concentration is 0.053, with a p -value far greater than 0.05, indicating no
414 significant correlation. However, after controlling for meteorological conditions (Fig.
415 6d), the partial correlation coefficient r is 0.426, with a p -value less than 0.05,
416 indicating a significant positive correlation. This phenomenon demonstrates that NO_3^-
417 is a secondary inorganic aerosol, whose formation depends not only on NO_x precursor
418 emissions but also strongly relies on the meteorological accumulation effect of high



419 humidity, low temperature, and stable atmospheric conditions on the gas-to-particle
420 conversion of NO_x to NO_3^- . This reflects the masking effect of meteorological
421 conditions (Zhong et al., 2020); meteorological conditions are the key driver of rising
422 NO_3^- concentrations, while NO_x emissions serve as the fundamental precursor for
423 NO_3^- formation—only by controlling meteorological interference can the true driving
424 effect of NO_x emission reductions on NO_3^- be observed.



425
426 **Figure 6.** Correlations between emissions and PM_{2.5} chemical components under
427 Pearson and partial correlation analyses: (a, b) primary particulate matter emissions
428 from civil combustion versus OM concentrations, and (c, d) total NO_x emissions
429 versus NO₃⁻ concentrations, before and after controlling for meteorological conditions
430 (relative humidity, temperature, and wind speed).

431

432 3.3.2 Model Simulation

433 Before examining the modeled responses between the two episodes, the model



434 performance was evaluated against hourly $PM_{2.5}$ observations over the period from
435 December 2023 to January 2024. The model yielded an R^2 of 0.35 and an NME of
436 47.9%, capturing the overall temporal evolution of $PM_{2.5}$ and supporting its use for
437 comparing relative changes between E1 and E2. The observed and simulated temporal
438 variations in $PM_{2.5}$, nitrate (NO_3^-), and organic matter (OM) during the two
439 consecutive pollution episodes are compared in Fig. S6.

440

441 The WRF-CAMx simulations further reproduced the observed increase in
442 concentration from E1 to E2 (Fig. 7). The observations indicate significant increases
443 in the provincial average concentrations of $PM_{2.5}$, NO_3^- , and OM by 33.9%, 48.3%,
444 and 27.9%, respectively, whereas the corresponding simulated increases were 15.5%,
445 16.2%, and 21.0%, respectively. Comparable ranges of the increasing amplitude
446 values within calculation uncertainties confirm that the deteriorated air quality from
447 E1 to E2 was not a coincidental meteorological fluctuation, but rather due to a
448 province-wide emission increment.

449

450 The observed increase amplitude in particulate OM (27.9%) aligns closely with the
451 simulated one (21.0%). Besides, the observed and simulated increase in $PM_{2.5}$ nitrate
452 were also comparable, considering uncertainties in data analysis. It corroborates the
453 claim that the rebound in primary PM and NO_x emissions were the dominating factors
454 for worsened $PM_{2.5}$ pollution during E2. We note that the simulated nitrate
455 concentrations were systematically lower than the observations. Accurately
456 representing particulate nitrate remains challenging because model predictions are
457 sensitive to precursor emissions, grid resolution, thermodynamic partitioning,
458 heterogeneous chemistry, N_2O_5 uptake, and aerosol scavenging (Milousis et al., 2026).
459 In the present simulations, the negative bias may partly reflect uncertainties in
460 precursor emissions and an incomplete representation of heterogeneous nitrate
461 formation under high aerosol loadings.

