1   **Investigating the impact of meteorology and emissions on PM$_{2.5}$ and PM$_{10}$ in Delhi using machine learning**

2   Shubhi Verma[1], Mohammad Rafiuddin[1], Uday Suryanarayanan[1,2], Shikhar Tiwari[1], Rishikesh Puravankara[1]

3   [1]Council on Energy, Environment and Water, New Delhi, 110070, India

4   [2]Our Common Air

5   *Correspondence to*: Mohammad Rafiuddin (mohammad.rafiuddin@ceew.in)

6   **Abstract**

7   Delhi is among the most polluted megacities in the world. Despite a range of interventions, the city's PM$_{2.5}$ and PM$_{10}$ levels

8   exceed Indian and WHO standards several times. India launched the ambitious National Clean Air Programme (NCAP) to

9   reduce air pollution in its most polluted cities, including Delhi, in 2019. While several studies have looked at the trends of

10   pollutant concentrations in Delhi, very few have adjusted for the effects of meteorology. In this study, we perform weather

11   normalisation or deweathering using a machine learning model to analyse the impact of meteorology and anthropogenic

12   emissions on PM$_{2.5}$ and PM$_{10}$ concentrations in Delhi. The study reveals a statistically insignificant decline in deweathered

13   PM$_{2.5}$ and PM$_{10}$ between 2019 and 2024 across seasons. Also, the average deweathered PM$_{2.5}$ and PM$_{10}$ concentrations almost

14   double (PM$_{2.5}$: 64.8 µg/m^3 vs 144.3 µg/m^3 and 142.4; PM$_{10}$: 138.1 µg/m^3 vs 261.8 µg/m^3 and 273.1 µg/m^3, respectively) in

15   post-monsoon and winter months (October to November and December to February, respectively) compared to those in

16   monsoon (June to September). Meteorological effects reduce PM$_{2.5}$ concentrations in summer (March to May) and monsoon

17   seasons by 3.4 µg/m^3 and 25.4 µg/m^3, respectively, on average. However, they worsen PM$_{10}$ concentrations during summer

18   by 7.7 µg/m^3, but reduce them by 25.4 µg/m^3 during the monsoon season, on average. They also worsen the concentrations of

19   PM$_{2.5}$ and PM$_{10}$ by 10.7 µg/m^3 and 18.2 µg/m^3 respectively, in post-monsoon. Meteorological effects play a role in reducing

20   PM$_{10}$ concentrations by 7.8 µg/m^3 and increasing PM$_{2.5}$ by 17 µg/m^3 in winter. Additionally, the effect of meteorology shows

21   no statistically significant trends across years for both pollutants, across seasons. Weekly averaged deweathered PM$_{2.5}$ - CO

22   ratio analysis between 2019 and 2024 reveals two distinct spikes in the ratio associated with the post-monsoon stubble burning

23   in the states surrounding Delhi and biomass burning for heating during winter months.

24

25   Keywords: deweathering, weather normalisation, PM$_{2.5}$-CO ratio, meteorology

26   **1 Introduction**

27   Air pollution is a global problem affecting around 90% of the world's population (World Health Organisation, 2018). India is

28   among the countries that suffer the most from air pollution, with its cities grappling with severe pollution levels (Sharma et

29   al., 2019). Delhi, in particular, has had alarming levels of air pollution in recent years, making it one of the most polluted cities

30   in the world (WHO, 2024). It observed the highest per capita economic loss owing to air pollution, followed by Haryana, a

31   state neighbouring it, in 2019 (Pandey et al., 2020). In 2019, the Indian government introduced the National Clean Air

32   Programme (NCAP) to mitigate air pollution. The programme initially sought to reduce PM_{10} concentrations by 20 - 30% by

33   2024-25 compared to the 2017 levels, focusing on 131 cities that failed to meet the National Ambient Air Quality Standards

34   (NAAQS), called Non Attainment cities (MoEFCC, 2019). This target has been revised to reduce PM_{10} concentrations by

35   40% or to meet the NAAQS, set at 60 μg/m^3, by 2025-2026 (PIB, 2024).

36

37   Delhi is one of the 131 Non-Attainment (NA) cities. However, the city's fight against air pollution started long before NCAP

38   was launched. Delhi has been working on managing emissions from the transport sector and pollution from the construction

39   and residential sectors to improve air quality. Alarmed by the rising vehicular emissions, the Supreme Court (SC) of India

40   mandated in 1998 that all public transport should convert from diesel to Compressed Natural Gas (CNG) by 31 March 2001.

41   This transition was completed by 1 December 2002, with all the buses converted to CNG (Kathuria, 2004). To manage

42   pollution from traditional cooking practices in households, the Ujjwala programme was launched by the Ministry of Petroleum

43   and Natural Gas (MoPNG) in 2016. This program aimed to reduce indoor pollution, improve health and promote cleaner

44   cooking practices by providing women from economically weak households in India with LPG connections (Kar et al., 2020).

45

46   In addition to vehicular emissions, road dust is considered a major contributor to the city's air pollution (Sharma and Dikshit,

47   2016). Multiple measures were implemented to tackle road dust as well, such as limiting the movement of heavy-duty vehicles

48   and using dust suppressants at construction sites and so on (Guttikunda et al., 2023). In addition to these, the city phased out

49   15-year-old petrol and 10-year-old diesel vehicles, expanded its metro rail network, and introduced an odd-even vehicle

50   scheme (Goel and Gupta, 2015; Tiwari et al.,2018; Sahu et al., 2023). The Government of India also implemented the Bharat

51   Stage VI (BS-VI) vehicular emission norms in Delhi in 2018, skipping Bharat Stage Emission Standards 5 (BSV), ahead of

52   the national schedule (Gajbhiye et al., 2023).

53

54   In January 2017, the Ministry of Environment, Forests & Climate Change (MoEFCC) implemented the Graded Response

55   Action Plan (GRAP) to address the air pollution episodes during and around the winter months (MoEFCC, 2019). GRAP is an

56   emergency response mechanism, on the basis of average AQI levels in Delhi, enabling the authorities to take action in response

57   to situations of worsening air quality in Delhi-NCR (Central Pollution Control Board of India). The Union Government also

58   established the Commission for Air Quality Management in the National Capital Region and Adjoining Areas (CAQM) in

59   2021, with the objective of curbing air pollution primarily in Delhi and the NCR (Ministry of Law and Justice, 2019).

60   These steps paved the way for proper air quality management, despite the challenges. Guttikunda et al. (2023) summarise the

61   air quality improvement-related interventions spanning from 1990 to 2022.

62

63   Air quality is a function of emissions and meteorology (Petetin et al., 2020). Therefore, it is essential to separate these

64   components to evaluate the effectiveness of air quality management interventions in reducing emissions (Liu et al., 2022).

65   'Meteorological Normalisation' or 'Deweathering' is one of the ways of achieving this (Grange and Carslaw, 2019). The

66   traditional approach to performing deweathering has been Chemical Transport Modelling (CTM), regarded as the 'Gold

67   Standard' for such evaluations (Gardner-Frolick et al., 2022). However, CTMs are computationally intensive and require a lot

68   of data and expertise (Xing et al., 2021; Zheng et al., 2023). Various methods have been suggested as alternatives to CTMs,

69   including Machine Learning (ML), Statistical Methods, and the Kolmogorov-Zurbenko filter, of which ML methods have been

70   considered the most accurate (Zheng et al., 2023).

71

72   Very few studies have applied deweathering methods for Delhi. They differ in the kinds of models used, the sources of data,

73   the choice of pollutants, and the location considered. For instance, Chetna et al. (2024) studied the impact of meteorology on

74    $PM_{2.5}$ trends in Delhi between 2007 and 2022. The study used the AirGAM2022rl model, based on a Generalised Additive

75   Model (GAM), to analyse meteorology-adjusted trends (trends where the inter-annual variation in meteorology was removed)

76   and meteorology-unadjusted trends (ambient trends). Xie et al. (2024) evaluated trends in surface $PM_{2.5}$ concentrations in India

77   between 2017 and 2022 and estimated the impact of air quality improvement interventions and meteorology. To achieve this,

78   they performed simulations using the Weather Research and Forecasting with Chemistry (WRF-Chem) model with fixed

79   anthropogenic emissions from 2017 levels and varying the meteorology from year to year. These simulations calculated the

80   extent to which meteorology impacted $PM_{2.5}$ concentrations. Observed data from around 500 Continuous Ambient Air Quality

81   Monitoring (CAAQM) stations, 5 stations in the US AirNow continuous monitoring network in Indian cities, were then used

82   to validate the results from the WRF-Chem model. They find that favourable meteorology was responsible for the air quality

83   improvement in Delhi and other Indian cities.

84

85   Chauhan et al. (2024) analysed variations in $PM_{2.5}$, PM_{10}, NOx, NH_3, SO_2, CO, and O_3 in 5 Indian cities- Delhi, Kolkata,

86   Bengaluru, Hyderabad, and Visakhapatnam, incorporating a weather normalisation technique to isolate the impact of

87   meteorology. The study used GAM to perform the said deweathering analysis, and only took into account the data from one

88   station for each city, utilising meteorological data from the India Meteorological Department (IMD). The study focused

89   primarily on two timeframes: prior the lockdown period, which is March 11, 2020 to March 24, 2020 and during the lockdown

90   period, lasting from March 25, 2020 to April 07, 2020 in the same year and in the different years (lockdown period in 2020

91   versus lockdown period in 2018, 2020, 2021 and 2022).

