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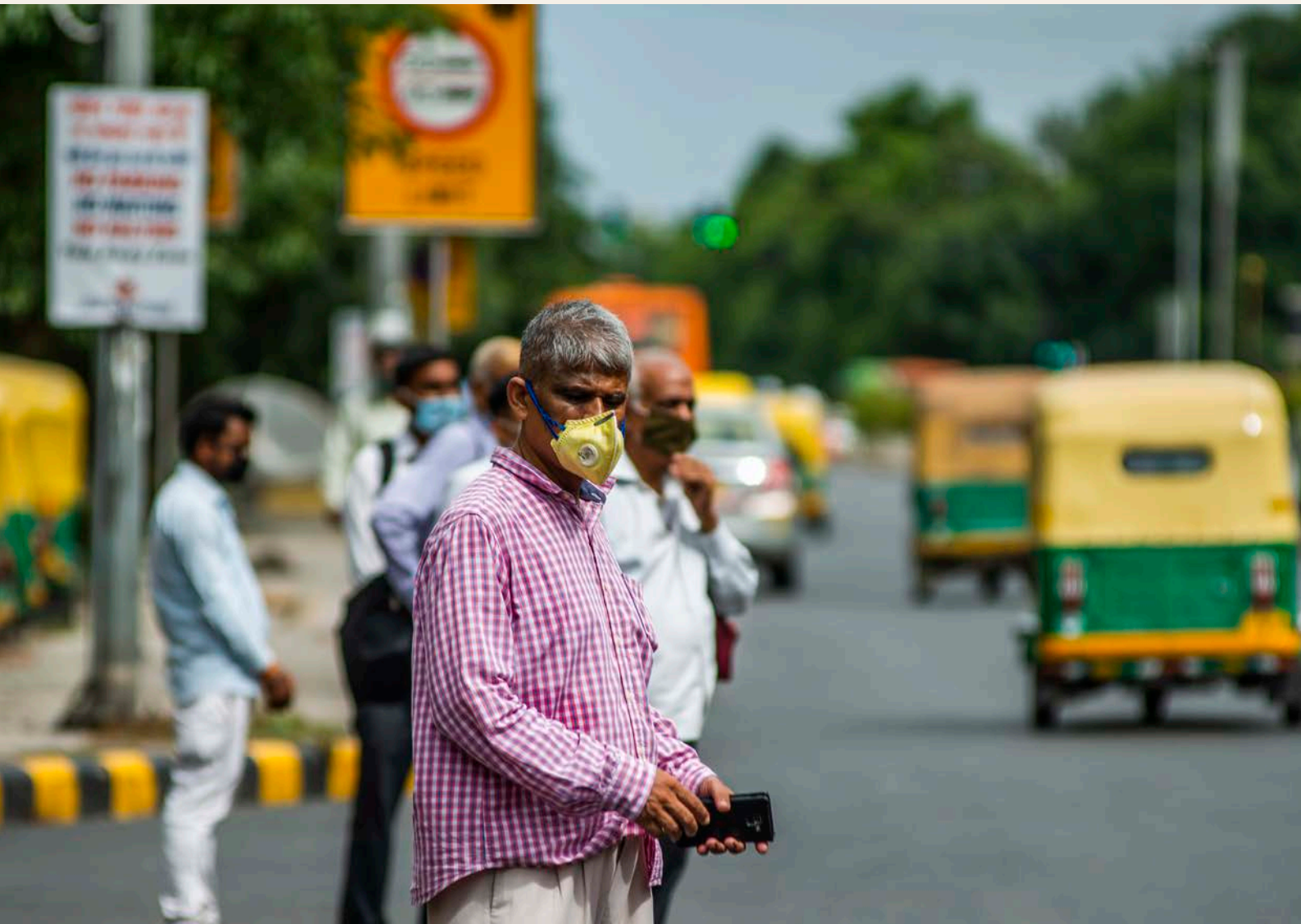
Issue Brief | October 2026

Methods for Long-Term Particulate Matter Trend Assessment

Interpreting Monitoring Data to Evaluate Air Quality Trends



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Shubhi Verma
Abinaya Sekar
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Council on Energy, Environment and Water

INTEGRATED | INTERNATIONAL | INDEPENDENT

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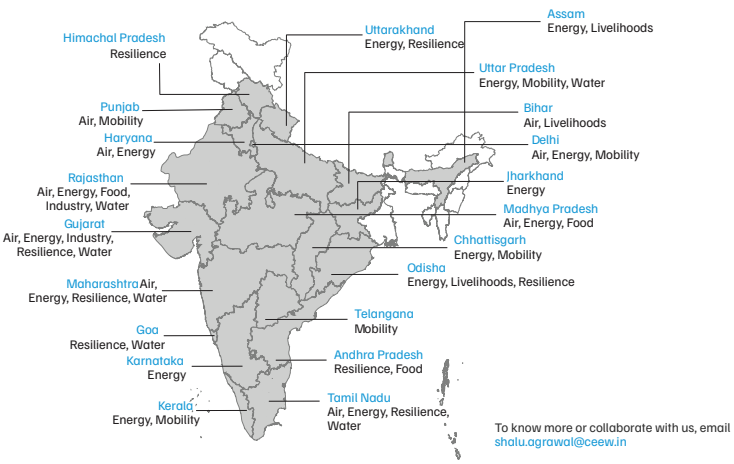