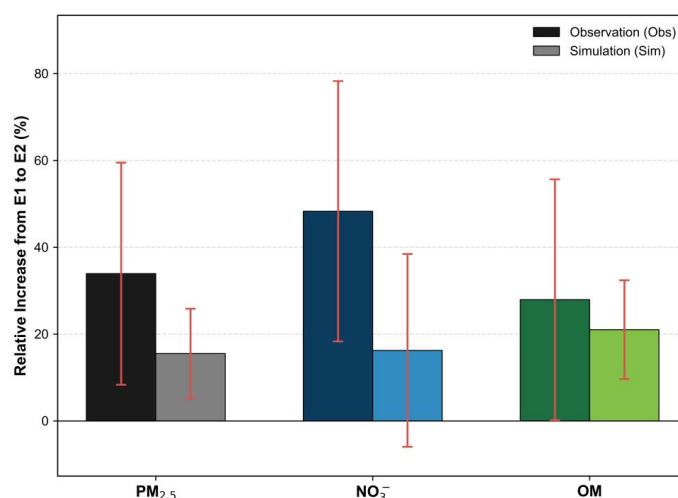


Figure 7. Comparison of the relative increases (%) in PM_{2.5}, NO₃⁻, and OM concentrations from the control period (E1) to the rebound period (E2) based on observations and WRF-CAMx simulations. The error bars represent the spatial heterogeneity (standard deviation) across four representative target cities (Anyang, Zhengzhou, Xinyang, and Zhoukou).

4. Conclusion and Implication

This study compared two consecutive PM_{2.5} pollution episodes in Henan Province under contrasting emergency-control intensities by integrating atmospheric observations, dynamically resolved emission inventories, partial correlation analysis, and WRF-CAMx simulations. Compared with E1, E2 exhibited faster pollution accumulation, broader regional deterioration, and a 36.5% increase in provincial mean PM_{2.5} concentration. NO₃⁻ was the dominant component driving this increase, with its mean concentration rising by 43.9% and its mass fraction increasing by 4 percentage points, while OM increased by 25.0%. These compositional changes coincided with delayed warning activation and weaker emergency controls during E2. Province-wide NO_x and primary PM emissions consequently increased by 13.2% and 13.6%, respectively, with mobile sources dominating the NO_x increase and residential combustion contributing most strongly to the increase in primary PM. The



482 meteorology-adjusted partial correlations further linked NO_x emissions to nitrate
483 concentrations and residential-combustion emissions to OM. Consistently, the
484 WRF-CAMx simulations reproduced the overall increases in $\text{PM}_{2.5}$, nitrate, and OM
485 from E1 to E2. Taken together, the observations, dynamic emission estimates, partial
486 correlation results, and model simulations consistently indicate that differences in
487 short-term control intensity and the associated emission levels contributed to the
488 contrasting pollution severity between the two episodes, in addition to meteorological
489 influences. The substantially larger increase in nitrate concentration than in NO_x
490 emissions, together with the more favorable nitrate-formation conditions during E2,
491 further suggests that secondary chemical production contributed to the enhanced
492 nitrate response, whereas the increase in OM was more directly associated with
493 changes in primary emissions from residential combustion.

494

495 This study extends previous episode-based assessments by resolving short-term
496 sectoral emission changes and linking them to the responses of individual $\text{PM}_{2.5}$
497 components. A key methodological advance is the use of satellite-derived information
498 to characterize daily variations in residential combustion, thereby extending dynamic
499 emission estimates to area sources that are difficult to characterize directly.
500 Nevertheless, uncertainties remain in the underlying inventory and source-specific
501 activity indicators, particularly for residential combustion and small- and
502 medium-scale industrial sources. In addition, WRF-CAMx systematically
503 underestimated particulate nitrate, reflecting uncertainties in precursor emissions and
504 the representation of thermodynamic partitioning and heterogeneous chemistry.
505 Future work should improve activity data for less well-constrained sources and the
506 representation of secondary nitrate formation to further reduce these uncertainties.

507

508 Based on the results of this study, mitigation of winter $\text{PM}_{2.5}$ heavy pollution in
509 Central China requires earlier warning, sustained implementation of emergency
510 measures, and more specific controls on traffic and residential sectors. For mobile
511 sources, priority should be given to reducing the activity levels of heavy-duty trucks



512 and non-road machinery through timely traffic restrictions, optimized freight
513 scheduling and routing, strengthened supervision of high-emitting vehicles and
514 machinery, and accelerated replacement with cleaner technologies. For residential
515 combustion, short-term restrictions should be complemented by long-term structural
516 measures, including reliable and affordable supplies of clean heating energy,
517 substitution of loose coal and biomass with cleaner fuels or electricity, improvements
518 in household heating efficiency and building insulation, and targeted support for
519 low-income rural households. Control strategies tailored to specific sources, regions,
520 and time periods would help constrain nitrate and OM accumulation and reduce $PM_{2.5}$
521 peaks under unfavorable meteorological conditions, and provide scientific support for
522 the development of more precise air pollution mitigation strategies in Central China.

