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Investigating the impact of meteorology and emissions on $PM_{2.5}$ and PM_{10} in Delhi using machine learning

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Abstract

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 exceed Indian and WHO standards several times. India launched the ambitious National Clean Air Programme (NCAP) to reduce air pollution in its most polluted cities, including Delhi, in 2019. While several studies have looked at the trends of pollutant concentrations in Delhi, very few have adjusted for the effects of meteorology. In this study, we perform weather normalisation or deweathering using a machine learning model to analyse the impact of meteorology and anthropogenic emissions on $PM_{2.5}$ and PM_{10} concentrations in Delhi. The study reveals a statistically insignificant decline in deweathered $PM_{2.5}$ and PM_{10} between 2019 and 2024 across seasons. Also, the average deweathered $PM_{2.5}$ and PM_{10} concentrations almost 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 post-monsoon and winter months (October to November and December to February, respectively) compared to those in monsoon (June to September). Meteorological effects reduce $PM_{2.5}$ concentrations in summer (March to May) and monsoon seasons by 3.4 μg/m^3 and 25.4 μg/m^3, respectively, on average. However, they worsen PM_{10} concentrations during summer 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 $PM_{2.5}$ 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 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 no statistically significant trends across years for both pollutants, across seasons. Weekly averaged deweathered $PM_{2.5}$ - CO ratio analysis between 2019 and 2024 reveals two distinct spikes in the ratio associated with the post-monsoon stubble burning in the states surrounding Delhi and biomass burning for heating during winter months.

Keywords: deweathering, weather normalisation, $PM_{2.5}$-CO ratio, meteorology

1 Introduction

Air pollution is a global problem affecting around 90% of the world's population (World Health Organisation, 2018). India is among the countries that suffer the most from air pollution, with its cities grappling with severe pollution levels (Sharma et al., 2019). Delhi, in particular, has had alarming levels of air pollution in recent years, making it one of the most polluted cities

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in the world (WHO, 2024). It observed the highest per capita economic loss owing to air pollution, followed by Haryana, a state neighbouring it, in 2019 (Pandey et al., 2020). In 2019, the Indian government introduced the National Clean Air Programme (NCAP) to mitigate air pollution. The programme initially sought to reduce PM_{10} concentrations by 20 - 30% by 2024-25 compared to the 2017 levels, focusing on 131 cities that failed to meet the National Ambient Air Quality Standards (NAAQS), called Non Attainment cities (MoEFCC, 2019). This target has been revised to reduce PM_{10} concentrations by 40% or to meet the NAAQS, set at 60 $\mu g/m^3$, by 2025-2026 (PIB, 2024).

Delhi is one of the 131 Non-Attainment (NA) cities. However, the city's fight against air pollution started long before NCAP was launched. Delhi's efforts to manage emissions from the transport sector and pollution from the construction and residential sectors to improve air quality span over two decades. Alarmed by the rising vehicular emissions, the Supreme Court (SC) of India mandated in 1998 that all public transport in the city should convert from diesel to Compressed Natural Gas (CNG) by 31 March 2001. This transition was completed by 1 December 2002, with all the buses converted to CNG (Kathuria, 2004). To manage pollution from traditional cooking practices in households, the Ujjwala programme was launched by the Ministry of Petroleum and Natural Gas (MoPNG) in 2016. This program aimed to reduce indoor pollution, improve health and promote cleaner cooking practices by providing women from economically weak households in India with LPG connections (Kar et al., 2020).

In addition to vehicular emissions, road dust is a major contributor to the city's air pollution (Sharma and Dikshit, 2016). Multiple measures were implemented to tackle road dust, like limiting the movement of heavy-duty vehicles and using dust suppressants at construction sites (Guttikunda et al., 2023). In addition to these, the city phased out 15-year-old petrol and 10-year-old diesel vehicles, expanded its metro rail network, and introduced an odd-even vehicle scheme (Goel and Gupta, 2015; Tiwari et al.,2018; Sahu et al., 2023). The Government of India also implemented the Bharat Stage VI (BS-VI) vehicular emission norms in Delhi in 2018, skipping Bharat Stage Emission Standards 5 (BSV), ahead of the national schedule (Gajbhiye et al., 2023).

In January 2017, the Ministry of Environment, Forests & Climate Change (MoEFCC) implemented the Graded Response Action Plan (GRAP) to address the air pollution episodes during and around the winter months (MoEFCC, 2019). GRAP is an emergency response mechanism, on the basis of the average AQI levels in Delhi, enabling the authorities to take action in response to situations of worsening air quality in Delhi-NCR (Central Pollution Control Board of India). The Union Government also established the Commission for Air Quality Management in the National Capital Region and Adjoining Areas (CAQM) in 2021, with the objective of curbing air pollution primarily in Delhi and the NCR (Ministry of Law and Justice, 2019).

These steps paved the way for proper air quality management, despite the challenges. Guttikunda et al. (2023) summarise the air quality improvement-related interventions spanning from 1990 to 2022.

