



Response of PM_{2.5} chemical composition to variations in anthropogenic emissions and meteorological conditions during COVID-19 lockdown

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Abstract: PM_{2.5} is a primary atmospheric pollutant with various sources and complicated chemical compositions that are influenced by various factors, such as anthropogenic emissions (AE) and meteorological conditions (MC). MC have significant impacts on variations of the atmospheric pollutant; therefore, emission
15 reduction policies and ambient air quality are non-linearly correlated, which hinders accurate assessments of the effectiveness of control measures. The online observations of PM_{2.5} and its chemical composition were conducted in Hohhot, China, from December 1, 2019, to February 29, 2020, to investigate PM_{2.5} chemical compositions respond to the variation of AE and MC. Moreover, the random forest
20 (RF) model was used to quantify the AE and MC contributions of PM_{2.5} and its chemical composition during severe hazes and the COVID-19 pandemic lockdown period. During the clean period, MC contributed -124% to PM_{2.5} concentrations, indicating that MC promoted PM_{2.5} dispersion. During severe pollution episodes, MC contributed 49% to PM_{2.5} concentrations, indicating that MC promoted PM_{2.5}
25 accumulation. The inorganic aerosols (SO₄²⁻, NO₃⁻, and NH₄⁺) showed the strongest response to MC. MC had significant contributions to the PM_{2.5} (36%), SO₄²⁻ (32%), NO₃⁻ (29%), NH₄⁺ (28%), OC (22%), and SOC (17%). From the pre-lockdown to lockdown period, AE (MC) contributed 52% (48%), 81% (19%), 48% (52%), 68% (32%), 59% (41%), and 288% (-188%) to the PM_{2.5}, SO₄²⁻, NO₃⁻, NH₄⁺, OC, and SOC



30 variations, respectively. The variations of MC (especially the increase in relative humidity) rapidly generated meteorologically sensitive species (SO_4^{2-} , NO_3^- , and NH_4^+), which led to severe winter pollution. This study provides reference for assessing the net benefits of emission reduction measures for $\text{PM}_{2.5}$ and its chemical compositions.

35 **1 Introduction**

Due to the increasing levels of industrialization and urbanization, air pollution in China has attracted a significant concern (Fuzzi et al., 2015). Frequent pollution episodes primarily driven by $\text{PM}_{2.5}$ have emerged as a crucial environmental challenge (Zhang et al., 2012). To improve the ambient air quality, China has implemented many strict strategies, resulting in a substantial decline in $\text{PM}_{2.5}$ (Zhang and Zheng, 2019). However, it remains a challenge to meet the new guideline of WHO (WHO, 2021). Particularly in northern China, the frequency of severe episodes remains high (An et al., 2019). The chemical composition of $\text{PM}_{2.5}$ is very complex, which is influenced by anthropogenic emissions (AE) and meteorological conditions (MC). The rapid generation of secondary inorganic aerosols (sulfates, nitrates, and ammonium, SNA) under adverse MC is the driving factor of severe haze in China (Yang et al., 2011).

In December 2019, the coronavirus pandemic (COVID-19) outbreak occurred in China. To prevent the spread of the virus, China implemented various control measures, including transport restrictions and home quarantine (Yang et al., 2022a). Due to reduced socio-economic activities during the lockdown period (LD), NO_x emissions across China decreased by 36% (Feng et al., 2020). However, despite a substantial reduction in primary emissions during LD, unexpected hazes occurred in Northern China Plain (Wang et al., 2020) and the Yangtze River Delta (YRD) region (Huang et al., 2021). It can be attributed to the counteracting effect of secondary aerosols induced by adverse MC. The variation of MC contributed over 70% of the $\text{PM}_{2.5}$ variations in China (He et al., 2017). MC are essential factors driving the



variations of atmospheric pollutants (Dominici et al., 2002). Therefore, quantifying the impacts of AE and MC on atmospheric pollutants is crucial for understanding haze events. Lockdown measures provided a opportunity to estimate the response of PM_{2.5} chemical composition to the variations of AE and MC; thus, evaluations of this period can shed light on the intricate non-linear correlation between air quality and emission reduction policies.