523

524 **Code and data availability.** The air quality monitoring, continuous emission
525 monitoring system, and satellite data, together with the code used to derive the
526 dynamic emissions, are currently being curated and documented, in order to facilitate
527 reuse by readers. The processed datasets and documented code will be deposited in a
528 public repository after acceptance, with a persistent link or DOI provided in the final
529 version. Until then, the materials are available from the corresponding author upon
530 reasonable request.

531

532 **Supplement.** The supplement related to this article is available online at: [link to be
533 inserted by Copernicus].

534

535 **Author contribution.** YZ was responsible for conceptualization, methodology,
536 data curation, formal analysis, visualization, and writing the original draft. XD
537 contributed to methodology, validation, and the WRF–CAMx model simulations. YS
538 contributed resources and methodology, developed and implemented the
539 satellite-derived residential-combustion emission-intensity index, and reviewed and



540 edited the manuscript. HZ contributed to the development and implementation of the
541 satellite-derived residential-combustion emission-intensity index. LW provided the
542 air-quality monitoring data. SM and NW conducted the chemical-component
543 monitoring and maintained the corresponding datasets. XC provided the
544 Environmental Meteorology Index data. DW and KZ contributed to methodology. JH
545 contributed to conceptualization, funding acquisition, and project administration. YC
546 contributed to conceptualization, methodology, supervision, project administration,
547 funding acquisition, and reviewing and editing the manuscript. All authors reviewed
548 and approved the final manuscript.

549

550 **Competing interests.** The authors declare that they have no conflict of interest.

551

552 **Acknowledgements.** This work was supported by the National Key Research and
553 Development Program of China (No. 2024YFC3712900, 2024YFC3713701), the
554 Jing-Jin-Ji Regional Integrated Environmental Improvement-National Science and
555 Technology Major Project (No. 2026ZD1214500), the Key Research and
556 Development Program of Henan Province (No. 241111212300), and the Energy
557 Remote Sensing Retrieval and Monitoring (No. E6M4110106).

558

559

560 **References**

561 An, J., Huang, Y., Huang, C., Wang, X., Yan, R., Wang, Q., Wang, H., Jing, S.,
562 Zhang, Y., Liu, Y., Chen, Y., Xu, C., Qiao, L., Zhou, M., Zhu, S., Hu, Q., Lu, J.,
563 and Chen, C.: Emission inventory of air pollutants and chemical speciation for
564 specific anthropogenic sources based on local measurements in the Yangtze
565 River Delta region, China, *Atmos. Chem. Phys.*, 21, 2003–2025,
566 <https://doi.org/10.5194/acp-21-2003-2021>, 2021.