92

93   Another study identified impact of meteorology on $PM_{2.5}$ levels and related mortality using $PM_{2.5}$ data from the US Embassy

94   in Delhi and reanalysis meteorological data during 2014–2021 in five Indian megacities (Chennai, Kolkata, Hyderabad,

95   Mumbai, Delhi), incorporating Multiple Linear Regression to perform weather normalisation (Wang et al., 2024).

96

97   Regardless of this existing literature, significant gaps exist. Previous studies usually cover short periods or do not include very
98   recent years, individual seasons (e.g., lockdown seasons) or rely on data from a single monitoring station or non-representative
99   locations such as the US Embassy station. Further, not many studies have tested the trend after removing periods such as
100   COVID-19 lockdowns, which could have affected the overall trend.

102   The current study uses a machine learning model to decouple the effects of meteorology and emissions on $PM_{2.5}$, PM_{10}, and
103   CO data from several CAAQM stations in Delhi between 2018 and 2024. The study period also intersects with the NCAP
104   period, which started in 2019. Not only does the current study estimate the deweathered $PM_{2.5}$ trends, but also the variation in
105   the meteorological effects across seasons and years. It also examines the impact of the phases of the El Niño-Southern
106   Oscillation (ENSO) on meteorology and thereby $PM_{2.5}$. Additionally, the study comments on the impact of stubble burning
107   and winter biomass burning on Delhi's air pollution through a deweathered $PM_{2.5}$-CO ratio, a proxy for secondary particulate
108   formation.

109   **2 Data and Methods**

110   **2.1 Data Selection**

111   Delhi had a network of 12 CAAQMS stations in 2016 (Central Control Room for Air Quality Management), which gradually
112   expanded over the years, with 30-plus stations in 2018 and more than 40 stations in 2024 (Guttikunda et al., 2023). These
113   stations are operated by various bodies like the Delhi Pollution Control Committee (DPCC), the IMD, and the Central Pollution
114   Control Board (CPCB). However, to have comparable data across years, we considered data from the 31 stations which have
115   been operating since February 2018. From these stations, we collected hourly data of key pollutants: $PM_{2.5}$, PM_{10}, and CO, for
116   the period from February 2018 to February 2025 (Central Control Room for Air Quality Management). However, PM_{10} data
117   was only available consistently from May 2018 onwards and for 28 of the 31 stations. Similarly, CO data was taken from May
118   2018, but was available for all 31 stations. A complete list of these stations is provided in the Supplementary Material (SM 1).

120   Weather parameters that generally impact air quality, such as temperature, wind speed and direction, precipitation rate, and
121   boundary layer height, are used as inputs in weather normalisation studies (Vu et al., 2019; Zhang et al., 2020; Shi et al., 2021).
122   Some studies also incorporate variables like the Monin-Obukhov length and air mass trajectories (Ma et al., 2020; Grange et
123   al., 2018). However, these variables are not commonly used in weather normalisation studies (Grange and Carslaw, 2019; Vu
124   et al., 2019; Zhang et al., 2020).

126   Emissions are generally associated with the hour of day and the day of the year (Derwent et al., 1995). Therefore, time variables
127   like Julian day, weekday, and hour of the day can be used as proxies for emissions (Grange and Carslaw, 2019). The current
128   study uses hourly data of meteorological variables namely temperature at a 2-metre height above the ground level (T2M),

129 mean sea-level pressure (MSL), boundary layer height (BLH), downward surface solar radiation (SSR), total cloud cover

130 (TCC), relative humidity (RH), wind speed (WS), wind direction (WD), and mean total precipitation rate (MTPR) obtained

131 from the European Centre for Medium-Range Weather Forecasting Reanalysis v5 (ERA5) dataset (Hersbach et al., 2023) and

132 temporal variables like hour of the day, Julian day, weekday, and Unix date. We obtain MTPR at an hourly level by multiplying

133 the rainfall rate in mm/s from the ERA5 reanalysis by 3600.

134

2.2 Data Preprocessing

136 We preprocess the data to ensure data quality. Our data preprocessing steps involve removing the observations for which $PM_{2.5}$

137 and PM_{10} were less than 5 $\mu g/m^3$ and where $PM_{2.5}$ was greater than PM_{10}. Since $PM_{2.5}$ is a subset of PM_{10}, the former being

138 greater would suggest erroneous measurement. Delhi's baseline $PM_{2.5}$ levels are above 20 $\mu g/m^3$ (Lavanyaa et al., 2023).

139 Therefore, values below 5 $\mu g/m^3$ can be considered unrealistic and hence removed. However, our threshold of 5 $\mu g/m^3$ is

140 arbitrary. To ensure adequate spatial representativeness, we only retain the hours for which at least 75% of the stations had

141 data. Figure 1 summarises the process.

142

143
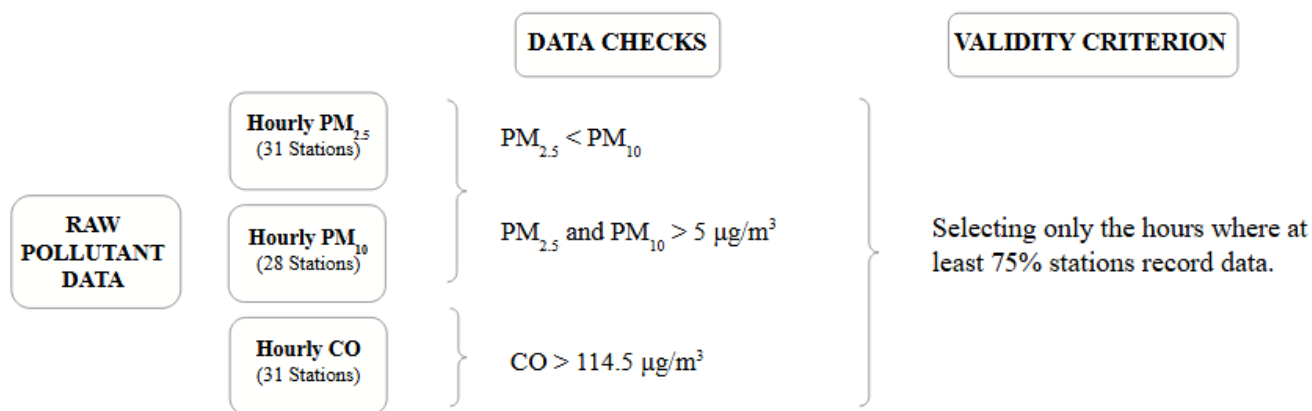
Figure 1. Data preprocessing procedure for the hourly pollutant data from the CAAQM stations - Raw data for $PM_{2.5}$, PM_{10},
and CO undergo checks regarding the lower limits of pollutants, $PM_{2.5}$ being greater than PM_{10} and validity criteria being
hours where at least 75% of stations record data.

2.3 Model Selection and Optimisation

148 We use 70% of the data for training and 30% for testing. Accounting for the non-linear relationship between the predicting

149 variables and the target variable (pollutant concentration), we choose a non-parametric machine learning model to predict the

150 pollutant concentrations (Ma et al., 2021). We choose the HistGradientBoostRegressor (HGBDT) model from the Scikit-Learn

151 package, which is a popular machine learning package in Python. HGDBT uses a histogram-based decision tree mechanism.

152 It is much faster than the Gradient Boosted Decision Tree (GBDT) model for large datasets with samples exceeding 10000

153 (HistGradientBoostingRegressor, Scikit-learn). The input features for the model include the previously mentioned

154 meteorological and temporal variables, and the target variable is the pollutant concentration. We tuned the hyperparameters of

155 the machine learning models to identify those with the best hyperparameters for the analysis. The details are available in the

156 supplementary material (SM 3).

157 **2.4 Weather normalisation**

158 Weather normalisation or deweathering involves shuffling the meteorological input to the trained model while keeping the

159 time variables intact and then predicting the pollutant concentrations (Grange et al., 2018; Vu et al., 2019). Although Grange's

160 methodology involved shuffling all the explanatory variables, even the temporal variables for weather normalisation, a

161 subsequent study found that if the temporal variables are excluded from shuffling or resampling, the results were more

162 reasonable in capturing the seasonal and long-term emission trends (Zheng et al., 2023). Therefore, we only shuffle the

163 meteorological variables for weather normalisation.

164

165 Generally, the meteorological data is shuffled and the predictions are made 1000 times, and then the average of the predictions

166 is used to obtain the deweathered concentrations (Grange et al., 2018; Vu et al., 2019; Zhang et al., 2020; Song et al., 2023).

167 We shuffle the meteorological variables in our dataset while keeping the time variables (Julian day, Unix date, hour and

168 weekday) intact and predict the pollutant concentrations 2000 times. Increasing the number of shuffles beyond 2000 did not

169 result in a significant change in the results. This is also observed in the study mentioned above, where, if predictions exceeded

170 a thousand, only a very small reduction in noise was achieved (Grange et al., 2018). We then average the 2000 predictions to

171 calculate the deweathered concentrations at an hourly level. The difference between the observed and deweathered

172 concentrations is the effect of meteorology.

173

174 We perform the deweathering analysis for all three pollutants - $PM_{2.5}$, PM_{10} and CO. While we use the deweathered $PM_{2.5}$ and

175 PM_{10} for analysing the trends and the effect of meteorology over the years, we use the deweathered CO concentrations to

176 estimate the deweathered $PM_{2.5}$ and CO ratio, which is discussed further in detail in Section 3.4.