Random forest (RF) model demonstrated sound performance in predicting environmental air quality and quantifying MC contributions (Grange et al., 2018). Furthermore, it can elucidate the relationship between independent predictors and dependent variables and reveal the importance of influencing factors (Vu et al., 2019). Zhang (Zhang et al., 2023) applied RF model to quantify the impacts of AE and MC on PM_{2.5} variations in Tibetan Plateau. The result suggested that the reduction in AE was the main driver for reducing PM_{2.5} in the region. Chen (Chen et al., 2023) found that from 2015 to 2019, the contributions of AE (MC) to the PM_{2.5} in Henan Province, Beijing-Tianjin-Hebei, and the YRD region were -41.8 (27.0), -38.6 (12.3), and -31.3 (2.9) μg/m³, respectively. Liu (2022) observed that in Hubei province during LD, the changes in AE reduced PM_{2.5} by 33.3%, whereas variations in MC increased PM_{2.5} contents by 8.8% compared to 2019. The adverse MC resulted in a 9.8% increase in PM_{2.5} in North China during LD, whereas the reduction in AE induced a 32.2% decrease in PM_{2.5} concentrations (Lv et al., 2023). In conclusion, significant differences have been observed in the response of PM_{2.5} concentrations to AE reductions and variations in MC in different regions. The contribution of MC to PM_{2.5} chemical composition remains poorly understood.

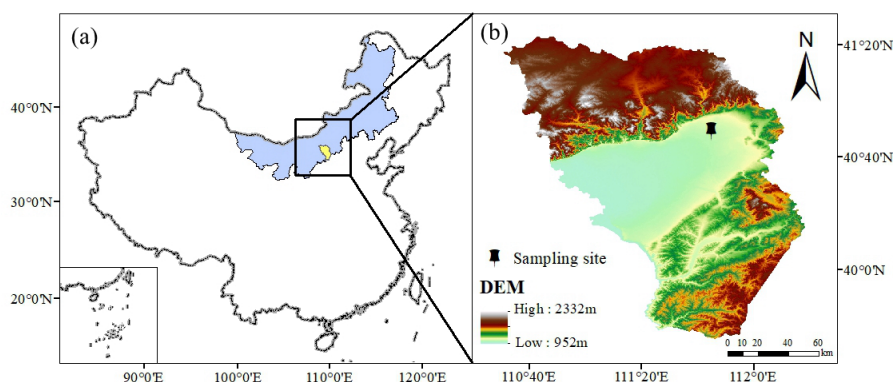
The present study employed online observations of PM_{2.5} chemical composition in Hohhot to reveal the response of PM_{2.5} chemical compositions to AE and MC. The RF model was utilized to quantify the contributions of AE and MC to PM_{2.5} chemical composition during severe pollution episodes and LD, revealing the intricate non-linear correlations between the chemical composition of PM_{2.5} and AE and MC.



2 Data and Methods

2.1 Data Sources

Eight water-soluble ions (SO_4^{2-} , NO_3^- , NH_4^+ , Cl^- , K^+ , Ca^{2+} , Na^+ , and Mg^{2+}) were
90 observed using an online ion chromatograph (MARGA, Metrohm, Switzerland) at
Environmental Monitoring Center of Inner Mongolia (Fig. 1). The hourly
concentrations of organic carbon (OC) and elemental carbon (EC) were measured
using an online OC/EC analyzer (Model 4, Sunset Lab, USA). The concentrations of
metals (K, Ca, Fe, Zn, Cu, Ba, Pb, Mn, Ti, Cr, V, Sc, Sn, Ni, Cs, Br, Sb, Se, Co, As,
95 Ag, Tl, Mo, Cd, Cs, and Te) were obtained using an online atmospheric metal
monitoring system (AMMS-100, Focused Photonics Inc., China). The hourly
concentrations of atmospheric pollutants and meteorological variables were
simultaneously measured at the same site.



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Figure 1. Location of the (a) study area and (b) sampling site

2.2 RF Model

RF model was used to quantify the contribution of AE and MC to atmospheric
pollutants (Grange et al., 2018). The hourly data (70% for training, 30% for testing) of
pollutant concentrations, meteorological parameters, and time variables were input
105 into the model to predict the pollutant concentrations free from the influence of MC.
The difference between observed and predicted values represents the MC contribution



to atmospheric pollutant concentrations (Guo et al., 2022). We assessed the model performance using nine statistical indicators (Table S1). The results indicated that all the performance metrics for pollutant predictions met the required criteria, indicating
110 that the model possesses adequate predictive capability and performance.