- 567 Bhattu, D., Tripathi, S. N., Bhowmik, H. S., Moschos, V., Lee, C. P., Rauber, M.,
568 Salazar, G., Abbaszade, G., Cui, T., Slowik, J. G., Vats, P., Mishra, S.,
569 Lalchandani, V., Satish, R., Rai, P., Casotto, R., Tobler, A., Kumar, V., Hao, Y.,
570 Qi, L., Khare, P., Manousakas, M. I., Wang, Q., Han, Y., Tian, J., Darfeuil, S.,
571 Minguillon, M. C., Hueglin, C., Conil, S., Rastogi, N., Srivastava, A. K., Ganguly,
572 D., Bjelic, S., Canonaco, F., Schnelle-Kreis, J., Dominutti, P. A., Jaffrezo, J.-L.,
573 Szidat, S., Chen, Y., Cao, J., Baltensperger, U., Uzu, G., Daellenbach, K. R., El
574 Haddad, I., and Prévôt, A. S. H.: Local incomplete combustion emissions define
575 the PM_{2.5} oxidative potential in Northern India, *Nat. Commun.*, 15, 3517,
576 <https://doi.org/10.1038/s41467-024-47785-5>, 2024.
- 577 Chuai, X., Fan, C., Wang, M., Wang, J., and Han, Y.: A study of the socioeconomic
578 forces driving air pollution based on a DPSIR model in Henan Province, China,
579 *Sustainability*, 12, 252, <https://doi.org/10.3390/su12010252>, 2019.
- 580 Cui, W., Wang, Z., Feng, W., Qin, C., Liao, H., Wang, Y., and Xie, M.: Evaluating
581 coarse PM composition and sources based on bulk and molecular speciation of
582 PM_{2.5} and PM₁₀ in Nanjing, East China, *J. Environ. Sci.*, 152, 155–166,
583 <https://doi.org/10.1016/j.jes.2024.04.038>, 2025.
- 584 Dao, X., Wang, Z., Yuan, X., Li, W., Meng, X., Ma, G., Tong, E., and Zhang, F.:
585 Spatiotemporal characteristics of PM_{2.5} components in the
586 Beijing-Tianjin-Hebei region and its surrounding areas during the heating seasons
587 from 2018 to 2023, *J. Clean. Prod.*, 538, 147210,
588 <https://doi.org/10.1016/j.jclepro.2025.147210>, 2026.
- 589 Du, H., Li, J., Wang, Z., Yang, W., Chen, X., and Wei, Y.: Sources of PM_{2.5} and its
590 responses to emission reduction strategies in the Central Plains Economic Region
591 in China: Implications for the impacts of COVID-19, *Environ. Pollut.*, 288,
592 117783, <https://doi.org/10.1016/j.envpol.2021.117783>, 2021.
- 593 Du, H., Li, J., Chen, X., Yang, W., Wang, Z., and Wang, Z.: Quantifying the source
594 contributions to poor atmospheric visibility in winter over the Central Plains
595 Economic Region in China, *Atmosphere*, 13, 2075,
596 <https://doi.org/10.3390/atmos13122075>, 2022.



- 597 Du, Z., Xu, X., Liu, R., He, J., Liu, Y., Duan, E., Wang, Y., and Ji, D.: Decadal
598 variability of PM_{2.5}-associated nitrate in the megacity of Beijing, China:
599 Revelations achieved through continuous real-time in-situ observation, *Atmos.*
600 *Res.*, 330, 108593, <https://doi.org/10.1016/j.atmosres.2025.108593>, 2026.
- 601 Fu, S., Liu, P., He, X., Song, Y., Liu, J., Zhang, C., and Mu, Y.: Significantly
602 mitigating PM_{2.5} pollution level via reduction of NO_x emission during
603 wintertime, *Sci. Total Environ.*, 898, 165350,
604 <https://doi.org/10.1016/j.scitotenv.2023.165350>, 2023.
- 605 Gong, S., Liu, H., Zhang, B., He, J., Zhang, H., Wang, Y., Wang, S., Zhang, L., and
606 Wang, J.: Assessment of meteorology vs. control measures in the China fine
607 particular matter trend from 2013 to 2019 by an environmental meteorology
608 index, *Atmos. Chem. Phys.*, 21, 2999–3013,
609 <https://doi.org/10.5194/acp-21-2999-2021>, 2021.
- 610 Han, Y.-S., Eun, D.-M., Lee, G., Gong, S. Y., and Youn, J.-S.: Enhancement of
611 PM_{2.5} source appointment in a large industrial city of Korea by applying the
612 elemental carbon tracer method for positive matrix factorization (PMF) model,
613 *Atmos. Pollut. Res.*, 14, 101910, <https://doi.org/10.1016/j.apr.2023.101910>, 2023.
- 614 He, C., Hong, S., Mu, H., Tu, P., Yang, L., Ke, B., and Huang, J.: Characteristics and
615 meteorological factors of severe haze pollution in China, *Adv. Meteorol.*, 2021,
616 6680564, <https://doi.org/10.1155/2021/6680564>, 2021.
- 617 Huang, X., Ding, A., Gao, J., Zheng, B., Zhou, D., Qi, X., Tang, R., Wang, J., Ren, C.,
618 Nie, W., Chi, X., Xu, Z., Chen, L., Li, Y., Che, F., Pang, N., Wang, H., Tong, D.,
619 Qin, W., Cheng, W., Liu, W., Fu, Q., Liu, B., Chai, F., Davis, S. J., Zhang, Q.,
620 and He, K.: Enhanced secondary pollution offset reduction of primary emissions
621 during COVID-19 lockdown in China, *Natl. Sci. Rev.*, 8, nwaa137,
622 <https://doi.org/10.1093/nsr/nwaa137>, 2021.
- 623 Kim, H., Zhang, Q., and Sun, Y.: Measurement report: Characterization of severe
624 spring haze episodes and influences of long-range transport in the Seoul
625 metropolitan area in March 2019, *Atmos. Chem. Phys.*, 20, 11527–11550,
626 <https://doi.org/10.5194/acp-20-11527-2020>, 2020.