177 **3 Results**

178 **3.1 Model performance**

179 We evaluated the performance of the models for three pollutants – $PM_{2.5}$, PM_{10} and CO. The R^2 value of the model for $PM_{2.5}$

180 was 0.90, whereas it was 0.88 for both PM_{10} and CO models. Figure 2 shows that the models underpredict high concentrations.

181 For instance, when the observed $PM_{2.5}$ values cross 400, the model underpredicts by 90.7 µg/m³ on average. This is an inherent

182 limitation of the machine learning models, seen across various studies where ML models struggle in handling extreme values.
183 (Makhdoomi et al., 2025)

184

185
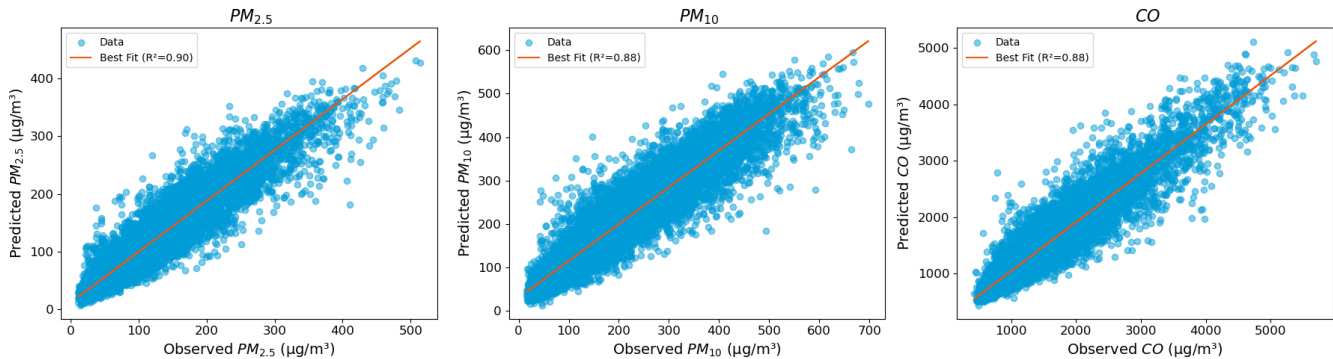
186 **Figure 2.** Scatter plots of predicted vs. actual concentrations for PM$_{2.5}$, PM$_{10}$, and CO.

187

188 We evaluate the model's performance using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Bias

189 Error (MBE), Mean Absolute Percentage Error (MAPE), and the Pearson correlation coefficient (R) as the evaluation metrics.

190 Table 1 summarises the models' performance.

	MAE	RMSE	MBE	MAPE	Pearson R
PM$_{2.5}$	16.839	24.528	0.177	20.986%	0.950
PM$_{10}$	30.152	41.978	0.216	19.266%	0.937
CO	167.168	251.563	-0.921	12.308%	0.940

191

192 **Table 1.** Model performance metrics for PM$_{2.5}$, PM$_{10}$, and CO predictions.

193

194 To assess the impact of each explanatory variable on the predicted pollutant concentrations, we calculate the feature importance

195 from our models. Permutation feature importance is a technique that gives each feature's contribution to the model's statistical

196 performance. It helps us determine how much the model relies on a particular feature (Pedregosa et al., 2011).
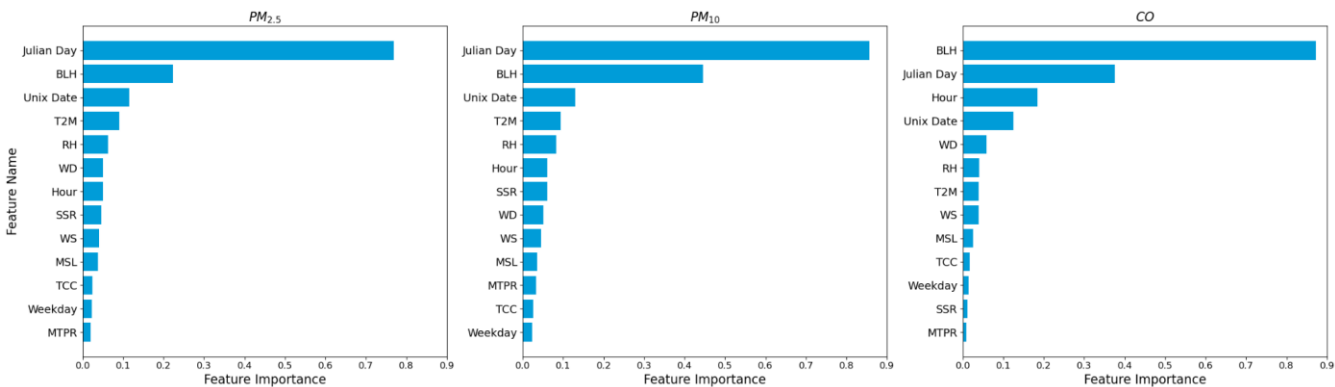
Figure 3. Feature Importance plots for $PM_{2.5}$, PM_{10}, and CO - Julian Day and Boundary Layer Height (BLH) are observed to be the most impactful variables.

Julian day, a proxy for seasonal emissions, is the most important feature in the models for $PM_{2.5}$ and PM_{10}, whereas BLH comes second. The sequence is reversed in the case of CO, where BLH is the most important feature in the model. In summary, Julian day, BLH, Unix date, T2M, RH, WS and WD were the most important features for pollutant concentrations. These findings are similar to those reported in other studies (Grange et al., 2018; Grange & Carslaw, 2019; Wang et al., 2021; Hou et al., 2022).

3.2 Seasonal Variation

Figures 3 and 4 show the change in deweathered and observed $PM_{2.5}$ and PM_{10} concentrations by season and year. We divided the data into four seasons: Summer (March - May), Monsoon (June - September), Post-Monsoon (October - November) and Winter (December - February). The winter season includes months across two years as per the classification. For instance, winter of 2019-2020 means December of 2019 and January and February of 2020.
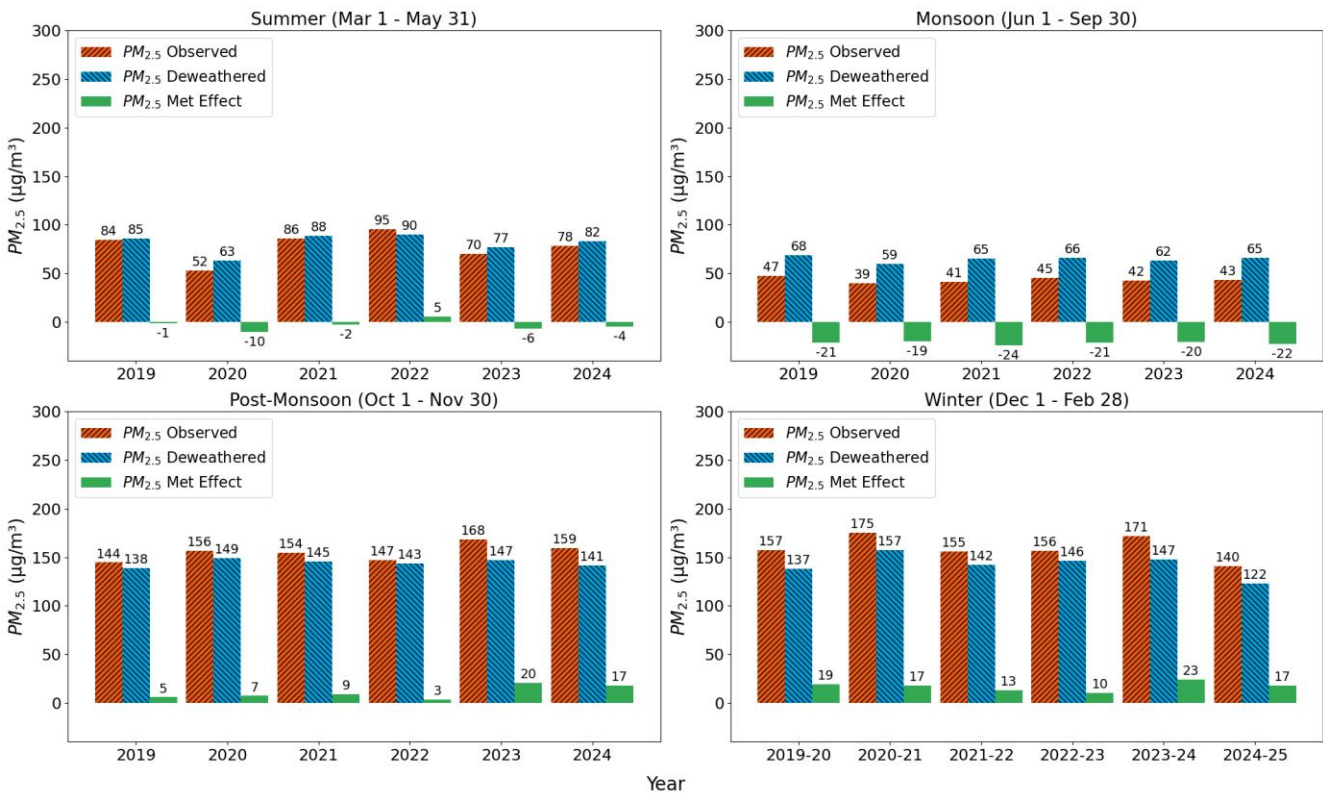
Figure 4. Seasonal variation in observed and deweathered PM$_{2.5}$ concentrations, along with the 'Met Effect' (ME) over the years in Delhi - Positive ME means worsening of PM$_{2.5}$ due to meteorology, while negative ME indicates a decrease in PM$_{2.5}$ due to favourable meteorology.
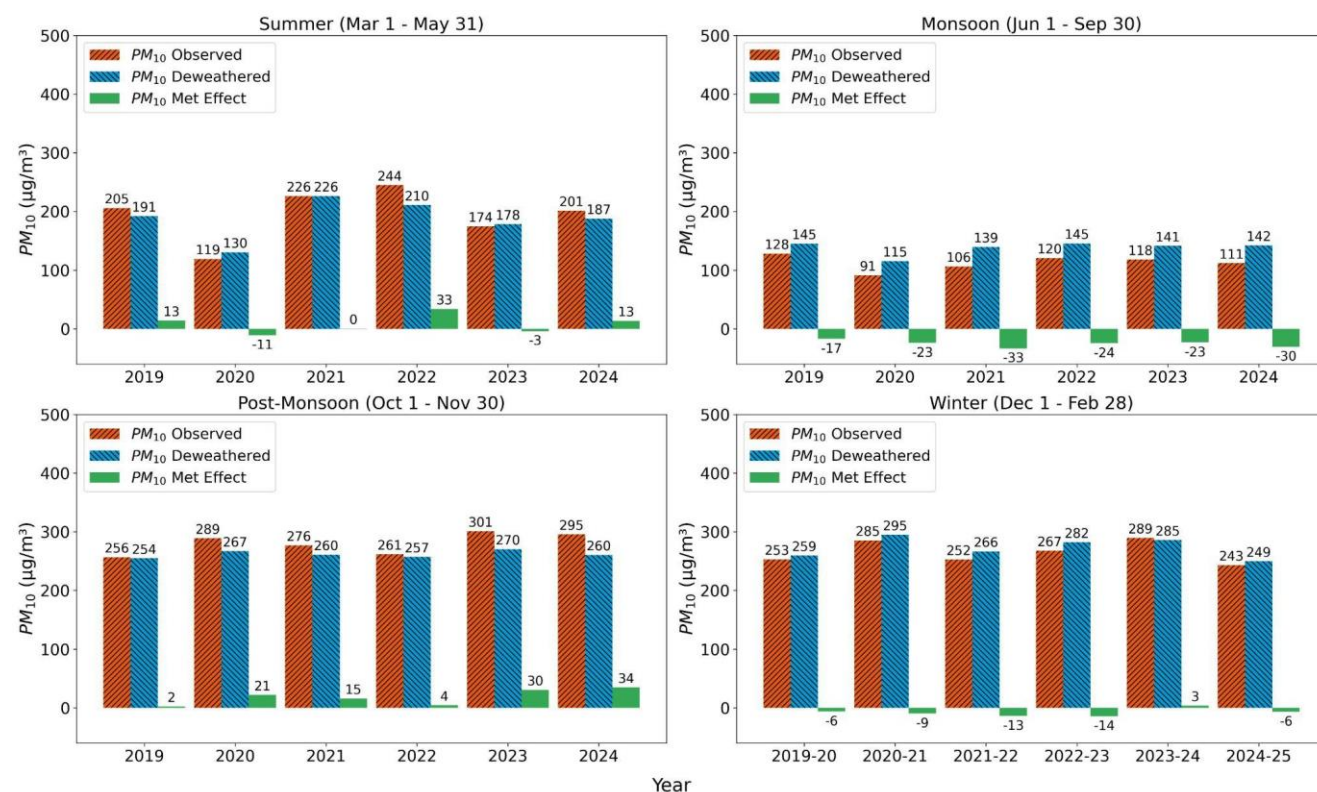
Figure 5. Seasonal variation in observed and deweathered PM$_{10}$ concentrations, along with 'Met Effect' (ME) over the years in Delhi.