3 Results and discussion

3.1 Variations in pollutant concentrations

The time series of meteorological variables and atmospheric pollutants in Hohhot are presented in Fig. 2. Thirty-three daily PM_{2.5} concentrations exceeded the National
115 Ambient Air Quality Standard (75 $\mu\text{g}\cdot\text{m}^{-3}$), which accounted for 36.2% of the total sampling days. Seven pollution episodes (PM_{2.5} daily concentrations exceeding 75 $\mu\text{g}\cdot\text{m}^{-3}$ for at least two consecutive days) were observed during these periods. The longest pollution episode lasted for 10 days (Fig. 2, EP6). The mean PM_{2.5} concentrations during the seven severe pollution episodes were 96±16, 120±35, 98±11,
120 142±46, 154±46, 120±37, and 100±2 $\mu\text{g}\cdot\text{m}^{-3}$. During the severe pollution episodes, higher concentrations of SO₂ and NO₂ were observed. Furthermore, the low wind speed (WS) and high relative humidity (RH) promote the accumulation and secondary aerosol formation. The proportion of SNA was relatively high in PM_{2.5}, accounting for 49%, 69%, 49%, 66%, 63%, 50%, and 55% of the total PM_{2.5} chemical composition
125 during these episodes.

To prevent the spread of COVID-19, Hohhot implemented a Level I public health emergency response on January 25, 2020, which was subsequently adjusted to Level III on February 25. This study defined the strict control period as LD (January 25, 2020, to February 24, 2020) and the preceding month as pre-lockdown (pre-LD,
130 December 25, 2019, to January 24, 2020). The mean concentrations of PM_{2.5} during the pre-LD and LD were 89.4±52.3 and 58.3±49.7 $\mu\text{g}\cdot\text{m}^{-3}$, respectively. Compared to pre-LD, the mean concentrations of PM_{2.5}, NO₂, and CO during LD decreased by 31.0 $\mu\text{g}\cdot\text{m}^{-3}$ (P<0.05), 24.3 $\mu\text{g}\cdot\text{m}^{-3}$ (P<0.001), and 0.6 mg m⁻³ (P<0.01). The mean SO₂



concentration declined by $2.8 \mu\text{g}\cdot\text{m}^{-3}$ ($P>0.05$). The decline in NO_2 and CO
135 concentrations was related to the significant reduction in vehicular emissions. In
addition to the reduction in AE, the significant decrease in $\text{PM}_{2.5}$ concentrations was
also influenced by variations in MC.