- 627 Lee, H.-J., Lee, H.-W., Park, S.-W., Jeon, J.-W., Kim, P.-R., Kwak, K.-H., Han, Y.-J.,
628 Holsen, T. M., Lee, S.-H., Jung, H.-G., Cha, S.-H., Park, J.-M., and Yoo, M.-S.:
629 Characteristics of elevated PM_{2.5} events driven by enhanced organic compound
630 concentrations in a South Korean residential city, *Atmos. Environ.*, 345, 121053,
631 <https://doi.org/10.1016/j.atmosenv.2025.121053>, 2025.
- 632 Li, Y., Zheng, Z., Qin, Y., and Rong, P.: Relative contributions of natural and
633 man-made factors to vegetation cover change of environmentally sensitive and
634 vulnerable areas of China, *J. Clean. Prod.*, 321, 128917,
635 <https://doi.org/10.1016/j.jclepro.2021.128917>, 2021.
- 636 Liang, P., Zhu, T., Fang, Y., Li, Y., Han, Y., Wu, Y., Hu, M., and Wang, J.: The role
637 of meteorological conditions and pollution control strategies in reducing air
638 pollution in Beijing during APEC 2014 and Victory Parade 2015, *Atmos. Chem.*
639 *Phys.*, 17, 13921–13940, <https://doi.org/10.5194/acp-17-13921-2017>, 2017.
- 640 Liu, S., Hua, S., Wang, K., Qiu, P., Liu, H., Wu, B., Shao, P., Liu, X., Wu, Y., Xue,
641 Y., Hao, Y., and Tian, H.: Spatial-temporal variation characteristics of air
642 pollution in Henan of China: Localized emission inventory, WRF/Chem
643 simulations and potential source contribution analysis, *Sci. Total Environ.*, 624,
644 396–406, <https://doi.org/10.1016/j.scitotenv.2017.12.102>, 2018.
- 645 Lv, L., Wei, P., Hu, J., Chen, Y., and Shi, Y.: Source apportionment and regional
646 transport of PM_{2.5} during haze episodes in Beijing combined with multiple
647 models, *Atmos. Res.*, 266, 105957,
648 <https://doi.org/10.1016/j.atmosres.2021.105957>, 2022.
- 649 Ministry of Ecology and Environment of the People's Republic of China: 2024 China
650 Ecological Environment Status Bulletin, Ministry of Ecology and Environment of
651 the People's Republic of China, Beijing, China,
652 [https://www.mee.gov.cn/hjzl/sthjzk/zghjzkgb/202506/P020250604527010717462](https://www.mee.gov.cn/hjzl/sthjzk/zghjzkgb/202506/P020250604527010717462.pdf).
653 pdf (last access: 30 July 2026), 2025.
- 654 Milousis, A., Scholz, S. M. C., Fuchs, H., Tsimpidi, A. P., and Karydis, V. A.: Global
655 perspectives on nitrate aerosol dynamics: a comprehensive sensitivity analysis,