We calculate the average meteorological effect or 'Met Effect' (ME) and deweathered concentrations for both pollutants for each season to analyse the variation in the ME and anthropogenic activities on PM$_{2.5}$ and PM$_{10}$ across seasons (Tables 2 and 3).

The ME on PM$_{2.5}$ is -3.4 µg/m^3 on average during summer, -21.5 µg/m^3 during monsoon, +10.7 µg/m^3 during post-monsoon and +17 µg/m^3 during winter. For PM$_{10}$, the ME is +7.7 µg/m^3 during summer, -25.4 µg/m^3 during monsoon, +18.2 µg/m^3 during post-monsoon and -7.8 µg/m^3 during winter (Table 2). The average deweathered concentrations of PM$_{2.5}$ are 81.2 µg/m^3 during summer, 64.8 µg/m^3 during monsoon, 144.3 µg/m^3 during post-monsoon, and 142.4 µg/m^3 during winter. For PM$_{10}$, the average deweathered concentrations are 187.5 µg/m^3 in summer, 138.1 µg/m^3 in monsoon, 261.8 µg/m^3 in post-monsoon, and 273.1 µg/m^3 in winter (Table 3).

The summer of 2020 saw a decrease in its observed and deweathered PM$_{2.5}$ concentrations, compared to 2019. They dropped by 32 µg/m^3 and 22 µg/m^3, respectively, due to a reduction in anthropogenic emissions during the pandemic. The summer of

232 the following two years witnessed an increase, with 2022 exhibiting an anomaly where the deweathered $PM_{2.5}$ concentration

233 was less than the observed one, reflecting the adverse effect of meteorology on $PM_{2.5}$. We observed a similar pattern in PM_{10}

234 during summer.

235

Season	$PM_{2.5}$ ME (μg/m^3)	PM_{10} ME (μg/m^3)
Summer	-3.4	+7.7
Monsoon	-21.5	-25.4
Post-Monsoon	+10.7	+18.2
Winter	+17	-7.8

236

237 **Table 2.** Season-wise average ME on $PM_{2.5}$ and PM_{10} concentrations (μg/m^3). Positive values denote that meteorology

238 contributed to elevating the concentrations, whereas negative values indicate lower concentrations due to favourable

239 meteorology.

240

Season	$PM_{2.5}$ Deweathered (μg/m^3)	PM_{10} Deweathered (μg/m^3)
Summer	81.2	187.5
Monsoon	64.8	138.1
Post-Monsoon	144.3	261.8
Winter	142.4	273.1

241

242 **Table 3.** Season-wise average deweathered $PM_{2.5}$ and PM_{10} concentrations (μg/m^3).

243

244 The reductions seen during the COVID lockdown period (March, April and May) in 2020 were reversed during the post-

245 monsoon and winter seasons. We observe a spike in deweathered $PM_{2.5}$ during winter 2020-21, possibly due to the relaxation

246 of restrictions and resumption of activities after the lockdown. Meteorology generally favours air quality during monsoon and

247 summer, with 2022 summer being an exception. Dust storms are a recurrent phenomenon in Delhi during the summer season

248 (Chakravarty et al., 2021). We analyse the average Dust Aerosol Optical Depth (DAOD) obtained using the ensemble of

249 products (ENS) algorithm version 1.4 between March and May over Delhi between the years 2019 and 2023 from the Infrared

250 Atmospheric Sounding Interferometer (IASI) sensor onboard the Meteorological Operational-A (METOP-A) and

251 Meteorological Operational (METOP-C) satellites (Copernicus Climate Change Service, 2019). The data is available only till

252 2023. The DOAD value was higher (0.34) in 2022 compared to the other years.

11

253
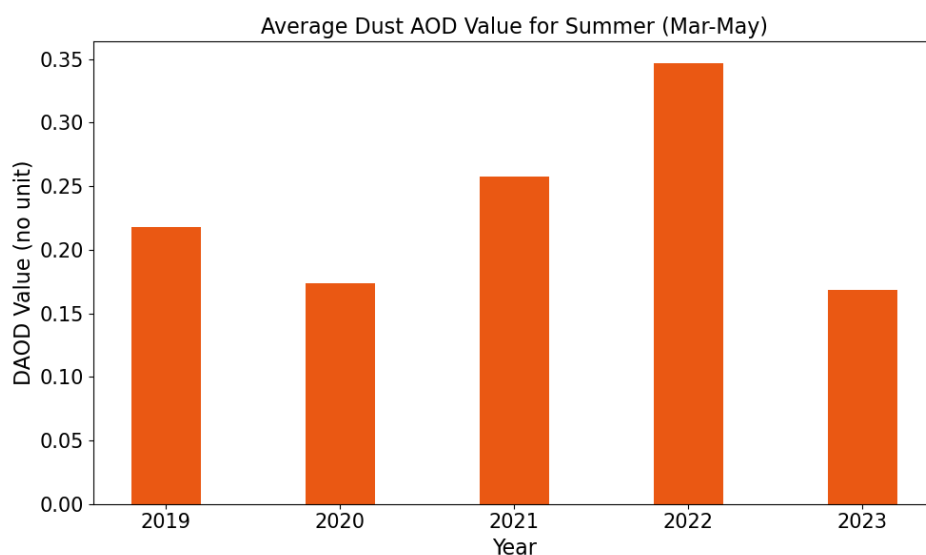
Figure 6. Average Dust Aerosol Optical Depth (DAOD) for summer months between 2019 and 2023 over Delhi. Elevated levels of DAOD in 2022 were possibly due to increased dust events that year.