Air quality is a function of emissions and meteorology (Petetin et al., 2020). Therefore, it is essential to separate these components to evaluate the effectiveness of air quality management interventions in reducing emissions (Liu et al., 2022). 'Meteorological Normalisation' or 'Deweathering' is one of the ways of achieving this (Grange and Carslaw, 2019). The traditional approach to performing deweathering has been Chemical Transport Modelling (CTM), regarded as the 'Gold Standard' for such evaluations (Gardner-Frolick et al., 2022). However, CTMs are computationally intensive and require a lot of data and expertise (Xing et al., 2021; Zheng et al., 2023). Various methods have been suggested as alternatives to CTMs, including Machine Learning (ML), Statistical Methods, and the Kolmogorov-Zurbenko filter, of which ML methods have been considered the most accurate (Zheng et al., 2023).

Very few studies have applied deweathering methods for Delhi. They differ in the kinds of models used, the sources of data, the choice of pollutants, and the location considered. For instance, Chetna et al. (2024) studied the impact of meteorology on $PM_{2.5}$ trends in Delhi between 2007 and 2022. The study used the AirGAM2022rl model, based on a Generalised Additive Model (GAM), to analyse meteorology-adjusted trends (trends where the inter-annual variation in meteorology was removed) and meteorology-unadjusted trends (ambient trends). Xie et al. (2024) evaluated trends in surface $PM_{2.5}$ concentrations in India between 2017 and 2022 and estimated the impact of air quality improvement interventions and meteorology. To achieve this, they performed simulations using the Weather Research and Forecasting with Chemistry (WRF-Chem) model with fixed anthropogenic emissions from 2017 levels and varying the meteorology from year to year. These simulations calculated the extent to which meteorology impacted $PM_{2.5}$ concentrations. Observed data from around 500 Continuous Ambient Air Quality Monitoring (CAAQM) stations, 5 stations in the US AirNow continuous monitoring network in Indian cities, were then used to validate the results from the WRF-Chem model. They find that favourable meteorology was responsible for the air quality improvement in Delhi and other Indian cities.

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, Bengaluru, Hyderabad, and Visakhapatnam, incorporating a weather normalisation technique to isolate the impact of meteorology. The study used a GAM to perform the deweathering analysis, and only took into account the data from one station for each city and used the meteorological data from the India Meteorological Department (IMD). The study focused primarily on two timeframes: prior the lockdown period, which is March 11, 2020 to March 24, 2020 and during the lockdown period, lasting from March 25, 2020 to April 07, 2020 in the same year and in the different years (lockdown period in 2020 versus lockdown period in 2018, 2020, 2021 and 2022).

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Another study identified impact of meteorology on $PM_{2.5}$ levels and related mortality using $PM_{2.5}$ data from the US Embassy in Delhi and reanalysis meteorological data during 2014–2021 in five Indian megacities (Chennai, Kolkata, Hyderabad, Mumbai, Delhi), using Multiple Linear Regression to perform weather normalisation (Wang et al., 2024).

Regardless of this existing literature, significant gaps exist. Previous studies usually cover short periods or do not include very recent years, do not study seasonal variations in detail or rely on data from a single monitoring station or non-representative locations such as the US Embassy stations. Further, not many studies have analysed the trends after removing the impact of COVID-19 lockdowns.

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

2 Data and Methods

2.1 Data Selection

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

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

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Emissions are generally associated with the hour of day and the day of the year (Derwent et al., 1995). Therefore, time variables like Julian day, weekday, and hour of the day can be used as proxies for emissions (Grange and Carslaw, 2019). The current study uses hourly data of meteorological variables namely temperature at a 2-metre height above the ground level (T2M), mean sea-level pressure (MSL), boundary layer height (BLH), downward surface solar radiation (SSR), total cloud cover (TCC), relative humidity (RH), wind speed (WS), wind direction (WD), and mean total precipitation rate (MTPR) obtained from the European Centre for Medium-Range Weather Forecasting Reanalysis v5 (ERA5) dataset (Hersbach et al., 2023) and temporal variables like hour of the day, Julian day, weekday, and Unix date. We obtain MTPR at an hourly level by multiplying the rainfall rate in mm/s from the ERA5 reanalysis by 3600.

2.2 Data Preprocessing

We preprocess the data to ensure data quality. Our data preprocessing steps involve removing the observations for which $PM_{2.5}$ and PM_{10} were less than 5 µg/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 greater would suggest erroneous measurement. Delhi's baseline $PM_{2.5}$ levels are above 20 µg/m^3 (Lavanyaa et al., 2023). Therefore, values below 5 µg/m^3 can be considered unrealistic and hence removed. However, our threshold of 5 µg/m^3 is arbitrary. To ensure adequate spatial representativeness, we only retain the hours for which at least 75% of the stations had data. Figure 1 summarises the process.