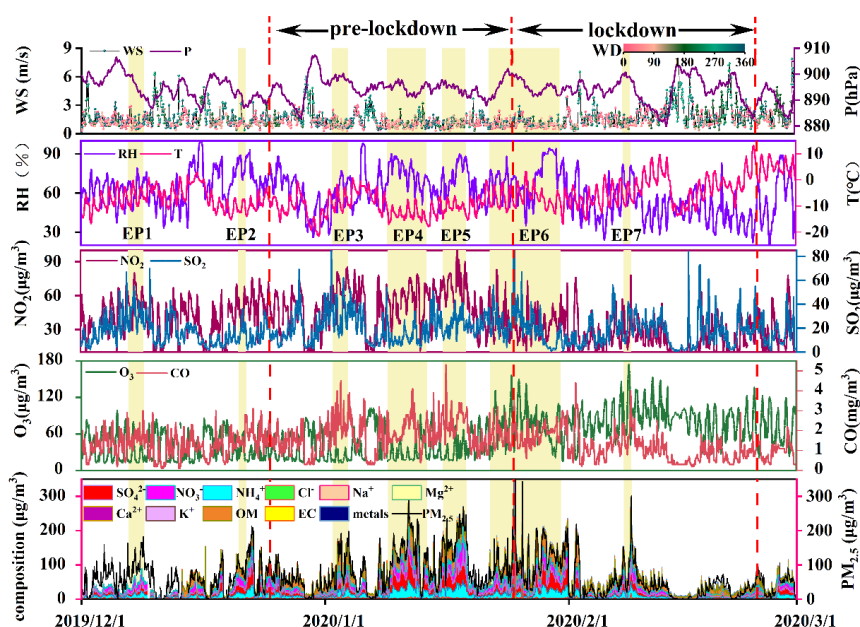


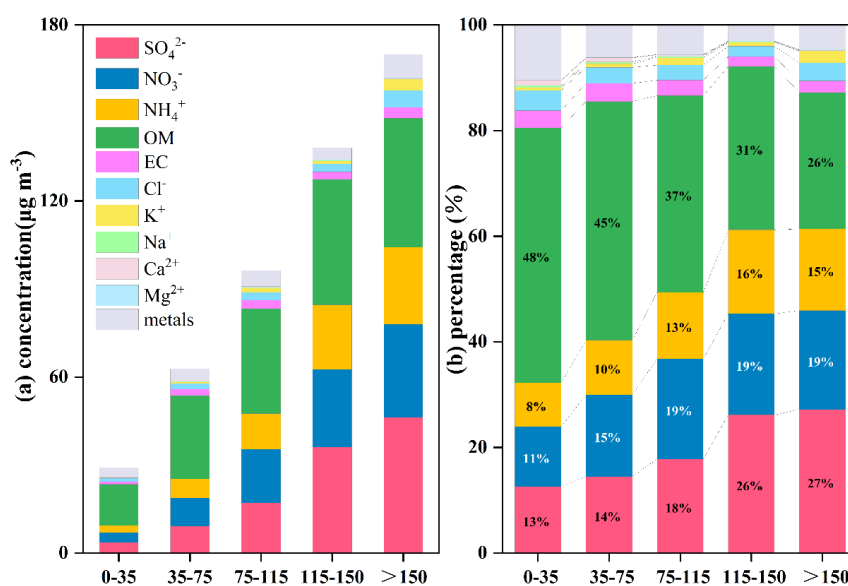
Figure 2. Variations in meteorological variables and atmospheric pollutants during the
140 observation period (yellow background indicating severe pollution episodes)

3.2 Variations in $\text{PM}_{2.5}$ chemical constituents across different pollution levels

The concentration and percentage of $\text{PM}_{2.5}$ chemical composition are presented in
Fig. 3 and Table S1. During the clean period ($\text{PM}_{2.5} < 35 \mu\text{g}\cdot\text{m}^{-3}$), organic matter (OM)
was the main composition (48%) of $\text{PM}_{2.5}$. From clean to severe pollution
145 ($\text{PM}_{2.5} > 150 \mu\text{g}\cdot\text{m}^{-3}$), the concentration of OM increased from 14 to $44 \mu\text{g}\cdot\text{m}^{-3}$;
however, its proportion decreased from 48% to 26%. Compared to the clean period,
the mean concentrations of SO_4^{2-} , NO_3^- , and NH_4^+ increased by 12, 9, and 10 times
during severe pollution, respectively. Furthermore, the proportion of SNA increased
from 32% to 61%, indicating that the rapid increase in secondary inorganic ions



150 significantly contributed to PM_{2.5} aggravation. Especially for SO₄²⁻, it was higher than
 that of NO₃⁻ in Hohhot, which is inconsistent with the results of megacities (Fu et al.,
 2020; Huang et al., 2019a; Yang et al., 2022b). Nitrate was the dominant component
 of SNA in Beijing since 2016, which could be attributed to the effective measure of
 SO₂ emissions (the precursor of SO₄²⁻). Nitrate has become the predominant
 155 composition of PM_{2.5} in Beijing (Fu et al., 2020). A similar result was also found in
 Zhongshan (Yang et al., 2022b). In Shanghai, NO₃⁻ was the most abundant species in
 winter, whereas SO₄²⁻ replaced NO₃⁻ as the dominant species in summer (Huang et al.,
 2019a). From clean to severe pollution, the concentrations of Cl⁻, K⁺, Na⁺, Mg²⁺, and
 metals in Hohhot increased by 4.2, 24.3, 0.03, 7.1, and 1.6 times, respectively,
 160 whereas the proportions of them decreased. The increase in Cl⁻, K⁺, and Mg²⁺
 concentrations can be attributed to fireworks during the Spring Festival period (Li et
 al., 2022).