It is not uncommon for dust storms to originate in the regions to the west of India, particularly in Rajasthan, and move towards Delhi through the winds during the summer season (Chakravarty et al., 2021; Sarkar et al., 2019). DAOD plots for northern India (Figure 6) show elevated values to the west of Delhi. DOAD to the west of Delhi was higher in 2022 compared to the other years. This windblown dust is likely a reason for elevated dust levels over Delhi in summer 2022, and hence elevated levels of $PM_{2.5}$ and PM_{10}.
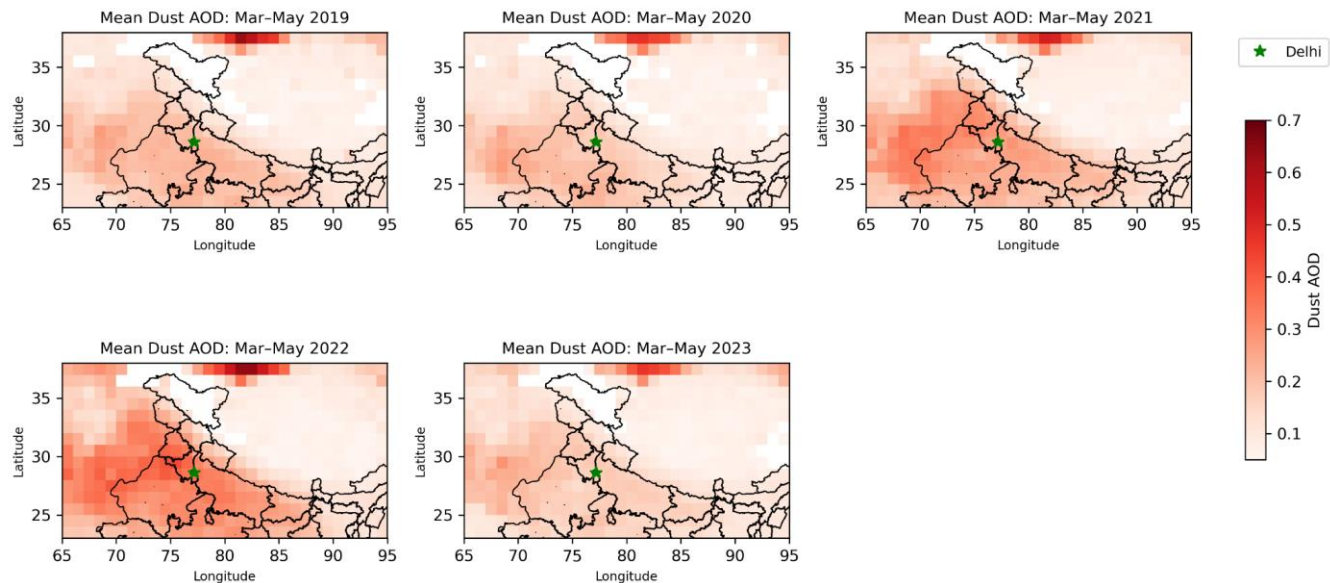
Figure 7. Average Dust AOD over the northern part of India, for the summer season (March - May) between the years 2019 and 2023.

However, we also see an unusual pattern in the winter weeks for PM_{10}, where the deweathered PM_{10} concentration is higher than the observed one (Figure 5). This suggests that meteorology favoured a decrease in PM_{10} while increasing $PM_{2.5}$, which is counterintuitive. Further, we performed a linear trend analysis from 2019 to 2024 to estimate the long-term trend of $PM_{2.5}$ and PM_{10}. For $PM_{2.5}$, the effect has been small, except for the deweathered trend during winter, which had a decrease of 2.88 $\mu g/m^3$ in the $PM_{2.5}$ concentrations per year. However, during the post-monsoon season, ME shows an increasing trend of 2.71 $\mu g/m^3$/year. In the case of PM_{10}, the ME increased during the post-monsoon season, with the concentrations increasing at an average of 5.07 $\mu g/m^3$ per year. The deweathered summer trend shows a fairly high annual increase of 3.08 $\mu g/m^3$.

We calculated the rate of change without including 2020, the year of the COVID pandemic. There has been an increase in the ME for $PM_{2.5}$ during the post-monsoon season, with the concentrations increasing on average by 2.87 $\mu g/m^3$ per year. A high increase of 6.45 $\mu g/m^3$ is observed for $PM_{2.5}$ during the post-monsoon season. However, the trends were not statistically significant.

Season-wise rate of change of meteorological effect and Deweathered Pollutant (Linear Trend Analysis)

	Season	ME Trend*	Deweathered Trend*	ME Trend* w/o COVID year- 2020	Deweathered Trend* w/o COVID year- 2020
$PM_{2.5}$	Summer	+0.08 $\mu g/m^3$/year	+0.84 $\mu g/m^3$/year	-0.74 $\mu g/m^3$/year	-1.22 $\mu g/m^3$/year

13

	Monsoon	-0.1 µg/m^3/year	-0.13 µg/m^3/year	+0.08 µg/m^3/year	-0.77 µg/m^3/year
	Post Monsoon	+2.71 µg/m^3/year	+0.21 µg/m^3/year	+2.78 µg/m^3/year	+0.85 µg/m^3/year
	Winter	+0.25 µg/m^3/year	-2.88 µg/m^3/year	+0.36 µg/m^3/year	-1.59 µg/m^3/year
PM$_{10}$	Summer	+1.52 µg/m^3/year	+3.08 µg/m^3/year	-0.49 µg/m^3/year	-3.32 µg/m^3/year
	Monsoon	-1.61 µg/m^3/year	+1.96 µg/m^3/year	-1.72 µg/m^3/year	-0.47 µg/m^3/year
	Post Monsoon	+5.07 µg/m^3/year	+1.04 µg/m^3/year	+6.45 µg/m^3/year	+1.86 µg/m^3/year
	Winter	1.05 µg/m^3/year	-1.7 µg/m^3/year	+1.03 µg/m^3/year	+0.66 µg/m^3/year

*not statistically significant

Table 4. Season-wise linear trends of meteorological effects and deweathered concentrations for PM$_{2.5}$ and PM$_{10}$. Trends are presented with and without including the COVID year (March 2020 to February 2021, i.e., the Summer to Winter period of 2020).

3.3 Role of La Niña and El Niño in determining the impact of meteorology

We saw a noticeable change in the ME for PM$_{2.5}$ in 2023, which was an El Niño year. In 2023, the post-monsoon and winter seasons witnessed a high positive ME (+20 µg/m^3 and +23 µg/m^3, respectively), indicating unfavourable meteorological conditions. During the winters of 2020, 2021, and 2022, which were La Niña winters, the ME was lower compared to the other years (+17 µg/m^3, +13 µg/m^3 and +10 µg/m^3, respectively). Therefore, even though meteorology worsens air quality during winter, its impact during La Niña winters is less severe. This is consistent with the findings of Beig et al. (2024), who attributed a 10% decrease in PM$_{2.5}$ concentrations in Delhi during the winter of 2022-23 compared to the three previous winters' averaged values, to the Triple Dip phenomenon. These variations also highlight the importance of keeping the ENSO cycle in account when interpreting the seasonal trends in air quality. However, our analysis includes only three La Niña and one El Niño years. An accurate estimation of the ME during La Niña and El Niño will require analysis over a more extended time period.

Year	Summer (MAM)	Monsoon (JJAS)	Post-monsoon (ON)	Winter (DJF)
2019	EL (-1 µg/m^3)	Neutral (-21 µg/m^3)	Neutral (+5 µg/m^3)	(DJF 2019–20 → Neutral) (+19 µg/m^3)
2020	Neutral (-10 µg/m^3)	LN (-19 µg/m^3)	LN (+7 µg/m^3)	(DJF 2020–21 → LN) (+17 µg/m^3)
2021	LN (-2 µg/m^3)	Neutral (-24 µg/m^3)	LN (+9 µg/m^3)	(DJF 2021–22 → LN) (+13 µg/m^3)
2022	LN (+5 µg/m^3)	LN (-21 µg/m^3)	LN (+3 µg/m^3)	(DJF 2022–23 →LN) (+10 µg/m^3)
2023	EL (-6 µg/m^3)	EL (-20 µg/m^3)	EL (+20 µg/m^3)	(DJF 2023–24 →EL) (+23 µg/m^3)
2024	EL (-4 µg/m^3)	Neutral (-22 µg/m^3)	Neutral (+17 µg/m^3)	(DJF 2024–25 → Neutral) (+17 µg/m^3)

Table 5. Seasonal ME on PM$_{2.5}$ concentrations, along with the ENSO phases - La Niña (LN), El Niño (EL), and Neutral. The table highlights the role of El Niño in the post-monsoon and winter period of 2023 on ME and of La Niña in the post monsoon and winter of 2022 (which was the third consecutive La Niña year), where we saw the ME to be lower compared to other years.