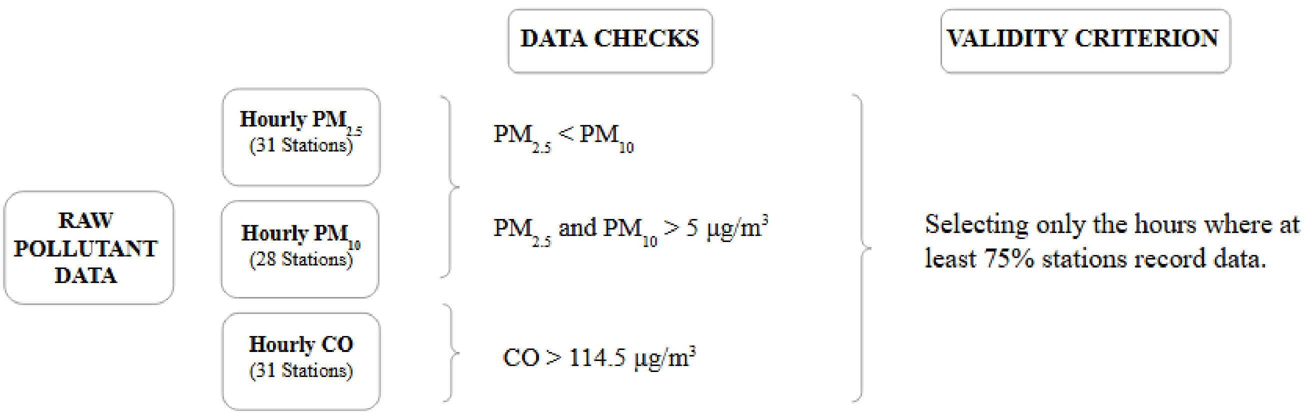

Figure 1. Data preprocessing procedure for the hourly pollutant data from the CAAQM stations - Raw data for $PM_{2.5}$, PM_{10}, and CO undergo checks regarding the lower limits of pollutants, $PM_{2.5}$ being greater than PM_{10} and validity criteria being hours where at least 75% of stations record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

2.3 Model Selection and Optimisation

We use 70% of the data for training and 30% for testing. Accounting for the non-linear relationship between the predicting variables and the target variable (pollutant concentration), we choose a non-parametric machine learning model to predict the pollutant concentrations (Ma et al., 2021). We choose the HistGradientBoostRegressor (HGBDT) model from the Scikit-Learn package, which is a popular machine learning package in Python. HGDBT uses a histogram-based decision tree mechanism. It is much faster than the Gradient Boosted Decision Tree (GBDT) model for large datasets with samples exceeding 10000 (HistGradientBoostingRegressor, Scikit-learn). The input features for the model include the previously mentioned meteorological and temporal variables, and the target variable is the pollutant concentration. We tuned the hyperparameters of the machine learning models to identify those with the best hyperparameters for the analysis. The details are available in the supplementary material (SM 3).

2.4 Weather normalisation

Weather normalisation or deweathering involves shuffling the meteorological input to the trained model while keeping the time variables intact and then predicting the pollutant concentrations (Grange et al., 2018; Vu et al., 2019). Although Grange's methodology involved shuffling all the explanatory variables, even the temporal variables for weather normalisation, a subsequent study found that if the temporal variables are excluded from shuffling or resampling, the results were more reasonable in capturing the seasonal and long-term emission trends (Zheng et al., 2023). Therefore, we only shuffle the meteorological variables for weather normalisation.

Generally, the meteorological data is shuffled and the predictions are made 1000 times, and then the average of the predictions is used to obtain the deweathered concentrations (Grange et al., 2018; Vu et al., 2019; Zhang et al., 2020; Song et al., 2023). We shuffle the meteorological variables in our dataset while keeping the time variables (Julian day, Unix date, hour and weekday) intact and predict the pollutant concentrations 2000 times. Increasing the number of shuffles beyond 2000 did not result in a significant change in the results. This is also observed in the study mentioned above, where, if predictions exceeded a thousand, only a very small reduction in noise was achieved (Grange et al., 2018). We then average the 2000 predictions to calculate the deweathered concentrations at an hourly level. The difference between the observed and deweathered concentrations is the effect of meteorology.

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 PM_{10} for analysing the trends and the effect of meteorology over the years, we use the deweathered CO concentrations to estimate the deweathered $PM_{2.5}$ and CO ratio, which is discussed further in detail in Section 3.4.

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3 Results

3.1 Model performance

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 $PM_{2.5}$ was 0.90, whereas it was 0.88 for both PM_{10} and CO models. Figure 2 shows that the models underpredict high concentrations. For instance, when the observed $PM_{2.5}$ values cross 400, the model underpredicts by 90.7 µg/m^3 on average. This is an inherent limitation of the machine learning models, seen across various studies where ML models struggle in handling extreme values. (Makhdoomi et al., 2025)