165 Figure 3. Variation in (a) concentration and (b) percentage of PM_{2.5} chemical compositions at different pollution levels



3.3 Factors influencing PM_{2.5} and its compositions

The correlations among the PM_{2.5} chemical compositions, meteorological variables, and atmospheric pollutants are presented in Fig. S1. PM_{2.5} negatively
170 correlated with WS ($P < 0.001$) and T ($P < 0.01$). The lower WS and surface T (inversion) hinder PM_{2.5} dispersion, thereby resulting in PM_{2.5} accumulation. Furthermore, PM_{2.5} positively correlated to SO₄²⁻, NO₃⁻, NH₄⁺, SOR, NOR, and RH ($P < 0.001$). High RH benefits the PM_{2.5} hygroscopic growth (Liao et al., 2017) and secondary formation of SNA (Cheng et al., 2016), thereby exacerbating PM_{2.5} pollution. However, when RH
175 is higher than the threshold of 80%, the PM_{2.5} concentration, SOR, and NOR decrease with increasing RH (Fig. 4). This may be related to the aggregation of suspended particles and sedimentation, thereby significantly reducing the PM_{2.5} concentration (Cheng et al., 2015). In addition to RH, oxidation capacity ($O_x = O_3 + NO_2$), and T are also considered to be vital factors influencing the formation of SO₄²⁻ and NO₃⁻. During
180 the observation period, SOR negatively correlated to T ($P < 0.01$). The intensity of coal-fired heating was increased at lower T situations, resulting in increased SO₂ emissions in these periods. Especially, under low WS and high RH condition, the increase of SO₂ emissions leads to the rapid formation of SO₄²⁻. SOR is not correlated with Ox ($P > 0.05$), indicating that SO₄²⁻ was primarily formed through the aqueous-phase oxidation pathway. Typically, the photochemical oxidation rate of SO₂ is
185 relatively slow (Zhang et al., 2015), whereas the aqueous-phase pathway plays a crucial role in SO₄²⁻ formation (Gao et al., 2016). Unlike SO₄²⁻, Ox plays an essential role in NO₃⁻ formation. During the observation period, NOR positively correlated to Ox ($P < 0.001$) and RH ($P < 0.001$), indicating that photochemical and aqueous-phase
190 oxidation both had a crucial role in NO₃⁻ formation in Hohhot. The homogeneous reaction between NO₂ and OH is the primary pathway for the daytime formation of HNO₃ (Finlayson-Pitts et al., 2003), and N₂O₅ hydrolysis is the primary pathway for the nighttime formation of HNO₃ (Pathak et al., 2011). Furthermore, HNO₃ can be converted to nitrate through reactions with alkaline species (Gard et al., 1998).



195 A higher OC/EC ratio was observed within the RH range of 20–40%, which may
be attributed to the high Ox and T levels that promote SOC formation. Throughout the
entire observation period, OC, EC, secondary organic carbon (SOC), and primary
organic carbon (POC) showed positively correlated to RH ($P < 0.001$) and Ox ($P < 0.01$)
and a significant negative correlation with T ($P < 0.05$). This is primarily related to the
200 increased intensity of coal-fired heating during low T, which often coincide with high
RH. Furthermore, high RH promotes SOC formation (Huang et al., 2019b; Xu et al.,
2017), whereas low T facilitates organic substances condensation (Galindo et al.,
2019).

In conclusion, MC has a vital impact on $PM_{2.5}$ and its compositions. Therefore,
205 this study utilized the RF model to evaluate the relative importance of time factors,
meteorological variables, and gaseous pollutants in influencing $PM_{2.5}$ chemical
composition (Fig. 5). The relative importance of SO_2 , RH, and NO_2 was 28.4%,
19.7%, and 13.4% to $PM_{2.5}$, respectively, indicating that gaseous precursors and RH
are the primary influencing factors for $PM_{2.5}$. This further confirms that under high
210 RH conditions, the secondary formation of SO_4^{2-} and NO_3^- had a considerable
contribution to $PM_{2.5}$ exacerbation (Han et al., 2016). Sulfate, NO_3^- , and NH_4^+ were
the most sensitive to RH variation, and the relative importance values were 28.0%,
38.8%, and 33.1%, respectively. Nitrite exhibited sensitivity to Ox, whereas SO_4^{2-} and
 NH_4^+ demonstrated little sensitivity to Ox. It suggested that NO_3^- is significantly
215 influenced by photochemical oxidation, whereas SO_4^{2-} is more affected by aqueous-
phase oxidation. OC and SOC were sensitive to trends, SO_2 , and NO_2 , which can be
attributed to periodic emissions variation.