3.4 PM$_{2.5}$-CO Ratio in Delhi
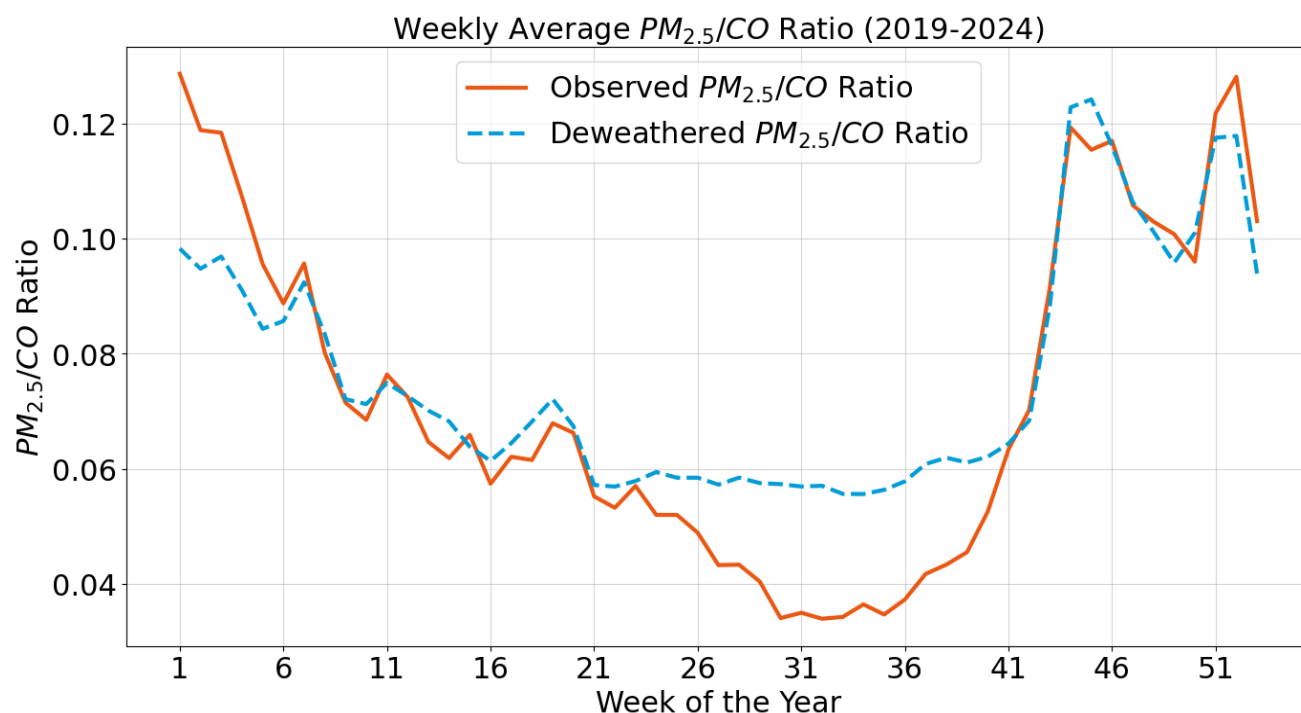
Figure 8. Weekly average PM$_{2.5}$ and CO (Deweathered and Observed) ratio. The plot shows two prominent peaks denoting the increased secondary particulate formation around the first 2 weeks of November (week 44) and the last weeks of December (week 52), the period of stubble burning and winter biomass burning, respectively.

PM$_{2.5}$-CO ratio in urban areas can be used to identify biomass burning's influence on PM$_{2.5}$ concentrations (Jaffe et al., 2022). This method can be used to identify traffic emissions, bushfire emissions and indoor emissions, among others (Xiu et al., 2022). Zhang and Cao (2015), in their study of 190 cities of China, showed that the ratio of PM$_{2.5}$ and CO peaked during afternoon hours, indicating secondary particulate formation across cities.

We analyse the weekly average observed and deweathered PM$_{2.5}$-CO ratio over Delhi between 2019 and 2024 to analyse the role of stubble burning and biomass burning for heating on secondary particulate formation in Delhi. We observe an increase in the PM$_{2.5}$-CO ratio beyond the first week of October (week 41) (Fig. 6). During this period, the ratio calculated using deweathered PM$_{2.5}$ and CO approximately doubled compared to the values between mid-May and September (weeks 21 and 40). This period coincides with the annual practice of stubble burning in the states surrounding Delhi (Abdurrahman et al., 2020) and increased biomass burning for heating purposes during winter (Lalchandani et al., 2021). The increase in the ratio based on the observed PM$_{2.5}$ and CO, and in the ratio based on deweathered PM$_{2.5}$ and CO, indicates that the high levels are

16

317 not only attributed to unfavourable meteorology but also to anthropogenic activity. This reiterates the finding that secondary

318 particulate formation, aggravated by biomass-related combustion sources, plays a significant role in deteriorating air quality

319 during the post-monsoon and winter seasons in Delhi (Mishra et al., 2023).


320 **4. Discussion**

321 Our study uses a machine learning approach to separate the effects of meteorology and air quality trends. Although the

322 deweathered concentrations of $PM_{2.5}$ and PM_{10} decreased across seasons in Delhi, except the post-monsoon season between

323 2019 and 2024, the trends remain statistically insignificant.

324

325 The average ME on $PM_{2.5}$ in Delhi varied across seasons. For instance, the average ME was -3.4 $\mu g/m^3$ during the summer

326 season, indicating the role of high temperature, wind speed and BLH in reducing ambient air pollution. During Monsoon, this

327 effect was stronger, with an average of -21.5 $\mu g/m^3$, indicating the role of higher wind speeds and precipitation in reducing air

328 pollution. On the other hand, the average ME is positive during the post-monsoon and winter period (+10.7 $\mu g/m^3$ and +17

329 $\mu g/m^3$, respectively) due to meteorological factors like lower temperature, lower BLH and lower wind speed.

330

331 The highest concentrations after decoupling the meteorological effect are observed during post-monsoon and winter, where

332 the deweathered $PM_{2.5}$ averaged across the years reaches 144.3 $\mu g/m^3$ and 142.4 $\mu g/m^3$ respectively, and the deweathered PM_{10}

333 rises to 261.8 $\mu g/m^3$ and 273.1 $\mu g/m^3$ respectively. These concentrations are nearly double the concentrations observed during

334 the monsoon season, for both $PM_{2.5}$ and PM_{10} (64.8 $\mu g/m^3$ and 138.1 $\mu g/m^3$, respectively). These elevated deweathered

335 concentrations suggest a major role of emissions in worsening the air quality during these months.

336

337 The anomaly we witnessed in the case of PM_{10} during winter can potentially be explained by how $PM_{2.5}$ and PM_{10} are affected

338 by meteorological variables like relative humidity and temperature. Lou et al. 2017 report a decrease in PM_{10} concentrations

339 as soon as RH crosses 45% in the Yangtze River Delta, China. They demonstrated that for PM_{10}, RH < 45% had an

340 accumulation effect, but RH > 45% had a mitigation effect, exhibiting an inverted V-shaped relationship. The Partial

341 Dependence (PD) of PM_{10} on RH from the current analysis shows a similar relationship (Figure 9). However, they also mention

342 that RH had an inverted U-shaped relationship with $PM_{2.5}$ concentrations. They observed peak $PM_{2.5}$ concentrations when RH

343 was between 45% and 70%. However, the PD of $PM_{2.5}$ on RH from the current study shows an increasing relationship between

344 $PM_{2.5}$ and RH (Figure 9).

345

346 From our analysis of the PD plots for RH, we found that PM_{10} increases once it reaches around 45% and then decreases from

347 there. Thus, this could be a major reason for the anomalous behaviour we see in PM_{10} during winter.
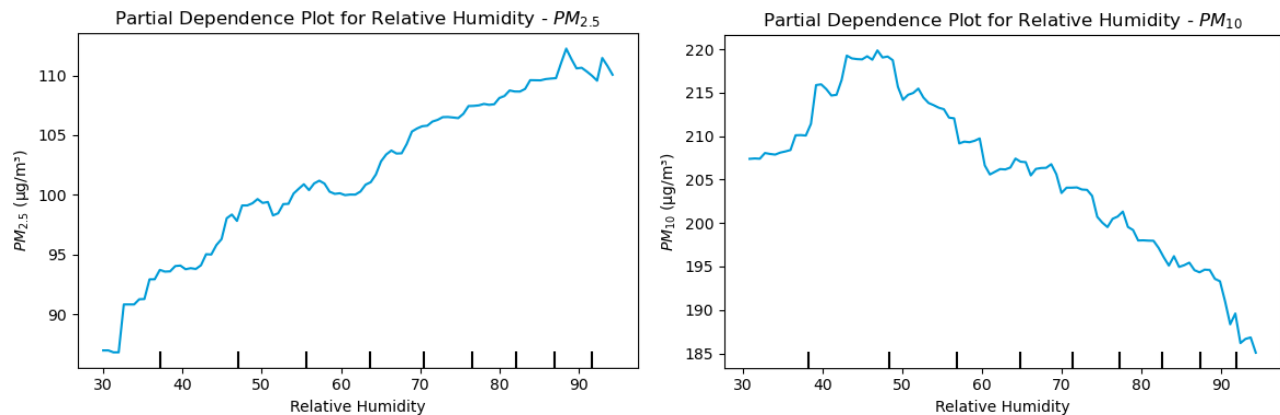
Figure 9. Partial Dependence plots for Relative Humidity for PM$_{2.5}$ and PM$_{10}$.

While Xie et al. (2024) say that meteorology improved the air quality in Delhi between 2017 and 2022, we do not see statistically significant trends for the ME between 2019 and 2024. As per their analysis, no notable trends in PM$_{10}$ pollution were observed in Delhi, which has had 6 years of continuous monitoring since 2017. Similarly, our study does not observe any statistically significant trends in either PM$_{2.5}$ or PM$_{10}$ between 2019 and 2024.

Wang et al. (2024) found that PM$_{2.5}$ decreased by 4.44 µg/m^3 per year. The meteorology-driven PM$_{2.5}$ trends in their study are -2.35 µg/m^3, -3.22 µg/m^3, and -6.51 µg/m^3 per year, contributing 67%, 65%, and 90% of the reductions in the observed PM$_{2.5}$ for Delhi during summer, monsoon, and winter, respectively. From our linear trend analysis, we observe that the ME on PM$_{2.5}$ increased by 0.08 µg/m^3 per year during summer, which is a negligible increase. However, when we calculate the trends without including 2020, the year of COVID, we see a reduction of 0.74 µg/m^3 per year in the ME on PM$_{2.5}$.