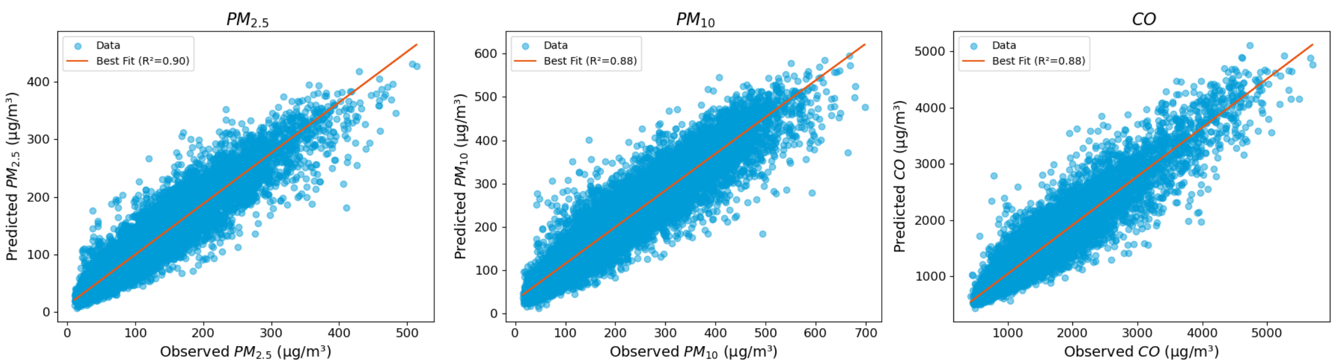

Figure 2. Scatter plots of predicted vs. actual concentrations for $PM_{2.5}$, PM_{10}, and CO.

We evaluate the model's performance using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Bias Error (MBE), Mean Absolute Percentage Error (MAPE), and the Pearson correlation coefficient (R) as the evaluation metrics. Table 1 summarises the models' performance.

	MAE (µg/m^3)	RMSE (µg/m^3)	MBE (µg/m^3)	MAPE	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

Table 1. Model performance metrics for $PM_{2.5}$, PM_{10}, and CO predictions.

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To assess the impact of each explanatory variable on the predicted pollutant concentrations, we calculate the feature importance from our models. Permutation feature importance is a technique that gives each feature's contribution to the model's statistical performance. It helps us determine how much the model relies on a particular feature (Pedregosa et al., 2011).

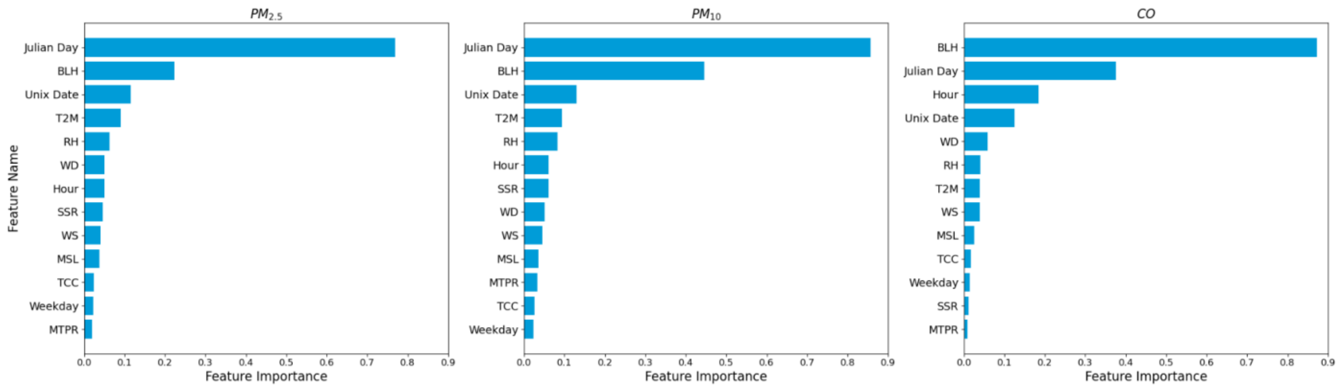

Figure 3. Feature Importance plots for $PM_{2.5}$, PM_{10}, and CO - Julian Day and Boundary Layer Height (BLH) are observed to be the most impactful variables.

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.