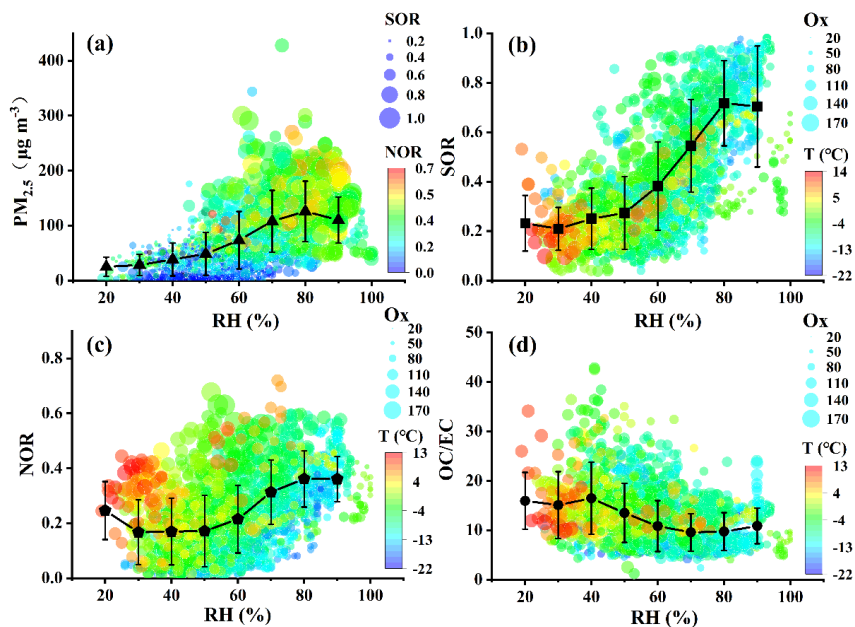
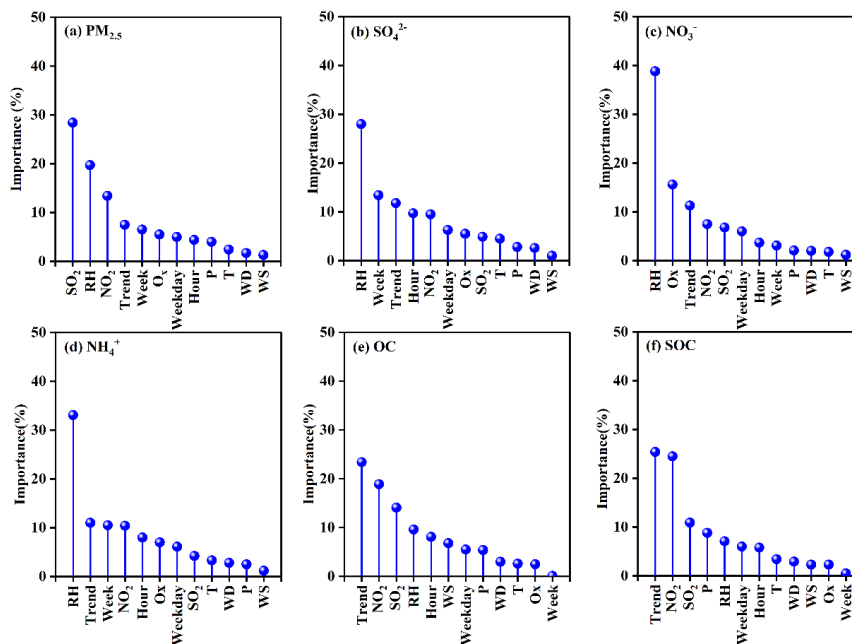


Figure 4. Correlations between RH and (a) $PM_{2.5}$, (b) SOR, (c) NOR, and (d) OC/EC