Chetna et al. (2024) found that over 16 years (2007-2022), the met adjusted and ambient concentrations of PM$_{2.5}$ decreased by 18 µg/m^3 and 14µg/m^3, respectively. The study revealed a decrease of -1.77 µg/m^3 per year for ambient PM$_{2.5}$ and -1.79 µg/m^3 per year for de-seasonalised PM$_{2.5}$. Citing Sharma and Mauzerall (2022), they found no significant trend in PM$_{2.5}$ over Delhi from 2015 to 2019, which they interpret as a "potential stabilisation" or "possible plateauing" in pollution levels. Our annual met-adjusted trend was estimated to be 1.1 µg/m.^{3}, which was statistically insignificant. The study also pointed out that since 2015, annual meteorological variations have had a minimal impact on PM$_{2.5}$ trends. We observe trends in the ME, but as stated earlier, they are statistically insignificant.

Overall, we observe statistically insignificant trends over the years in both meteorological effect trends and deweathered trends across the various seasons. It is important to note that the current study considers a different time period for the analysis

compared to the other studies discussed above. The current study's classification of the seasons is also different from the others.

Furthermore, even though previous literature exists around the use of the $PM_{2.5}$-CO ratio in the global context to identify the contribution of biomass burning to air pollution, there have not been attempts to deweather this ratio to reveal the actual influence of biomass burning emissions. The current study is therefore the first to do so and identifies two distinct peaks in deweathered $PM_{2.5}$-CO ratio over Delhi corresponding to stubble burning and winter biomass burning.

5. Limitations

While deweathering is considered an effective technique for decoupling the effects of meteorology and anthropogenic activities, it has some limitations. Its use depends on strong assumptions that are difficult to fulfil in a real-world scenario. One of the limitations is that shuffling the meteorological variables can generate impossible combinations such as simultaneous rain, low temperatures and sun in summer (Petric´et al., 2024). Further, deweathering using machine learning cannot capture other factors that contribute to air pollution, such as socioeconomic variables and land use patterns. These methods also do not explicitly take the physical and chemical processes into account unlike chemical transport models. However, Zheng et al. (2024) state that these limitations do not hinder us from capturing the trend of $PM_{2.5}$ effectively. Future research can include similar analyses for different Indian cities where adequate data for pollutants and meteorological variables are available and also compare the results from such exercises with outputs from chemical transport models.

Code Availability

The codes used in this study can be found at github.com/sv-156/Deweathering-Data-and-Codes/

Data Availability

The data used in this study can be found at github.com/sv-156/Deweathering-Data-and-Codes/

Author Contributions:

SV and MR contributed equally to the manuscript. MR conceptualised the study. SV performed the majority of the analysis. US, ST and RP contributed to the analysis.

Competing Interests:

The authors declare that they have no competing interests.

401

405

6. References

Abdurrahman, M. I., Chaki, S., & Saini, G.: Stubble burning: Effects on health & environment, regulations and management practices. Environmental Advances, 2, 100011. https://doi.org/10.1016/j.envadv.2020.100011, 2020

Beig, G., Anand, V., Korhale, N., Sobhana, S., Harshitha, K., & Kripalani, R.: Triple dip La-Niña, unorthodox circulation and unusual spin in air quality of India. The Science of the Total Environment, 920, 170963. https://doi.org/10.1016/j.scitotenv.2024.170963, 2024

Chakravarty, K., Vincent, V., Vellore, R., Srivastava, A., Rastogi, A., & Soni, V. Revisiting Andhi in northern India: A case study of severe dust storm over the urban megacity of New Delhi. Urban Climate, 37, 100825. https://doi.org/10.1016/j.uclim.2021.100825, 2021.

Chauhan, A., Sai, G. P., & Hsu, C.: Advanced Statistical Analysis of Air Quality and its Health Impacts in India: Quantifying Significance by Detangling Weather-Driven Effects. Heliyon, 11(2), e41762. https://doi.org/10.1016/j.heliyon.2025.e41762, 2025

Chetna, Dhaka, S. K., Longiany, G., Panwar, V., Kumar, V., Malik, S., Rao, A., Singh, N., Dimri, A., Matsumi, Y., Nakayama, T., & Hayashida, S.: Trends and Variability of $PM_{2.5}$ at Different Time Scales over Delhi: Long-term Analysis 2007–2021. Aerosol and Air Quality Research, 23(5), 220191. https://doi.org/10.4209/aaqr.220191, 2023

Copernicus Climate Change Service, Climate Data Store: Aerosol properties gridded data from 1995 to present derived from satellite observation. Copernicus Climate Change Service (C3S) Climate Data Store (CDS). DOI: 10.24381/cds.239d815c, 2019 (Accessed on 22-04-2025)

Derwent, R., Middleton, D., Field, R., Goldstone, M., Lester, J., and Perry, R.: Analysis and interpretation of air quality data from an urban roadside location in Central London over the period from July 1991 to July 1992, Atmos. Environ., 29, 923–946, https://doi.org/10.1016/1352-2310(94)00219-B, 1995.

433

434   Gajbhiye, M. D., Lakshmanan, S., Aggarwal, R., Kumar, N., & Bhattacharya, S.: Evolution and mitigation of vehicular

435   emissions due to India's Bharat Stage Emission Standards – A case study from Delhi. Environmental Development, 45,

436   100803. https://doi.org/10.1016/j.envdev.2023.100803, 2023

437

438   Gardner-Frolick, R., Boyd, D., & Giang, A.: Selecting data analytic and modeling methods to support air pollution and

439   environmental justice investigations: A Critical Review and Guidance framework. Environmental Science & Technology,

440   56(5), 2843–2860. https://doi.org/10.1021/acs.est.1c01739, 2022

441

442   Goel, D., & Gupta, S.: The Effect of Metro Expansions on Air Pollution in Delhi. The World Bank Economic Review, 31(1),

443   271–294. https://doi.org/10.1093/wber/lhv056, 2015

444

445   Grange, S. K., & Carslaw, D. C.: Using meteorological normalisation to detect interventions in air quality time series. Sci.

446   Total Environ. 653, 578–588.https://doi.org/10.1016/j.scitotenv.2018.10.344, 2019

447

448   Grange, S. K., Carslaw, D. C., Lewis, A. C., Boleti, E., & Hueglin, C. Random forest meteorological normalisation models for

449   Swiss PM10 trend analysis. Atmos. Chem. Phys., 18(9), 6223–6239. https://doi.org/10.5194/acp-18-6223-2018, 2018

450

451   Guttikunda, S. K., Dammalapati, S. K., Pradhan, G., Krishna, B., Jethva, H. T., & Jawahar, P. What Is Polluting Delhi's Air?

452   A Review from 1990 to 2022. Sustainability, 15, 4209. https://doi.org/10.3390/su15054209, 2023

453

454   Hersbach, H., Bell, B., Berrisford, P., Biavati, G., Horányi, A., Muñoz Sabater, J., Nicolas, J., Peubey, C., Radu, R., Rozum,

455   I., Schepers, D., Simmons, A., Soci, C., Dee, D., and Thépaut, J.-N.: ERA5 hourly data on single levels from 1940 to present,

456   Copernicus Climate Change Service (C3S) Climate Data Store (CDS), https://doi.org/10.24381/cds.adbb2d47, 2023.

457

458   Hou, L., Dai, Q., Song, C., Liu, B., Guo, F., Dai, T., Li, L., Liu, B., Bi, X., Zhang, Y., & Feng, Y.: Revealing drivers of haze

459   pollution by explainable machine learning. Environmental Science & Technology Letters, 9, 112–119.

460   https://doi.org/10.1021/acs.estlett.1c00865, 2022

461

462   Jaffe, D. A., Schnieder, B., and Inouye, D.: Technical note: Use of $PM_{2.5}$ to CO ratio as an indicator of wildfire smoke in

463   urban areas, Atmos. Chem. Phys., 22, 12695–12704, https://doi.org/10.5194/acp-22-12695-2022, 2022.

464

465 Kar, A., Pachauri, S., Bailis, R., & Zerriffi, H.: Capital cost subsidies through India's Ujjwala cooking gas programme promote

466 rapid adoption of liquefied petroleum gas but not regular use. Nature Energy, 5(2), 125–126. https://doi.org/10.1038/s41560-

467 019-0536-6, 2020

468

469 Kathuria, V.: Impact of CNG on vehicular pollution in Delhi: a note. Transportation Research Part D Transport and

470 Environment, 9(5), 409–417. https://doi.org/10.1016/j.trd.2004.05.003, 2004

471

472 Lalchandani, V., Srivastava, D., Dave, J., Mishra, S., Tripathi, N., Shukla, A. K., Sahu, R., Thamban, N. M., Gaddamidi, S.,

473 Dixit, K., Ganguly, D., Tiwari, S., Srivastava, A. K., Sahu, L., Rastogi, N., Gargava, P., & Tripathi, S. N.:. Effect of biomass

474 burning on PM$_{2.5}$ composition and secondary aerosol formation during Post-Monsoon and winter Haze episodes in Delhi.