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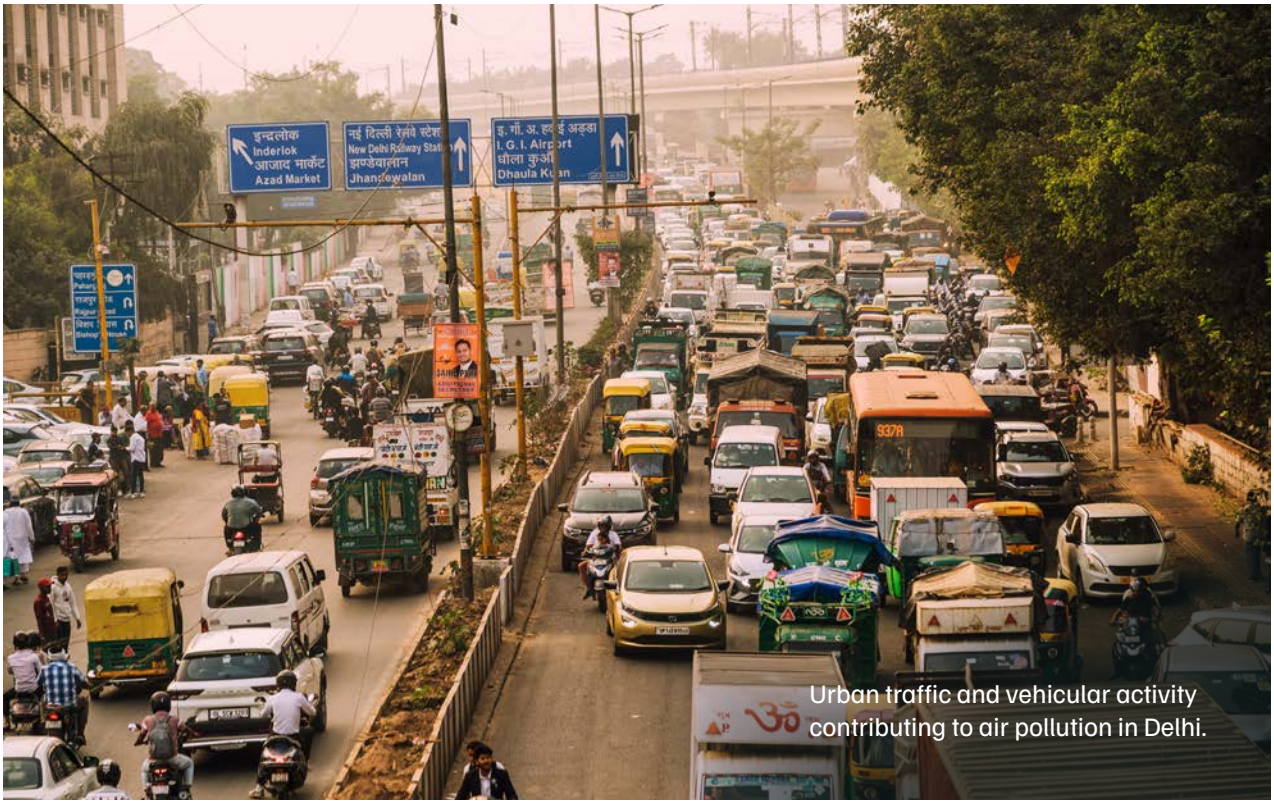
Executive summary



Urban traffic and vehicular activity contributing to air pollution in Delhi.

Image: iStock

Poor air quality has been associated with significant health, economic, and societal impacts in India. In response, over the past decade, India has made substantial investments in air quality monitoring, leading to a rapid expansion of continuous ambient air quality monitoring stations (CAAQMS) and the generation of air quality data. Additionally, India has substantially expanded its clean air programme and city-level initiatives while augmenting financial support for clean air action.

With the expansion of air quality monitoring networks and increased financial support for pollution control initiatives, there is a growing need to critically evaluate the real-world impact of air pollution interventions. However, reliably assessing long-term air quality trends remains challenging due to variations in data availability and completeness, as well as meteorological and seasonal influences that can obscure underlying changes in air quality. Daily and annual averages are influenced not only by pollution sources but also by seasonal emission patterns, episodic events, and variations in meteorological conditions. If these factors are not accounted for, changes in air quality may appear to be greater during meteorologically favourable periods, while actual reductions in emissions may not register at all during unfavourable periods. Furthermore, all monitoring data must be subject to a series of systematic quality checks, including data completeness thresholds, consistency across monitoring stations, and outlier removal. At present, methods for outlier detection and quality checks are neither standardised nor formally documented by regulatory agencies, resulting in variations across different organisations.

Globally, researchers utilise a range of approaches to track long-term air quality trends and assess the effectiveness of interventions, with the choice of approach largely depending on data availability and resource requirements. This issue brief outlines

guidelines for air quality trend analysis comprising three independent approaches, including:

- **Data smoothing using rolling averages** to eliminate random fluctuations in measurements
- **Data deseasonalisation** to remove recurring seasonal patterns
- **Deweathering** to isolate meteorological influence

Monitoring stations were randomly selected from the regulatory monitoring network in Amritsar, Kolkata, and Hyderabad to demonstrate the application of each method. The strengths, weaknesses, and appropriate applications of each approach are discussed and demonstrated through a case study of Delhi.

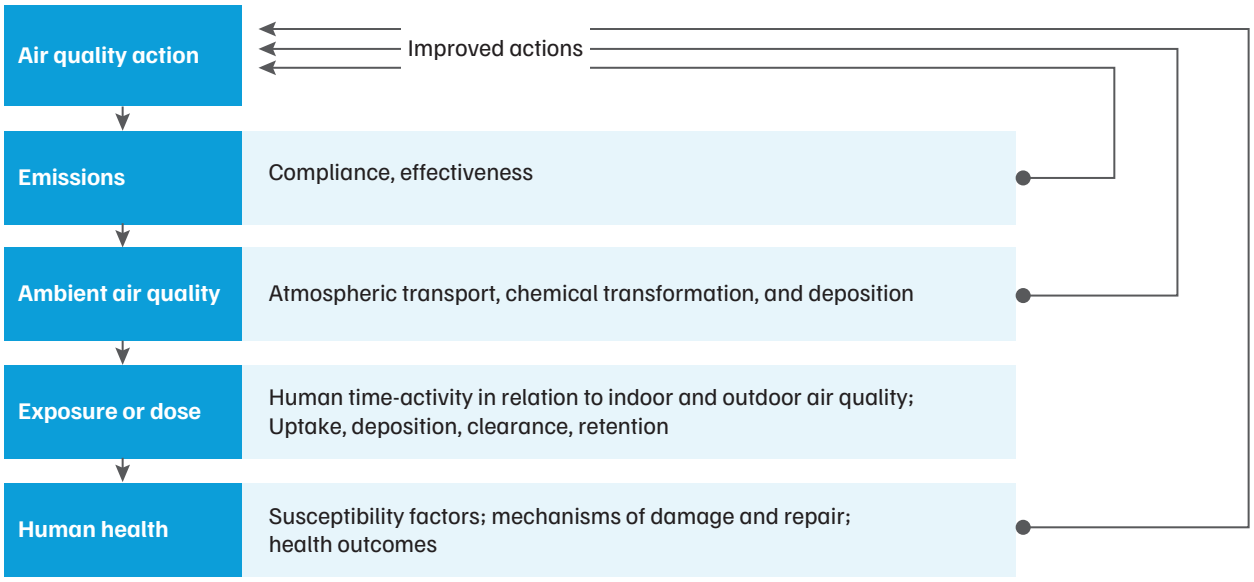
This approach provides regulatory institutions, including pollution control boards, the Commission for Air Quality Management (CAQM), and urban local bodies, with a practical and scientifically robust approach for interpreting monitoring data, evaluating interventions, and supporting evidence-based air quality policies. It could also strengthen the allocation of funds and the evaluation of city performance under the *National Clean Air Programme* (NCAP).