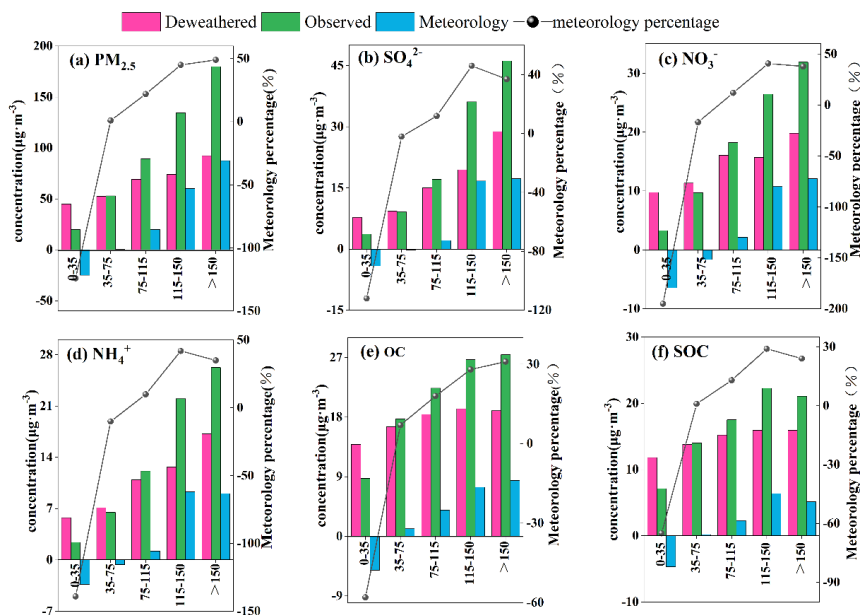
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Figure 5. Relative importance of meteorological variables and atmospheric pollutants to (a) $PM_{2.5}$, (b) SO_4^{2-} , (c) NO_3^- , (d) NH_4^+ , (e) OC, and (f) SOC



3.4 Response of PM_{2.5} compositions to the variation of AE and MC

From clean to severe pollution, the contributions of AE and MC to PM_{2.5} concentration increase by 1.1 and 4.5 times (Fig. 6), respectively, indicating that PM_{2.5} concentration is more sensitive to variations in MC. During the clean period, MC contributed negatively to PM_{2.5} concentrations, indicating that MC was conducive to pollutant dispersion. The contribution of MC increased with the increase of PM_{2.5} concentration, with the highest contribution of 49% during severe pollution episodes. The MC contribution of SO₄²⁻, NO₃⁻, NH₄⁺, OC, and SOC during severe pollution periods were 6.2, 3.9, 4.7, 3.6, and 3.1 times those of the clean period, respectively. The contribution of MC to SO₄²⁻, NO₃⁻, and NH₄⁺ can reach 46%, 41%, and 35%, respectively. In conclusion, the rapid increase of SNA under adverse MC is the primary driver for PM_{2.5} aggravation.



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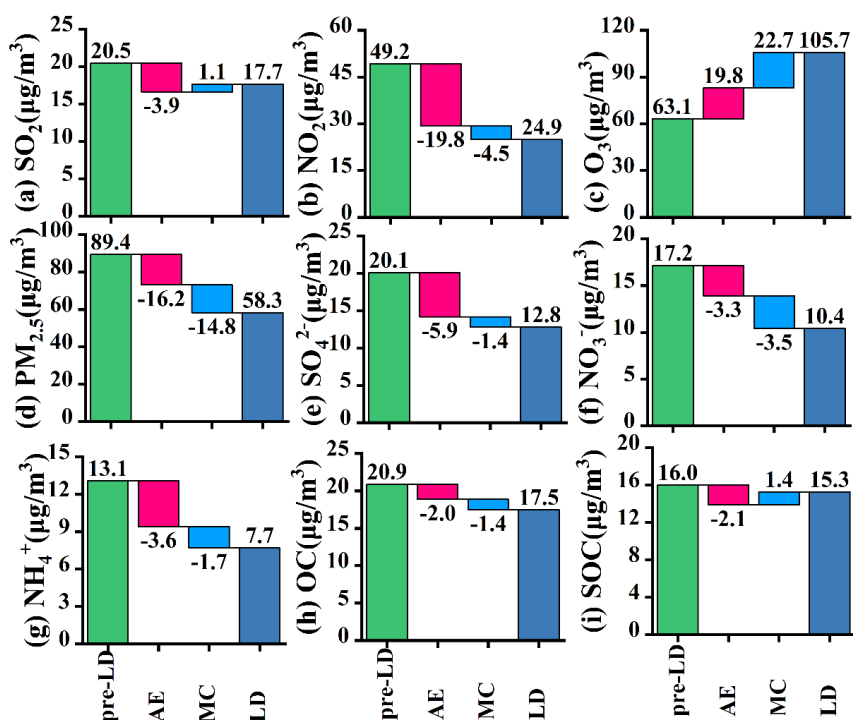
Figure 6. Contributions of AE and MC to (a) PM_{2.5}, (b) SO₄²⁻, (c) NO₃⁻, (d) NH₄⁺, (e) OC, and (f) SOC at different pollution levels