475 Journal of Geophysical Research Atmospheres, 127(1). https://doi.org/10.1029/2021jd035232, 2021

476

477 Lavanyaa, V., Harshitha, K., Beig, G., & Srikanth, R. Background and baseline levels of PM$_{2.5}$ and PM$_{10}$ pollution in major

478 cities of peninsular India. Urban Climate, 48, 101407. https://doi.org/10.1016/j.uclim.2023.101407, 2023

479

480 Liu, H., Yue, F., & Xie, Z.: Quantify the role of anthropogenic emission and meteorology on air pollution using machine

481 learning approach: A case study of PM$_{2.5}$ during the COVID-19 outbreak in Hubei Province, China. Environmental Pollution,

482 300, 118932. https://doi.org/10.1016/j.envpol.2022.118932, 2022

483

484 Lou, C., Liu, H., Li, Y., Peng, Y., Wang, J., & Dai, L.: Relationships of relative humidity with PM$_{2.5}$ and PM$_{10}$ in the Yangtze

485 River Delta, China. Environmental Monitoring and Assessment, 189(11). https://doi.org/10.1007/s10661-017-6281-z, 2017

486

487 Ma, L., Graham, D. J., & Stettler, M. E.: Air quality impacts of new public transport provision: A causal analysis of the Jubilee

488 Line Extension in London. Atmospheric Environment, 245, 118025. https://doi.org/10.1016/j.atmosenv.2020.118025, 2020

489

490 Makhdoomi, A., Sarkhosh, M., & Ziaei, S.: PM$_{2.5}$ concentration prediction using machine learning algorithms: An approach

491 to virtual monitoring stations. Scientific Reports, 15(1), 1-11. https://doi.org/10.1038/s41598-025-92019-3, 2025

492

493 Ministry Of Law And Justice: The Commission For Air Quality Management In National Capital Region And Adjoining Areas

494 Act, 2021. In The Gazette Of India Extraordinary [Legislation]

495 https://prsindia.org/files/bills_acts/bills_parliament/2021/The%20Commission%20for%20Air%20Quality%20Management

496 %20in%20National%20Capital%20Region%20and%20Adjoining%20Areas%20Act,%202021.pdf, 2021

497

498   Mishra, S., Tripathi, S. N., Kanawade, V. P., Haslett, S. L., Dada, L., Ciarelli, G., Kumar, V., Singh, A., Bhattu, D., Rastogi,
499   N., Daellenbach, K. R., Ganguly, D., Gargava, P., Slowik, J. G., Kulmala, M., Mohr, C., El-Haddad, I., & Prevot, A. S. H.:
500   Rapid night-time nanoparticle growth in Delhi driven by biomass-burning emissions. Nature Geoscience, 16, 224–230.
501   https://doi.org/10.1038/s41561-023-01138-x, 2023

503   MoEFCC (Ministry of Environment, Forest and Climate Change): National Clean Air Programme (NCAP), Government of
504   India. https://mpcb.gov.in/sites/default/files/air-quality/National_Clean_Air_Programme09122019.pdf, 2019.

506   Pandey, A., Brauer, M., Cropper, M. L., Balakrishnan, K., Mathur, P., Dey, S., Turkgulu, B., Kumar, G. A., Khare, M., Beig,
507   G., Gupta, T., Krishnankutty, R. P., Causey, K., Cohen, A. J., Bhargava, S., Aggarwal, A. N., Agrawal, A., Awasthi, S.,
508   Bennitt, F., . . . Reddy, K. S.: Health and economic impact of air pollution in the states of India: the Global Burden of Disease
509   Study 2019. The Lancet Planetary Health, 5(1), e25–e38. https://doi.org/10.1016/s2542-5196(20)30298-9, 2020

511   Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R.,
512   Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., and Duchesnay, É.: Scikit-learn: Machine
513   Learning in Python, J. Mach. Learn. Res., 12, 2825–2830, https://jmlr.csail.mit.edu/papers/v12/pedregosa11a.html, 2011.

515   Petetin, H., Bowdalo, D., Soret, A., Guevara, M., Jorba, O., Serradell, K., and Pérez García-Pando, C.: Meteorology-
516   normalized impact of the COVID-19 lockdown upon NO2 pollution in Spain, Atmos. Chem. Phys., 20, 11119–11141,
517   https://doi.org/10.5194/acp-20-11119-2020, 2020.

519   Petrić V, Lovrić M, Geiger BC.: Meteorological Normalization or Deweathering for Predicting Air Pollutant Concentration:
520   Pitfalls and Limitations. ChemRxiv. doi:10.26434/chemrxiv-2024-sw2cm-v2, 2024

522   Press Information Bureau - Goals set under NCAP. 2024 https://www.pib.gov.in/PressReleasePage.aspx?PRID=2043004

524   Sahu, S. K., Mangaraj, P., & Beig, G.: Decadal growth in emission load of major air pollutants in Delhi. Earth System Science
525   Data, 15(7), 3183–3202. https://doi.org/10.5194/essd-15-3183-2023, 2023

527   Sarkar, S., Chauhan, A., Kumar, R., & Singh, R. P.: Impact of deadly dust storms (May 2018) on air quality, meteorological,
528   and atmospheric parameters over the northern parts of India. GeoHealth, 3(3), 67–80. https://doi.org/10.1029/2018gh000170,
529   2019b
530

531   Sharma, R., Kumar, R., Sharma, D. K., Son, L. H., Priyadarshini, I., Pham, B. T., Bui, D. T., & Rai, S.: Inferring air pollution
532   from air quality index by different geographical areas: case study in India. Air Quality Atmosphere & Health, 12(11), 1347–
533   1357. https://doi.org/10.1007/s11869-019-00749-x, 2019

535   Shi, Z., Song, C., Liu, B., Lu, G., Xu, J., Van Vu, T., Elliott, R. J. R., Li, W., Bloss, W. J., & Harrison, R. M. (2021). Abrupt
536   but smaller than expected changes in surface air quality attributable to COVID-19 lockdowns. Science Advances, 7(3).
537   https://doi.org/10.1126/sciadv.abd6696, 2021

539   Song, C., Liu, B., Cheng, K., Cole, M. A., Dai, Q., Elliott, R. J. R., & Shi, Z.: Attribution of Air Quality Benefits to Clean
540   Winter Heating Policies in China: Combining Machine Learning with Causal Inference. Environmental Science & Technology,
541   57(46), 17707–17717. https://doi.org/10.1021/acs.est.2c06800, 2023

543   Tiwari, S., Thomas, A., Rao, P., Chate, D., Soni, V., Singh, S., Ghude, S., Singh, D., & Hopke, P. K.: Pollution concentrations
544   in Delhi India during winter 2015–16: A case study of an odd-even vehicle strategy. Atmospheric Pollution Research, 9(6),
545   1137–1145. https://doi.org/10.1016/j.apr.2018.04.008, 2018

547   Vu, T. V., Shi, Z., Cheng, J., Zhang, Q., He, K., Wang, S., & Harrison, R. M. (2019). Assessing the impact of clean air action
548   on air quality trends in Beijing using a machine learning technique. Atmos. Chem. Phys., 19(17), 11303–11314.
549   https://doi.org/10.5194/acp-19-11303-2019, 2019

551   Wang, X., Zhu, J., Li, K., Chen, L., Yang, Y., Zhao, Y., Yue, X., Gu, Y., & Liao, H.: Meteorology-driven trends in $PM_{2.5}$
552   concentrations and related health burden over India. Atmospheric Research, 308, 107548.
553   https://doi.org/10.1016/j.atmosres.2024.107548, 2024

555   World Health Organization. WHO global ambient air quality database (update), 2024. World Health Organization: Geneva,
556   Switzerland, 2024.

558   Xie, Y., Zhou, M., Hunt, K. M. R., & Mauzerall, D. L.: Recent $PM_{2.5}$ air quality improvements in India benefited from
559   meteorological variation. Nature Sustainability, 7, 983–993. https://doi.org/10.1038/s41893-024-01366-y, 2024

561   Xing, J., Zheng, S., Li, S., Huang, L., Wang, X., Kelly, J. T., Wang, S., Liu, C., Jang, C., Zhu, Y., Zhang, J., Bian, J., Liu, T.,
562   & Hao, J.: Mimicking atmospheric photochemical modeling with a deep neural network. Atmospheric Research, 265, 105919.
563   https://doi.org/10.1016/j.atmosres.2021.105919, 2021
564

565 Xiu, M., Jayaratne, R., Thai, P., Christensen, B., Zing, I., Liu, X., & Morawska, L.: Evaluating the applicability of the ratio of

566 PM$_{2.5}$ and carbon monoxide as source signatures. Environmental Pollution, 306, 119278.

567 https://doi.org/10.1016/j.envpol.2022.119278, 2022

569 Zhang, Y., & Cao, F.: Fine particulate matter (PM$_{2.5}$) in China at a city level. Scientific Reports, 5(1).

570 https://doi.org/10.1038/srep14884, 2015

572 Zhang, Y., Van Vu, T., Sun, J., He, J., Shen, X., Lin, W., Zhang, X., Zhong, J., Gao, W., Wang, Y., Fu, T. M., Ma, Y., Li, W.,

573 & Shi, Z.: Significant Changes in Chemistry of Fine Particles in Wintertime Beijing from 2007 to 2017: Impact of Clean Air

574 Actions. Environmental Science & Technology, 54, 1344–1352. https://doi.org/10.1021/acs.est.9b04678, 2019

576 Zheng, H., Kong, S., Zhai, S., Sun, X., Cheng, Y., Yao, L., Song, C., Zheng, Z., Shi, Z., & Harrison, R. M.: An intercomparison

577 of weather normalization of PM$_{2.5}$ concentration using traditional statistical methods, machine learning, and chemistry

578 transport models. Npj Climate and Atmospheric Science, 6. https://doi.org/10.1038/s41612-023-00536-7, 2023