The issue brief was developed based on the HEI study, *Assessment of Changes in Air Quality in Indian Cities Since the Launch of the National Clean Air Programme* (HEI 2025), and the preprint by CEEW researchers, *Investigating the impact of meteorology and emissions on $PM_{2.5}$ and PM_{10} in Delhi using machine learning* (Verma et al. 2025)

1. Introduction

Air quality depends on the amount of pollution released, weather conditions, atmospheric chemical processes, and the transport and dispersion of pollutants (Petetin et al. 2020; Seo et al. 2018). Assessing the effectiveness of air quality management policies, regulations, or interventions is a sequential process that requires multiple data sets. Figure 1 presents a framework for evaluating the effectiveness of air quality policies in terms of air quality and health outcomes. It illustrates how regulations influence emissions, ambient air quality, personal exposure, and, ultimately, public health. For example, assessing changes in emissions requires emission data, along with additional information, such as details of other regulations implemented during the same period, efficiency gains, compliance levels, and fuel prices.

Figure 1. Framework for assessing the effectiveness of an air quality intervention



Source: Health Effects Institute (HEI). 2003. Assessing Health Impact of Air Quality Regulations: Concepts and Methods for Accountability Research. Health Effects Institute.

Similarly, understanding changes in air quality requires comprehensive monitoring data, along with information on meteorology, atmospheric transport mechanisms, chemical processes, deposition, and other relevant factors (HEI 2003). There is no 'one-size-fits-all' method or framework for assessing the relationships between interventions and changes in emissions, air quality, exposure, and health. With the rapid expansion of monitoring networks across India, these data must be used systematically to assess long-term changes in air quality. Currently, Indian regulators provide no formal technical guidance on assessing long-term air quality trends, apart from guidance issued by the Ministry of Finance (MoF 2021), which focuses primarily on year-on-year change assessment. Similarly, the methods deployed under the Swachh Vayu Survekshan (MoEFCC 2022b) also evaluate year-on-year changes in particulate matter (PM_{10}) concentrations.

Developing technical guidance will help states and cities report air quality in a uniform and scientifically robust manner. The most appropriate approach for assessing long-term trends or evaluating the effectiveness of a policy intervention depends largely on data availability and quality. In regions with strong seasonal influences (for example: cities in Indo-Gangetic plains), meteorological variables should be considered to distinguish genuine emission reductions from changes driven by seasonal or interannual variability (Box 1). Without accounting for this differentiation, improvements or deteriorations in observed pollution levels may be incorrectly attributed to policy interventions rather than to favourable (or unfavourable) weather conditions, such as episodic pollution events, regional dust storms, or activities like biomass burning.

In this issue brief, we discuss the available methodologies for assessing long-term changes in pollutant concentrations, including rolling averages, deseasonalisation, and a machine learning–based deweathering approach. It is intended to serve as a practical guide for cities and authorities seeking to evaluate air quality interventions without relying on complex modelling techniques.

Box 1. Why accounting for meteorology is important

Air quality is a function of emissions, meteorology, atmospheric chemistry, transport, and dispersion of pollutants. Recent studies conducted in India have found that changes in air quality in certain cities are largely attributable to favourable meteorological conditions between 2017—2023 (Xie et al. 2024; Beig et al. 2024). For example, seasonal variations in Delhi are partly driven by meteorological conditions (Verma et al. 2025). Meteorological variables, such as wind speed and direction, boundary-layer height, temperature, humidity, and precipitation, strongly influence pollutant dispersion. Favourable meteorology—for example, higher wind speeds or a higher planetary boundary layer height—can reduce pollutant levels even when anthropogenic emissions remain unchanged. Conversely, stagnant conditions can aggravate pollution levels even as emissions remain stable or decline. Thus, it is crucial to separate the influence of meteorology from that of emissions when evaluating the effectiveness of air quality interventions.

2. Data availability and quality checks

Before using pollutant concentration data for calculating daily, monthly, or annual averages, or for long-term trend assessments, it is essential to perform appropriate data quality checks. The Central Pollution Control Board's (CPCB) Technical Handbook for Installation, Maintenance, Calibration, Data Connectivity, and Data Quality Checks of Continuous Ambient Air Quality Monitoring Stations (CAAQMS) recommends the following quality checks:

- Identification of negative values, zero values, repeated values, and assessment of diurnal variations.
- Validation based on acceptable ranges, maximum and minimum values, averages, and missing data.
- Trend validation, including comparisons with historical trends, inter-pollutant correlations, and correlations with meteorological parameters, such as wind speed, wind direction, temperature, humidity, and solar radiation.