The contributions of AE and MC to PM_{2.5} major chemical compositions during the seven severe pollution episodes are presented in Fig. S2. The AE (MC)



240 contributed 64% (36%), 68% (32%), 71% (29%), 72% (28%), 78% (22%), and 83%
(17%) to the $PM_{2.5}$, SO_4^{2-} , NO_3^- , NH_4^+ , OC, and SOC concentrations, respectively. AE
had a considerable contribution to all pollutants (>64%), whereas MC had a higher
impact on $PM_{2.5}$, SO_4^{2-} , NO_3^- , and NH_4^+ (>28%).

Compared to the pre-LD, the temperatures (T) were higher during LD, in
245 response to this variation the heating intensity had a considerable reduction, resulting
in a 33% and 23% decrease in SO_2 and NO_x emissions, respectively (Fig. S3). Apart
from heating enterprises, other key pollution sources have experienced a 22%
decrease in SO_2 emissions, whereas NO_x emissions exhibited a relatively minor
variation. Therefore, the substantial reduction of $PM_{2.5}$ and NO_2 concentrations during
250 LD can be attributed to the combined effects of reduced heating intensity, lockdown
control measures, decreased RH (from 65% to 54%), and increased WS (from 1.4 to
1.8 m/s). Compared to pre-LD, the concentration of O_3 exhibited a rapid increase
during LD, with AE and MC contributing 19.8 and 22.7 $\mu g \cdot m^{-3}$, respectively. The
swift increase in O_3 concentration during LD could be primarily attributed to the
255 substantial reduction in NO_x emissions, leading to a decreased titration of O_3 by NO
(Wang et al., 2013). Specifically, AE contributed 16.2, 5.9, 3.2, 3.6, 2.0, and 2.1 $\mu g \cdot m^{-3}$
to the reductions in $PM_{2.5}$, SO_4^{2-} , NO_3^- , NH_4^+ , OC, and SOC, which accounted for
52%, 81%, 48%, 68%, 59%, and 288% of the total variation, respectively. MC
contributed 14.8, 1.4, 3.5, 1.7, 1.4, and -1.4 $\mu g \cdot m^{-3}$ to the variations in $PM_{2.5}$, SO_4^{2-} ,
260 NO_3^- , NH_4^+ , OC, and SOC, which accounted for 48%, 19%, 52%, 32%, 41%, and -
188% of the total variations, respectively. The lockdown measures had a significant
reduction effect on SO_2 and NO_2 concentrations, with 138% (-38%) and 82% (18%)
attributed to AE (MC), respectively.



265 Figure 7. Contributions of AE and MC to variations in (a) SO₂, (b) NO₂, (c) O₃, (d)
 PM_{2.5}, (e) SO₄²⁻, (f) NO₃⁻, (g) NH₄⁺, (h) OC, and (i) SOC during the pre-LD and LD
 270 periods.

4. Conclusion

To reveal the causes of pollution episodes and the relationship among
 270 atmospheric pollutants, AE, and MC, online observations of PM_{2.5} and its chemical
 compositions were conducted in Hohhot during the winter season. SNA was the
 predominant composition of PM_{2.5} in Hohhot, particularly during severe pollution
 episodes. The concentration and proportion of SNA increased rapidly from clean to
 severe pollution episodes. The formation of SO₄²⁻ in winter was primarily attributed to
 275 aqueous-phase oxidation, whereas both aqueous-phase and photochemical oxidation
 played vital roles in NO₃⁻ formation. The results from the RF model indicated that



gaseous pollutants (SO_2 and NO_2) and MC (RH) had significant impacts on $\text{PM}_{2.5}$. SNA was the most sensitive to RH. From clean to severe pollution, MC had a considerable contribution to the SNA concentrations, suggesting that the rapid
280 generation of SNA was the driving factor of $\text{PM}_{2.5}$ aggravation in Hohhot. The lockdown measures contributed to the reduction of most of the pollutants, whereas variations in MC contributed significantly to the decrease of $\text{PM}_{2.5}$ and NO_3^- levels during the LD. Therefore, when assessing the effectiveness of pollution control policies in the future, it is essential to fully consider the contribution of MC to
285 pollutants.

Acknowledgments

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