- 656 Atmos. Chem. Phys., 26, 571–605, <https://doi.org/10.5194/acp-26-571-2026>,
657 2026.
- 658 Nirmalkar, J., Lee, J. Y., Lee, K., Ahn, J., Qiu, Y., Wu, Z., Natsagdorj, A., Jang, K.-S.,
659 Kim, C., and Song, M.: Impact of biomass burning on PM_{2.5} and organic aerosol:
660 Quantitative estimates and spatial distributions in four Northeast Asian sites,
661 Atmos. Environ., 333, 120635, <https://doi.org/10.1016/j.atmosenv.2024.120635>,
662 2024.
- 663 Oh, S.-H., Park, K., Park, M., Song, M., Jang, K.-S., Schauer, J. J., Bae, G.-N., and
664 Bae, M.-S.: Comparison of the sources and oxidative potential of PM_{2.5} during
665 winter time in large cities in China and South Korea, Sci. Total Environ., 859,
666 160369, <https://doi.org/10.1016/j.scitotenv.2022.160369>, 2023.
- 667 Panda, U., Dey, S., Sharma, A., Singh, A., Reyes-Villegas, E., Darbyshire, E.,
668 Carbone, S., Das, T., Allan, J., McFiggans, G., Ravikrishna, R., Coe, H., Liu, P.,
669 and Gunthe, S. S.: Exploring the chemical composition and processes of
670 submicron aerosols in Delhi using aerosol chemical speciation monitor driven
671 factor analysis, Sci. Rep., 15, 14383, <https://doi.org/10.1038/s41598-025-99245-9>,
672 2025.
- 673 Ravish, P.: Stage-wise evaluation of the Graded Response Action Plan (GRAP) under
674 meteorological constraints in Delhi-NCR hotspot regions, Discov. Atmos., 4, 10,
675 <https://doi.org/10.1007/s44292-026-00078-6>, 2026.
- 676 Shen, F., Ge, X., Hu, J., Nie, D., Tian, L., and Chen, M.: Air pollution characteristics
677 and health risks in Henan Province, China, Environ. Res., 156, 625–634,
678 <https://doi.org/10.1016/j.envres.2017.04.026>, 2017.
- 679 Song, J., Kim, Y., Kim, K., Kim, M. J., Ma, Y., Lee, J.-B., Lee, Y., Park, J.-S., Lee,
680 K., Hong, S.-C., and Lee, T.: Insights into nighttime chemistry and formation
681 mechanism of nitrate aerosols, ACS EST Air, 3, 1533–1544,
682 <https://doi.org/10.1021/acsestair.5c00502>, 2026.
- 683 Sulaymon, I. D., Zhang, Y., Hopke, P. K., Guo, S., Ye, F., Sun, J., Zhu, Y., and Hu, J.:
684 Using the COVID-19 lockdown to identify atmospheric processes and
685 meteorology influences on regional PM_{2.5} pollution episodes in the