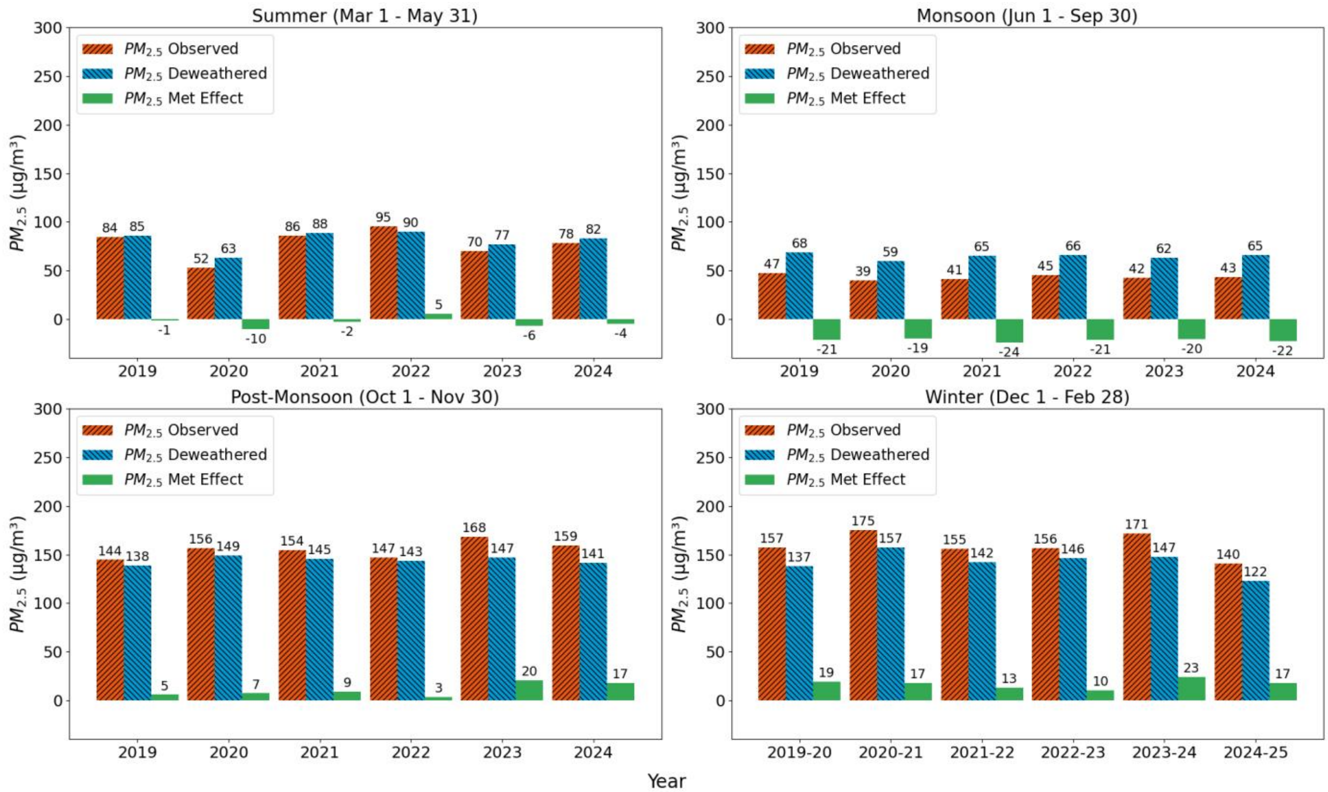

Figure 4. Seasonal variation in observed and deweathered $PM_{2.5}$ concentrations, along with the 'Met Effect' (ME) over the years in Delhi - Positive ME means worsening of $PM_{2.5}$ due to meteorology, while negative ME indicates a decrease in $PM_{2.5}$ due to favourable meteorology.

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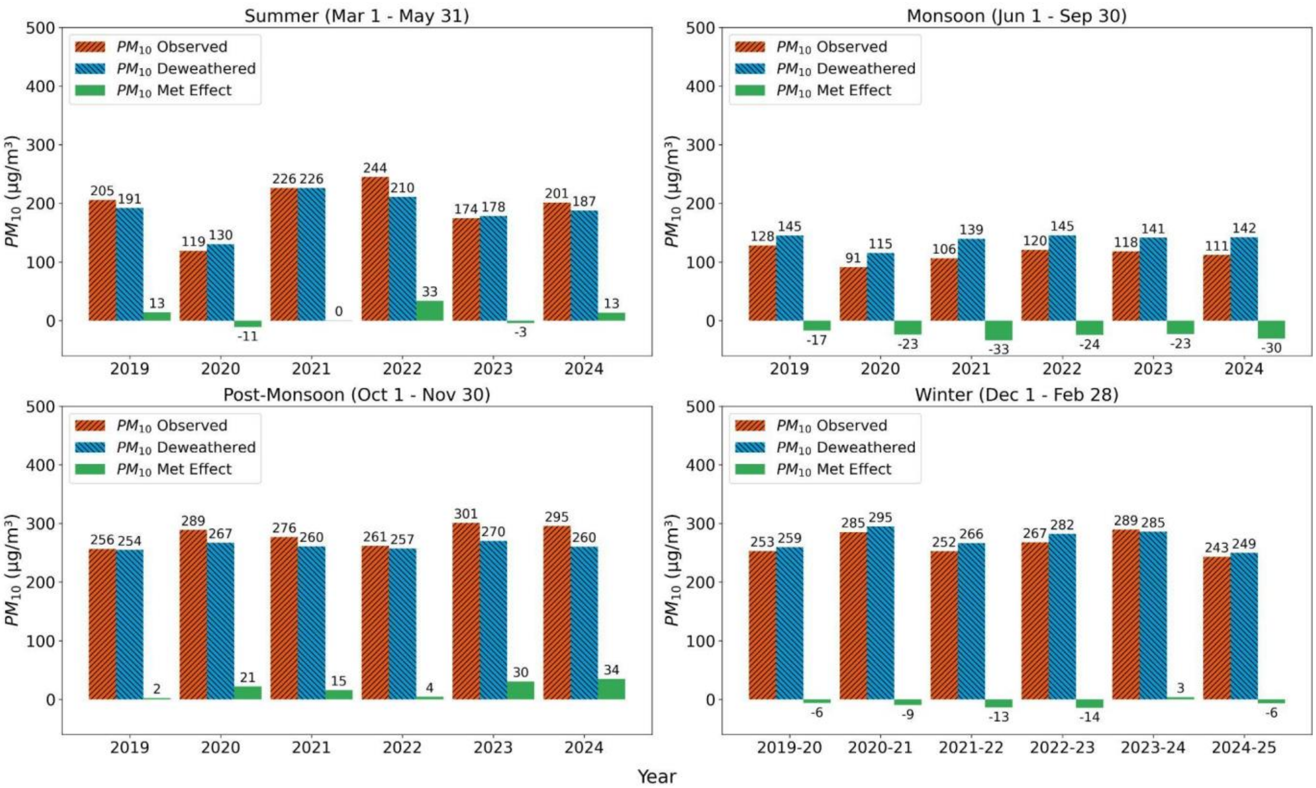

Figure 5. Seasonal variation in observed and deweathered PM_{10} concentrations, along with 'Met Effect' (ME) over the years in Delhi.