In addition to the CPCB's *Technical Handbook*, the guidelines for the release and use of funds under the *National Clean Air Programme* issued by the MoEFCC (2022a) specify that the two-sigma ($\pm 2\sigma$) method should be used to remove outliers. However, neither the aggregation period for applying the $\pm 2\sigma$ method nor the practical implementation of these data quality checks is clearly defined. For example, while the handbook states that consistent values should be removed, it does not specify the duration over which values are considered consistent. It is therefore uncertain whether this refers to consistent values recorded over several hours within a day or over multiple days.

Once data quality has been assessed, it is essential to determine how much data remain available for analysis. The CPCB's *Technical Handbook* specifies that only monitors with at least 85 per cent daily data availability and 90 per cent or more monthly data availability should be connected to the data acquisition system. These granular data availability requirements help ensure that monitoring data are representative at the daily and monthly scales.

However, when calculating seasonal or annual averages, or conducting long-term trend assessments, it is equally important to consider annual data availability. Several previous studies have used uptime thresholds of around 75 per cent, or even 50 per cent, to calculate annual averages (CREA 2023; Climate Trends and Respirer Living Sciences 2023; Vohra et al. 2025). Recent assessments show that an annual uptime of 75 per cent can result in the loss of more than two to three months of data, potentially excluding an entire season from the analysis (HEI 2025). Most parts of India experience pronounced seasonal variations in air pollution. Therefore, ensuring data coverage for at least 11 months of the year is crucial to producing meaningful, representative long-term assessments. In fact, the guidelines issued by the MoEFCC exclude stations with more than 30 consecutive days of missing data from the calculation of year-on-year changes in pollution levels (MoEFCC 2022a).

Although multiple guidelines exist for data quality checks and data availability assessment, there remains a need for comprehensive, technically robust guidelines that clearly define the methodology, criteria, aggregation periods, and implementation procedures for data validation and outlier removal.

Step 1: Apply data quality checks, including screening for negative, zero, or repeated values, as well as physically inconsistent observations.

Data points with $PM_{2.5}$ or PM_{10} values below 2 $\mu g/m^3$, the minimum detectable limit specified for reference-grade continuous PM analysers (such as those used in CAAQMS networks), should not be included in the analysis (CPCB 2019). Observations where

$PM_{2.5}$ > PM_{10} should not be included in the analysis. By definition, $PM_{2.5}$ is a subset of PM_{10}. Data points with $PM_{2.5}$ > PM_{10} are physically impossible and, therefore, incorrect. To identify invalid 'consistent' values resulting from instrument malfunction or data transmission errors, sequences of identical hourly concentrations that persist for several hours can be flagged and excluded (e.g., three identical consecutive hourly mean values) (Ministry of Environment, Republic of Lebanon 2019). The same quality-control criteria and thresholds can be applied uniformly across data sets from all agencies to ensure consistency in data processing.

Step 2: Apply granular data completeness criteria such that a station is considered suitable for long-term trend assessment only when it meets defined thresholds; for instance, at least 18 hours per day, 23 days per month, and 11 months per year for PM_{10} and $PM_{2.5}$ (HEI 2025).

Note: All results and examples presented to illustrate each methodology are based on air quality data retrieved from regulatory monitoring stations available on the Central Pollution Control Board (CPCB) website. No modelled air quality estimates were used, and the air quality index (AQI) was not considered. The analysis is based solely on PM_{10} and $PM_{2.5}$ data. The AQI is not designed to quantify long-term air quality changes. In India, AQI is calculated based on the maximum subindex across at least three of the eight regularly monitored pollutants. It represents the worst AQI subindex for that location. For example, if $PM_{2.5}$ dominates the AQI and its levels improve, the AQI may remain high due to another pollutant (e.g., ozone). Hence, AQI does not reflect cumulative air quality improvement across all pollutants. Thus, it is crucial to conduct analyses using pollutant concentration data to evaluate long-term air quality trends and understand the impacts of policies or interventions.

3. Methods for trend assessment

A variety of methods can be used to assess long-term air quality trends. Their complexity increases as additional factors influencing pollutant concentrations are incorporated into the analysis. These methods range from simple smoothing techniques to advanced statistical normalisation approaches. Rolling averages, for instance, are among the simplest methods for analysing time-series data because they require only air quality data. They smooth short-term variability and highlight broader trends over time. However, they do not explicitly account for seasonal cycles or meteorological conditions; rather, they reflect underlying emission-related trends.

Deseasonalisation involves a moderate increase in analytical complexity. It relies solely on air quality data but incorporates assumptions regarding the time series. However, it does not account for day-to-day meteorological variability. To account for the influence of unusual weather events, which are prevalent in India, the time series should be meteorologically-normalised. At the highest level of complexity, chemical transport models (CTMs) explicitly simulate emissions, dispersion, chemical transformation, and meteorological processes (Brasseur and Jacob 2017). They are more complex because they do not rely solely on ground-based monitoring data. These models require detailed emissions inventories, meteorological inputs, and substantial computational resources (Yang et al. 2024).

In this issue brief, we discuss the following three methods:

- Rolling averages
- Deseasonalisation
- Meteorological normalisation (deweathering)

Each of these methods can be applied either at the level of individual monitoring stations or aggregated across a city's monitoring network, depending on the study's objective (Box 2).

Box 2. The choice of averaging across stations depends on the study objective

Both station-wise and city-aggregated analyses are important because they serve complementary purposes:

- **Station-wise analysis** captures local emission sources and meteorological influences, enabling the identification of spatial variability and heterogeneity among CAAQMS stations.
- **City-aggregated analysis** provides representative values for the entire city. This is essential for policy evaluation and effective communication of results. At the city level, meteorological influences can be represented using gridded reanalysis data sets (e.g., ERA5 at ~25 × 25 km resolution), which provide consistent spatial coverage across the city.

Long-term trend assessment for a city should be based on a network of representative monitoring stations. Representative stations should be selected based on factors such as population exposure, influence of emission sources, background concentrations, and regional transport patterns. Continuous monitoring and periodic evaluation of the network are essential to ensure that it remains representative of evolving urban dynamics, emission patterns, and population exposure across India's rapidly growing cities (HEI 2025).

Note: In cities with only one monitoring station, these methods can still be applied using data from that station. However, the results may not be representative of city-wide conditions and should therefore be interpreted accordingly.