- 686 Beijing-Tianjin-Hebei, China, *Atmos. Res.*, 294, 106940,
687 <https://doi.org/10.1016/j.atmosres.2023.106940>, 2023.
- 688 Tobler, A., Bhattu, D., Canonaco, F., Lalchandani, V., Shukla, A., Thampan, N. M.,
689 Mishra, S., Srivastava, A. K., Bisht, D. S., Tiwari, S., Singh, S., Močnik, G.,
690 Baltensperger, U., Tripathi, S. N., Slowik, J. G., and Prévôt, A. S. H.: Chemical
691 characterization of PM_{2.5} and source apportionment of organic aerosol in New
692 Delhi, India, *Sci. Total Environ.*, 745, 140924,
693 <https://doi.org/10.1016/j.scitotenv.2020.140924>, 2020.
- 694 Wang, G., Wang, M., Sun, L., Zhao, W., Ma, L., Li, H., Huang, H., Fan, L., and Ye,
695 D.: Differences in the chemical compositions and formation mechanisms of
696 PM_{2.5} between urban and rural areas in Xinxiang, Central China around the
697 Beijing Winter Olympics, *Atmos. Environ.*, 312, 119999,
698 <https://doi.org/10.1016/j.atmosenv.2023.119999>, 2023.
- 699 Wang, J., Li, X., Zhang, W., Jiang, N., Zhang, R., and Tang, X.: Secondary PM_{2.5} in
700 Zhengzhou, China: Chemical species based on three years of observations,
701 *Aerosol Air Qual. Res.*, 16, 91–104, <https://doi.org/10.4209/aaqr.2015.01.0007>,
702 2016.
- 703 Wang, Y., Wang, F., Min, R., Song, G., Song, H., Zhai, S., Xia, H., Zhang, H., and
704 Ru, X.: Contribution of local and surrounding anthropogenic emissions to a
705 particulate matter pollution episode in Zhengzhou, Henan, China, *Sci. Rep.*, 13,
706 8771, <https://doi.org/10.1038/s41598-023-35399-8>, 2023.
- 707 Wei, J., Li, Z., Lyapustin, A., Sun, L., Peng, Y., Xue, W., Su, T., and Cribb, M.:
708 Reconstructing 1-km-resolution high-quality PM_{2.5} data records from 2000 to
709 2018 in China: spatiotemporal variations and policy implications, *Remote Sens.*
710 *Environ.*, 252, 112136, <https://doi.org/10.1016/j.rse.2020.112136>, 2021.
- 711 Wei, J., Li, Z., Lyapustin, A., Wang, J., Dubovik, O., Schwartz, J., Sun, L., Li, C., Liu,
712 S., and Zhu, T.: First close insight into global daily gapless 1 km PM_{2.5} pollution,
713 variability, and health impact, *Nat. Commun.*, 14, 8349,
714 <https://doi.org/10.1038/s41467-023-43862-3>, 2023.



- 715 Wen, Z., Ma, X., Xu, W., Si, R., Liu, L., Ma, M., Zhao, Y., Tang, A., Zhang, Y.,
716 Wang, K., Zhang, Y., Shen, J., Zhang, L., Zhao, Y., Zhang, F., Goulding, K., and
717 Liu, X.: Combined short-term and long-term emission controls improve air
718 quality sustainably in China, *Nat. Commun.*, 15, 5169,
719 <https://doi.org/10.1038/s41467-024-49539-9>, 2024.
- 720 Wu, R., Qin, X., Liu, S., Chen, Y., Zhao, Y., Wang, W., and Zhang, Q.: A
721 high-resolution simplified atmospheric chemistry model for the
722 Beijing–Tianjin–Hebei region: Development, validation, and refined source
723 apportionment, *Atmos. Environ.*, 373, 121937,
724 <https://doi.org/10.1016/j.atmosenv.2026.121937>, 2026.
- 725 Yan, Y., Zhou, Y., Kong, S., Lin, J., Wu, J., Zheng, H., Zhang, Z., Song, A., Bai, Y.,
726 Ling, Z., Liu, D., and Zhao, T.: Effectiveness of emission control in reducing
727 PM_{2.5} pollution in central China during winter haze episodes under various
728 potential synoptic controls, *Atmos. Chem. Phys.*, 21, 3143–3162,
729 <https://doi.org/10.5194/acp-21-3143-2021>, 2021.
- 730 Yang, L., Wang, G., Wang, Y., Ma, Y., and Zhang, X.: Causes and transmission
731 characteristics of the regional PM_{2.5} heavy pollution process in the urban
732 agglomerations of the Central Taihang Mountains, *Atmosphere*, 16, 205,
733 <https://doi.org/10.3390/atmos16020205>, 2025.
- 734 Yang, S., Yuan, B., Peng, Y., Huang, S., Chen, W., Hu, W., Pei, C., Zhou, J., Parrish,
735 D. D., Wang, W., He, X., Cheng, C., Li, X.-B., Yang, X., Song, Y., Wang, H., Qi,
736 J., Wang, B., Wang, C., Wang, C., Wang, Z., Li, T., Zheng, E., Wang, S., Wu, C.,
737 Cai, M., Ye, C., Song, W., Cheng, P., Chen, D., Wang, X., Zhang, Z., Wang, X.,
738 Zheng, J., and Shao, M.: The formation and mitigation of nitrate pollution:
739 Comparison between urban and suburban environments, *Atmos. Chem. Phys.*, 22,
740 4539–4556, <https://doi.org/10.5194/acp-22-4539-2022>, 2022.
- 741 Yin, Y., Zhang, F., Wu, Q., Sun, L., Li, Y., Wang, P., Liu, Z., Cui, T., Zhou, Z., Hou,
742 R., Zhang, M., Liu, J., and Hu, Q.: Spatiotemporal evolution and influencing
743 factors of air pollutants in the three major urban agglomerations of the Yellow
744 River Basin, *Atmosphere*, 17, 242, <https://doi.org/10.3390/atmos17030242>, 2026.