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

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the following two years witnessed an increase, with 2022 exhibiting an anomaly where the deweathered $PM_{2.5}$ concentration was less than the observed one, reflecting the adverse effect of meteorology on $PM_{2.5}$. We observed a similar pattern in PM_{10} during summer.

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

Table 2. Season-wise average ME on $PM_{2.5}$ and PM_{10} concentrations (μg/m^3). Positive values denote that meteorology contributed to elevating the concentrations, whereas negative values indicate lower concentrations due to favourable meteorology.

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

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

The reductions seen during the COVID lockdown period (March, April and May) in 2020 were reversed during the post-monsoon and winter seasons. We observe a spike in deweathered $PM_{2.5}$ during winter 2020-21, possibly due to the relaxation of restrictions and resumption of activities after the lockdown. Meteorology generally favours air quality during monsoon and summer, with 2022 summer being an exception. Dust storms are a recurrent phenomenon in Delhi during the summer season (Chakravarty et al., 2021). We analyse the average Dust Aerosol Optical Depth (DAOD) obtained using the ensemble of products (ENS) algorithm version 1.4 between March and May over Delhi between the years 2019 and 2023 from the Infrared Atmospheric Sounding Interferometer (IASI) sensor onboard the Meteorological Operational-A (METOP-A) and Meteorological Operational (METOP-C) satellites (Copernicus Climate Change Service, 2019). The data is available only till 2023. The DOAD value was higher (0.34) in 2022 compared to the other years.

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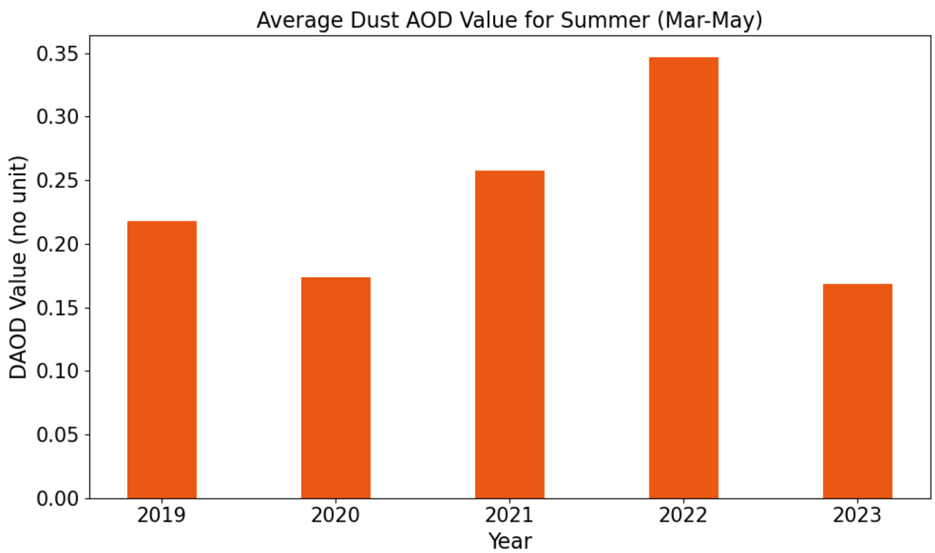

Figure 6. Average Dust Aerosol Optical Depth (DAOD) for summer months between 2019 and 2023 over Delhi. Elevated levels of DAOD in 2022 were possibly due to increased dust events that year.

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}.