3.1 Rolling averages

Rolling averages, also known as moving averages, is a statistical technique used to smooth time-series data by repeatedly calculating the average over a fixed window as it moves through the dataset. For instance, a three-year rolling average is calculated by averaging data from years 1, 2, and 3, then years 2, 3, and 4, and so on. This method is particularly useful for visualising trends and supporting regulatory compliance reporting.

Purpose

Regulatory agencies, such as the United States Environmental Protection Agency (US EPA), commonly use rolling averages for air quality trend analysis (US EPA 2025). For example, when calculating $PM_{2.5}$ trends, a three-year average, also known as the design value, is used to assess compliance with the *National Ambient Air Quality Standards* (NAAQS). Rolling averages reduce short-term variability in extreme events and highlight underlying trends. This method also minimises the impact of anomalous periods, such as unusual meteorological conditions or episodic pollution events.

Inputs and data

Daily 24-hour average PM concentrations for at least 3 years are required to apply this method.

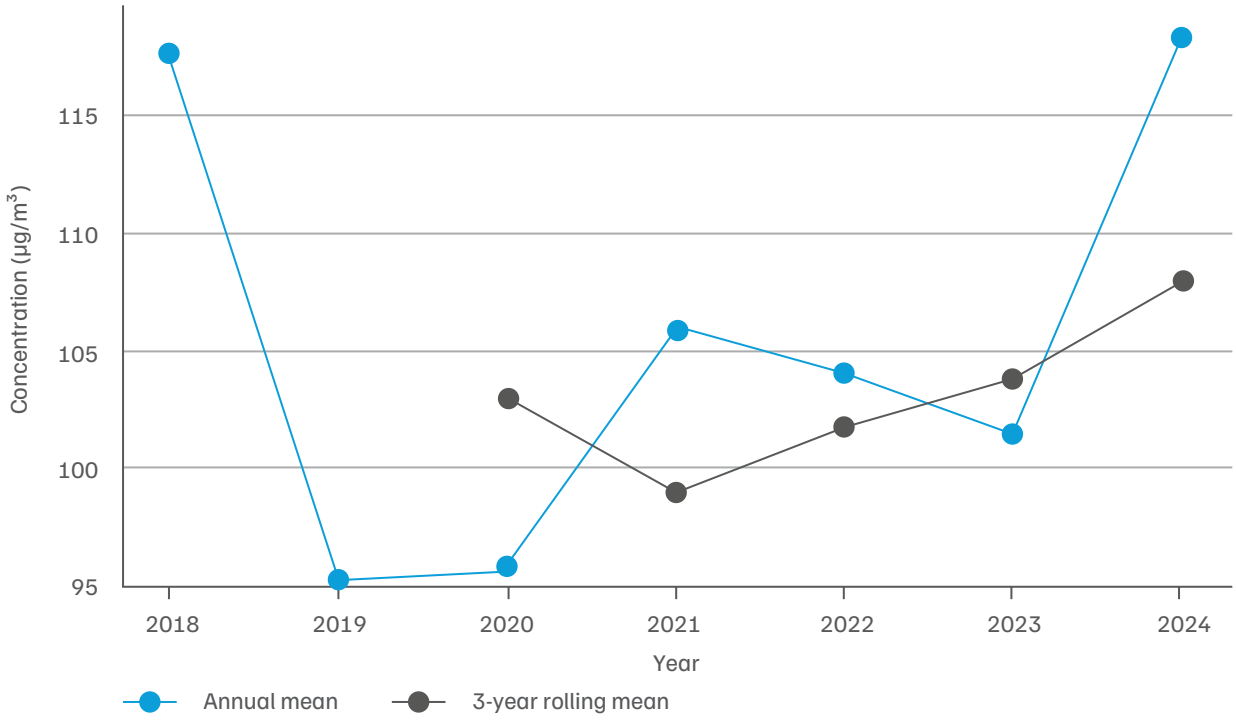
Methodology

Rolling averages can be calculated using annual pollutant concentrations derived from daily measurements that meet defined data completeness criteria.

Example

Here, we illustrate how the impact of short-term or annual anomalies can be adjusted using rolling averages. At a monitoring station in Amritsar (Figure 2), the annual PM_{10} average shows peaks in 2018 and 2024, with lower values in the intervening years. The rolling average smooths the curve and shows a gradual upward trend towards 2024. This rolling average filters out the noise from edge-year (2024) peaks and shows a gradual increase. Hence, the increase observed in 2024 may reflect an underlying long-term trend rather than a one-off event. This enables regulatory agencies to assess more reliably whether air quality is improving, worsening, or remaining stable over time based on multi-year-averaged pollutant concentrations.

Figure 2. PM_{10} (µg/m^3) annual average versus rolling average at a monitoring station in Amritsar



Source: Authors' analysis

3.2 Deseasonalisation

This method is suitable for long-term trend analysis because it accounts for predictable seasonal variation, making it particularly useful for regulatory and research applications.

Purpose

Air pollution in India often exhibits strong seasonality. Time-series decomposition can therefore be used to separate long-term pollution trends from seasonal cycles and short-term fluctuations caused by meteorological conditions or other episodic events. Seasonal decomposition techniques partition a time series into three components: **(a) trend, (b) seasonal, and (c) residual (or error)**. The trend component represents the underlying long-term progression or direction of air quality levels over time. The seasonal component captures repeating patterns or cycles that occur at regular intervals, such as daily, monthly, or annual variations. The residual component represents random fluctuations or noise in the data that cannot be explained by either the trend or the seasonal pattern.

Among the available decomposition approaches, seasonal decomposition of time series by locally estimated weighted scatterplot smoothing (LOESS) (STL) is particularly well suited for air quality data, as it accommodates flexible, time-varying seasonality and is robust to the non-linearity and outliers commonly observed in pollution time series (Carslaw and Ropkins 2012).

Inputs and data

This method requires monthly average air quality data.

Methodology

Monthly air quality time-series data are deseasonalised using the STL method. The STL decomposition can be implemented using existing software packages, such as the openair package in R, which is specifically designed for analysing atmospheric composition and air quality data.