- 745 Zhang, L., Lee, C. S., Zhang, R., and Chen, L.: Spatial and temporal evaluation of
746 long term trend (2005–2014) of OMI retrieved NO₂ and SO₂ concentrations in
747 Henan Province, China, *Atmos. Environ.*, 154, 151–166,
748 <https://doi.org/10.1016/j.atmosenv.2016.11.067>, 2017.
- 749 Zhang, X., Yuan, C., and Zhuang, Z.: Exploring the change in PM_{2.5} and ozone
750 concentrations caused by aerosol–radiation interactions and aerosol–cloud
751 interactions and the relationship with meteorological factors, *Atmosphere*, 12,
752 1585, <https://doi.org/10.3390/atmos12121585>, 2021.
- 753 Zhang, Y., Zhu, B., Gao, J., Kang, H., Yang, P., Wang, L., and Zhang, J.: The source
754 apportionment of primary PM_{2.5} in an aerosol pollution event over
755 Beijing–Tianjin–Hebei region using WRF-Chem, *China, Aerosol Air Qual. Res.*,
756 17, 2966–2980, <https://doi.org/10.4209/aaqr.2016.10.0442>, 2017.
- 757 Zhang, Y., Ma, Z., Gao, Y., and Zhang, M.: Impacts of the meteorological condition
758 versus emissions reduction on the PM_{2.5} concentration over
759 Beijing–Tianjin–Hebei during the COVID-19 lockdown, *Atmos. Ocean. Sci.*
760 *Let.*, 14, 100014, <https://doi.org/10.1016/j.aosl.2020.100014>, 2021.
- 761 Zheng, J., Zheng, Z., Yu, Y., and Zhong, L.: Temporal, spatial characteristics and
762 uncertainty of biogenic VOC emissions in the Pearl River Delta region, China,
763 *Atmos. Environ.*, 44, 1960–1969, <https://doi.org/10.1016/j.atmosenv.2010.03.001>,
764 2010.
- 765 Zhi, G., Du, J., Chen, A., Jin, W., Ying, N., Huang, Z., Xu, P., Wang, D., Ma, J.,
766 Zhang, Y., Qu, J., Zhang, H., Yang, L., Ma, Z., Ren, Y., Dang, H., Cui, J., Lin, P.,
767 He, Z., Zhao, J., Qi, S., Zhang, W., Zhao, W., Li, Y., Liu, Q., Zhao, C., Tang, Y.,
768 Wei, P., Wang, J., Song, Z., Kong, Y., Zhu, X., Shen, Y., Zhang, T., Chu, Y.,
769 Zhang, X., Fu, J., Gao, Q., Hu, J., and Xue, Z.: Progression of an emission
770 inventory of China integrating CO₂ with air pollutants: A chance to learn the
771 influence of development on emissions, *Atmos. Environ.*, 316, 120184,
772 <https://doi.org/10.1016/j.atmosenv.2023.120184>, 2024.
- 773 Zhong, B., Wang, X., Ye, L., Ma, M., Jia, S., Chen, W., Yan, F., Wen, Z., and
774 Padmaja, K.: Meteorological variations impeded the benefits of recent NO_x



775 mitigation in reducing atmospheric nitrate deposition in the Pearl River Delta
776 region, Southeast China, Environ. Pollut., 266, 115076,
777 <https://doi.org/10.1016/j.envpol.2020.115076>, 2020.
778 Zhu, Y., Liang, Y., and Chen, S. X.: Assessing local emission for air pollution via
779 data experiments, Atmos. Environ., 252, 118323,
780 <https://doi.org/10.1016/j.atmosenv.2021.118323>, 2021.
781