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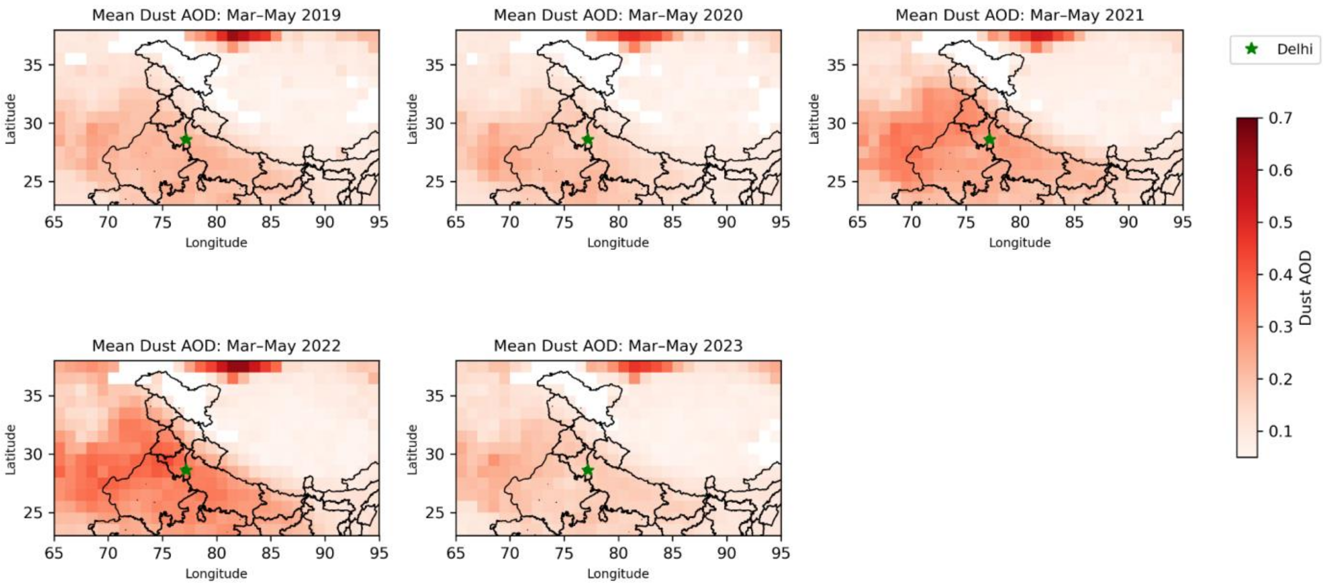

Figure 7. Average Dust AOD over the northern part of India, for the summer season (March - May) between the years 2019 and 2023.

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

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	Monsoon	-0.1 $\mu g/m^3$/year	-0.13 $\mu g/m^3$/year	+0.08 $\mu g/m^3$/year	-0.77 $\mu g/m^3$/year
	Post Monsoon	+2.71 $\mu g/m^3$/year	+0.21 $\mu g/m^3$/year	+2.78 $\mu g/m^3$/year	+0.85 $\mu g/m^3$/year
	Winter	+0.25 $\mu g/m^3$/year	-2.88 $\mu g/m^3$/year	+0.36 $\mu g/m^3$/year	-1.59 $\mu g/m^3$/year
PM_{10}	Summer	+1.52 $\mu g/m^3$/year	+3.08 $\mu g/m^3$/year	-0.49 $\mu g/m^3$/year	-3.32 $\mu g/m^3$/year
	Monsoon	-1.61 $\mu g/m^3$/year	+1.96 $\mu g/m^3$/year	-1.72 $\mu g/m^3$/year	-0.47 $\mu g/m^3$/year
	Post Monsoon	+5.07 $\mu g/m^3$/year	+1.04 $\mu g/m^3$/year	+6.45 $\mu g/m^3$/year	+1.86 $\mu g/m^3$/year
	Winter	1.05 $\mu g/m^3$/year	-1.7 $\mu g/m^3$/year	+1.03 $\mu g/m^3$/year	+0.66 $\mu g/m^3$/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 $\mu g/m^3$ and +23 $\mu g/m^3$, 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 $\mu g/m^3$, +13 $\mu g/m^3$ and +10 $\mu g/m^3$, 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.

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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.

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3.4 $PM_{2.5}$-CO Ratio in Delhi