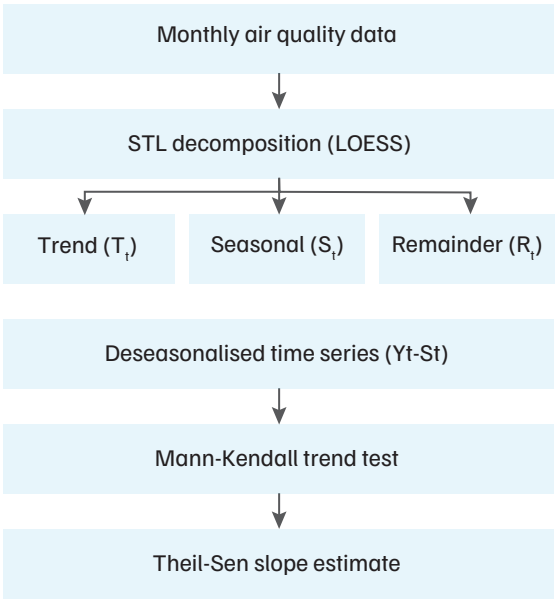
The STL algorithm iteratively estimates each component using LOESS smoothing:

- **Seasonal component estimation:** Smoothing is applied to corresponding months across years, allowing the seasonal component to vary gradually over time.
- **Trend component estimation:** The seasonal component is removed from the original series, after which LOESS smoothing is applied to the resulting data to estimate the underlying long-term trend in air quality levels.
- **Remainder component calculation:** The remainder component is obtained by subtracting the estimated trend and seasonal components from the observed series.
- **Deseasonalisation:** The deseasonalised series is generated by removing the seasonal component from the original data. This time series is used for further non-parametric trend analysis.

Trend analysis using non-parametric methods

Following deseasonalisation, non-parametric trend-detection methods can be applied to the deseasonalised time series (Figure 3). The Mann–Kendall test is used to determine whether air pollution levels are increasing or decreasing over time and whether this change is statistically significant. The Theil–Sen slope is then used to estimate the rate at which air quality is improving or deteriorating, providing a reliable measure of the rate of change even when the data include extreme values or gaps.

Figure 3. Long-term trend assessment using deseasoned time-series data



Mann–Kendall
Positive Z → Increasing trend
Negative Z → Decreasing trend
$p < 0.05$ → Statistically significant trend
$p \geq 0.05$ → Trend not statistically significant

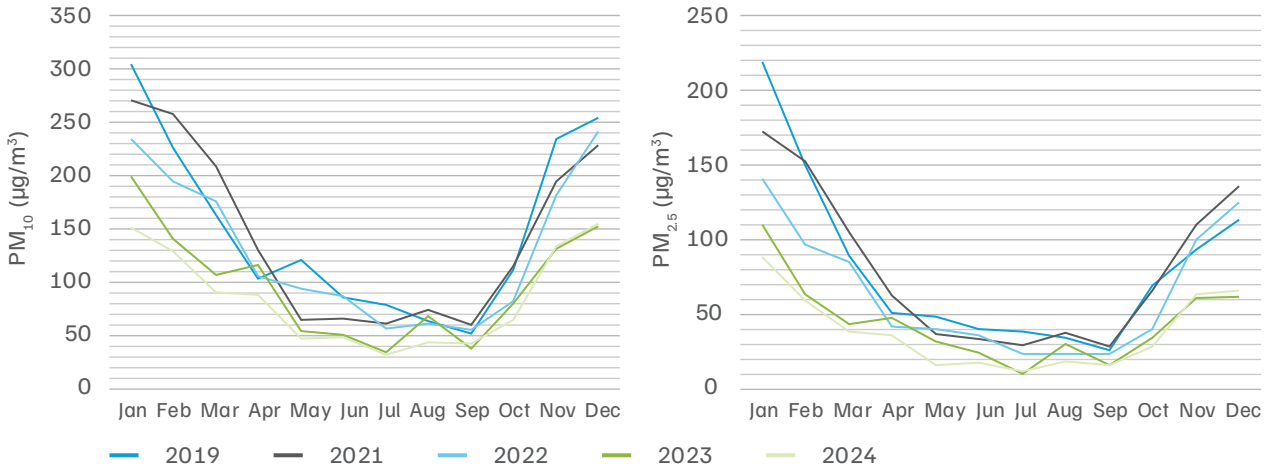
Interpretation of Theil–Sen slope
Positive slope → Rate of increase
Negative slope → Rate of decrease
Slope magnitude → Change per time unit (e.g., μg m^{-3} per year)
Near–zero slope → Little or no estimated change

Source: Authors' illustration

Example

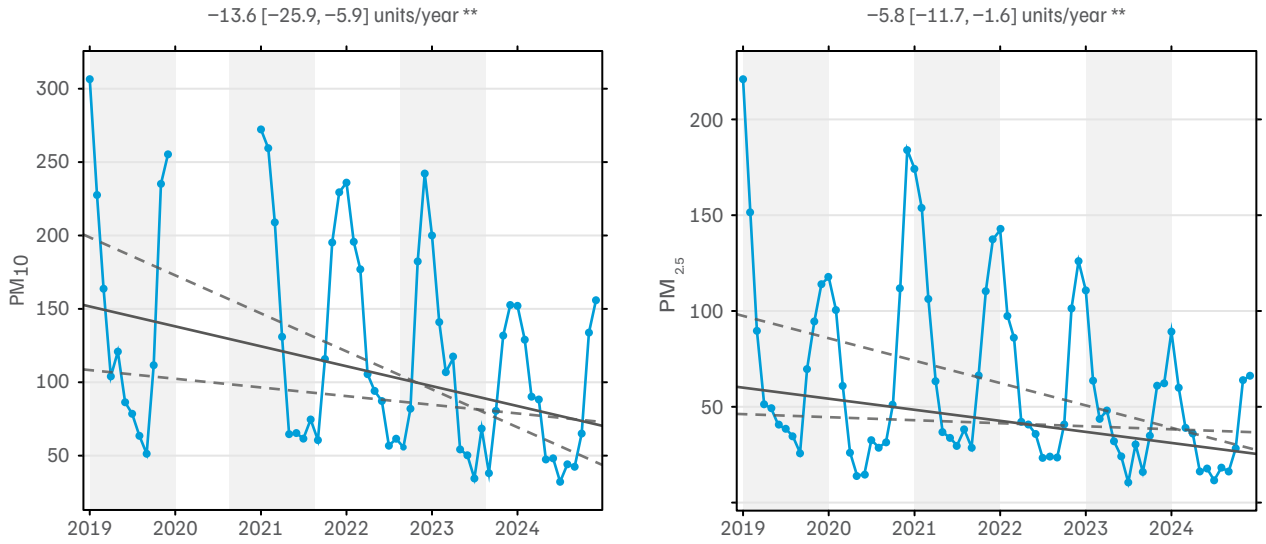
Figure 4 shows PM_{10} and $PM_{2.5}$ trends at a monitoring station in Kolkata. Significant seasonal variation is observed, with substantially higher pollution concentrations during the winter months. Numerous studies in northern Indian cities report strong seasonal variation in $PM_{2.5}$, with peaks in the post-monsoon and winter seasons and lows during the monsoon or pre-monsoon seasons (Mogno et al. 2021; Tiwari et al. 2013). When the data are deseasoned (Figure 5), a steeper actual decline is observed for both PM_{10} and $PM_{2.5}$ than the raw data suggest (Figure 6).

Figure 4. (a) PM_{10} and (b) $PM_{2.5}$ levels at a monitoring station in Kolkata



Source: Authors' analysis

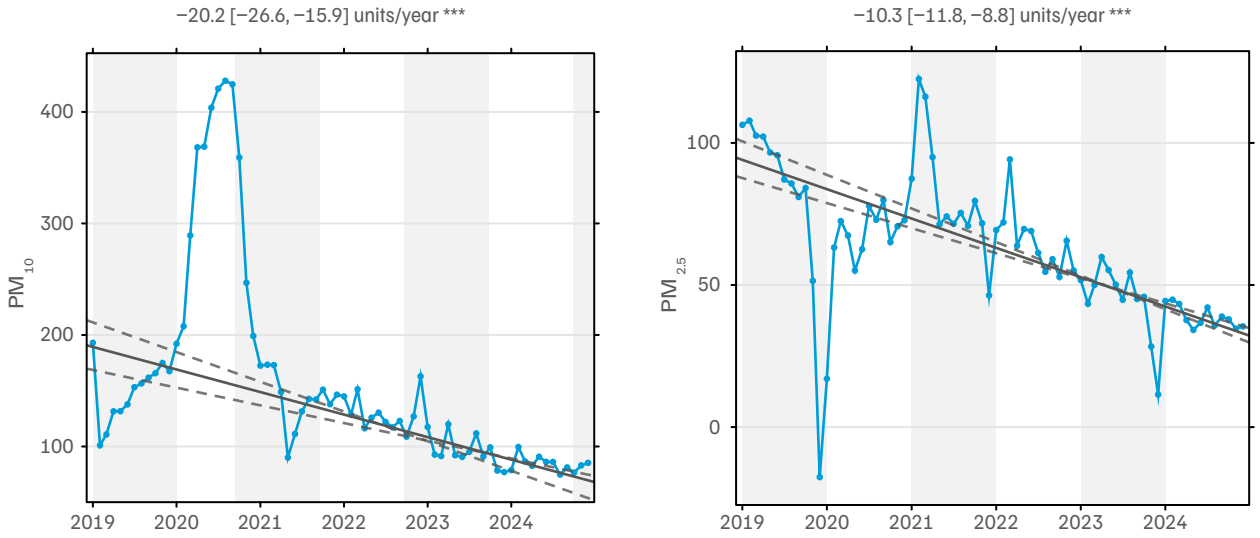
Figure 5. Trend plots for (a) PM_{10} and (b) $PM_{2.5}$ levels at a monitoring station in Kolkata (observed data), ** p<0.01.



Source: Authors' analysis

Note: In the trend plots presented in Figures 5, 6, 8, and 11b, deseasonalised monthly mean concentrations of PM_{10} and $PM_{2.5}$ are shown. The solid grey line represents the estimated trend, and the dashed grey lines denote the 95% confidence intervals. The blue line represents the observed data over time; the recurring intra-annual peaks and troughs indicate substantial seasonal variability.

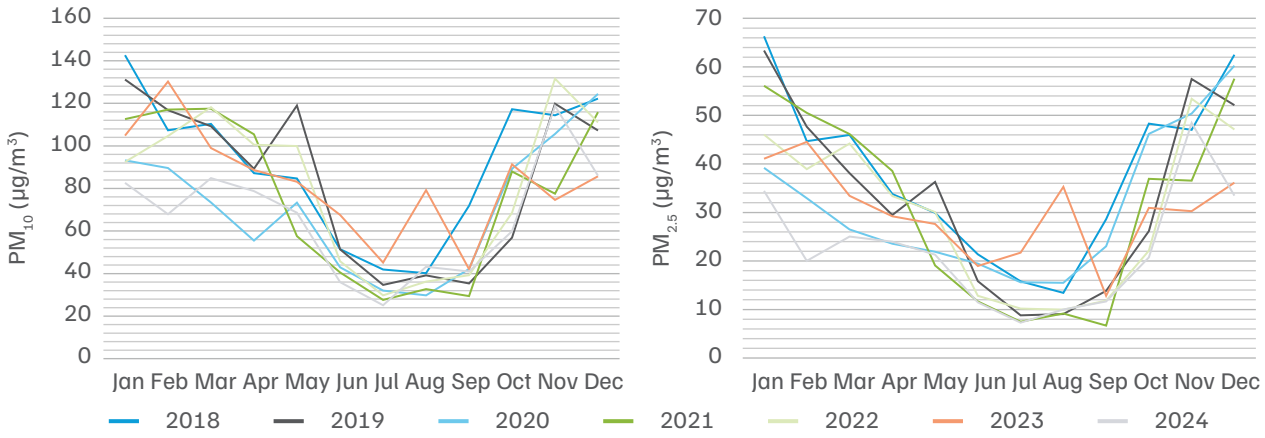
Figure 6. Trend plots for (a) PM_{10} and (b) $PM_{2.5}$ levels at a monitoring station in Kolkata (deseasoned data), ***p<0.001