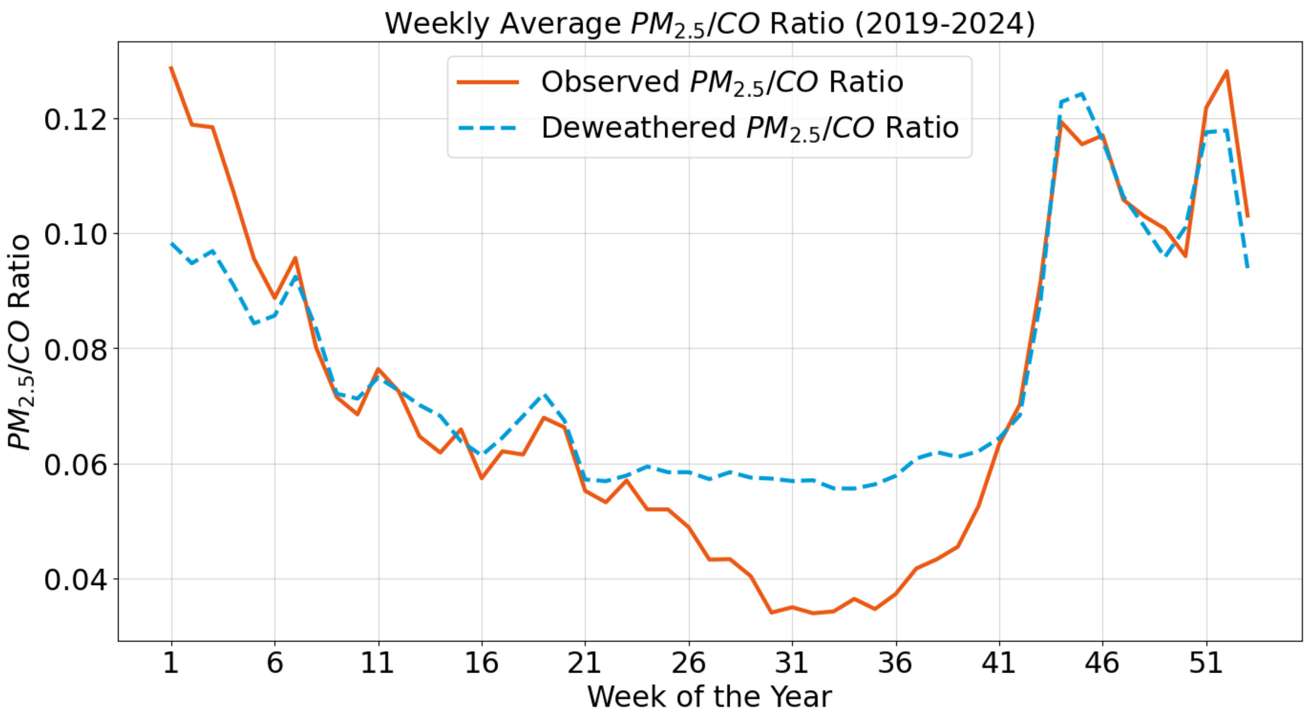

Figure 8. Weekly average $PM_{2.5}$ and CO (Deweathered and Observed) ratio. The plot shows two prominent peaks denoting the increased secondary particulate formation around the first 2 weeks of November (week 44) and the last weeks of December (week 52), the period of stubble burning and winter biomass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

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not only attributed to unfavourable meteorology but also to anthropogenic activity. This reiterates the finding that secondary particulate formation, aggravated by biomass-related combustion sources, plays a significant role in deteriorating air quality during the post-monsoon and winter seasons in Delhi (Mishra et al., 2023).

4. Discussion

Our study uses a machine learning approach to separate the effects of meteorology and air quality trends. Although the deweathered concentrations of $PM_{2.5}$ and PM_{10} decreased across seasons in Delhi, except the post-monsoon season between 2019 and 2024, the trends remain statistically insignificant.

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 season, indicating the role of high temperature, wind speed and BLH in reducing ambient air pollution. During Monsoon, this 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 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 $\mu g/m^3$, respectively) due to meteorological factors like lower temperature, lower BLH and lower wind speed.

The highest concentrations after decoupling the meteorological effect are observed during post-monsoon and winter, where 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} 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 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 concentrations suggest a major role of emissions in worsening the air quality during these months.

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 by meteorological variables like relative humidity and temperature. Lou et al. 2017 report a decrease in PM_{10} concentrations as soon as RH crosses 45% in the Yangtze River Delta, China. They demonstrated that for PM_{10}, RH < 45% had an accumulation effect, but RH > 45% had a mitigation effect, exhibiting an inverted V-shaped relationship. The Partial Dependence (PD) of PM_{10} on RH from the current analysis shows a similar relationship (Figure 9). However, they also mention that RH had an inverted U-shaped relationship with $PM_{2.5}$ concentrations. They observed peak $PM_{2.5}$ concentrations when RH was between 45% and 70%. However, the PD of $PM_{2.5}$ on RH from the current study shows an increasing relationship between $PM_{2.5}$ and RH (Figure 9).

From our analysis of the PD plots for RH, we found that PM_{10} increases once it reaches around 45% and then decreases from there. Thus, this could be a major reason for the anomalous behaviour we see in PM_{10} during winter.

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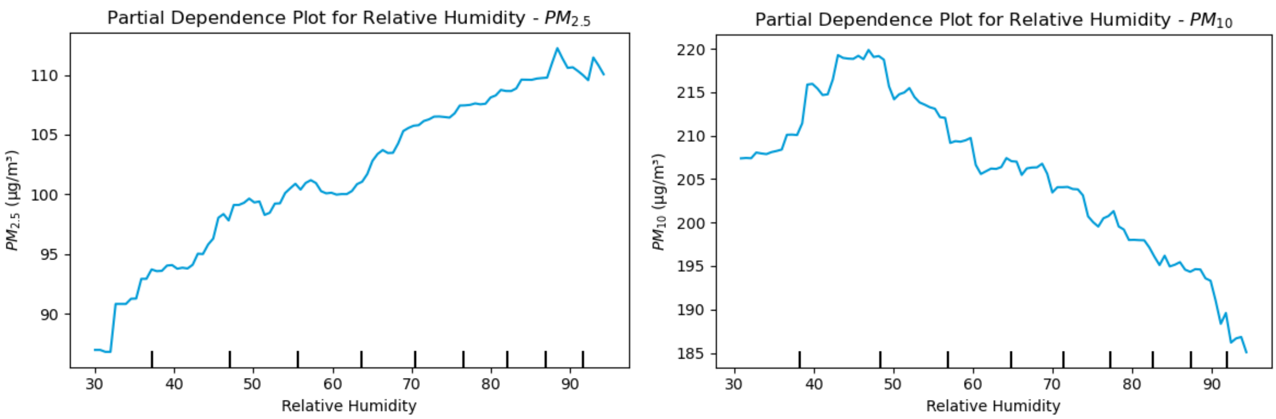

Figure 9. Partial Dependence plots for Relative Humidity for $PM_{2.5}$ and PM_{10}.

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

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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.

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