Source: Authors' analysis

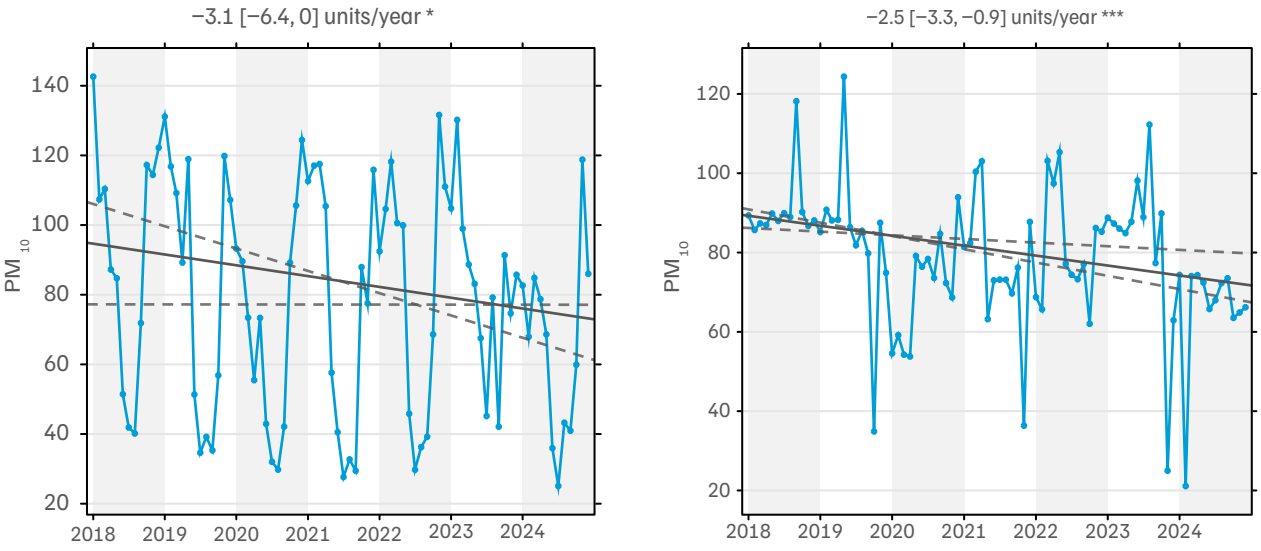
In Hyderabad, pollution levels are higher during the winter months (Figure 7). Deseasoned PM_{10} trend plots show a statistically significant decline, consistent with the observed data. However, the decline is more statistically significant in the deseasoned data (Figure 8).

Figure 7. (a) PM_{10} and (b) $PM_{2.5}$ levels at a monitoring station in Hyderabad



Source: Authors' analysis

Figure 8. Trend plots for PM_{10} levels at a monitoring station in Hyderabad: (a) observed data and (b) deseasoned data, *p<0.05 and ***p<0.001.



Source: Authors' analysis

3.3 Deweathering

This method is suitable when the objective is to quantify emission-driven changes in air quality and evaluate the effectiveness of air quality policy interventions.

Purpose

Meteorological normalisation, or deweathering, accounts for meteorological variability by estimating pollutant concentrations under average meteorological conditions. The technique enables observed trends to be more directly linked to changes in emissions rather than variations in meteorological conditions.

Inputs and data

- This method requires at least three to five years of hourly air quality data.
- Additionally, hourly data of meteorological variables—namely, temperature at a 2-metre height above 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) from weather stations or reanalysis data—are required (Verma et al. 2025). It must be ensured that the meteorological data are at the same time resolution as the air quality data. If the analysis is conducted at the level of individual monitoring stations, meteorological data recorded at each CAAQMS may be used.
- Time variables, such as hour of the day, Julian day (day of the year), weekday, and Unix date (the number of seconds elapsed since 1 January 1970 at 00:00:00 UTC), are also considered. These time variables can serve as proxies for emissions, as emissions are often associated with the time of day and the day of the year (Derwent 1995; Grange and Carslaw 2019).

Methodology

Meteorological normalisation involves adjusting the meteorological inputs to a trained model while preserving the time variables, and then predicting pollutant concentrations (Grange et al. 2018; Vu et al. 2019). To conduct meteorological normalisation, a machine learning model is first trained to capture the relationships between pollutant concentrations, meteorological variables, and time variables. The data should then be divided into training and testing sets, usually in an 80:20 or 70:30 ratio.

As these relationships are non-linear, a non-parametric, tree-based model, such as gradient-boosted decision trees (GBDT), can be used (Ma et al. 2021). The Scikit-learn library in Python offers an implementation of this approach through the histogram gradient boosting regressor (HGBT), which is faster than standard gradient boosting methods for data sets containing more than 10,000 samples. The model uses the meteorological and time variables mentioned earlier as input features and pollutant concentration as the target variable.

Meteorological inputs are then repeatedly shuffled 1,000–2,000 times while the time variables are held constant, and the trained model is used to predict concentrations under a range of meteorological conditions. This process predicts pollutant concentrations under average meteorological conditions. Model performance can be assessed using the R^2 value, mean absolute error (MAE), root mean squared error (RMSE), mean bias error (MBE), mean absolute percentage error (MAPE), and the Pearson correlation coefficient (R). Studies have found that these machine learning techniques struggle to handle extreme values. For example, when observed $PM_{2.5}$ values exceed 400 µg/m^3, the model underpredicts concentrations by an average of 90.7 µg/m^3 (Verma et al. 2025; Makhdoomi et al. 2025).

The codes for machine learning–based meteorological normalisation are available here—Verma, Shubhi. n.d. Deweathering Data and Codes. GitHub repository. Accessed March 15, 2026.

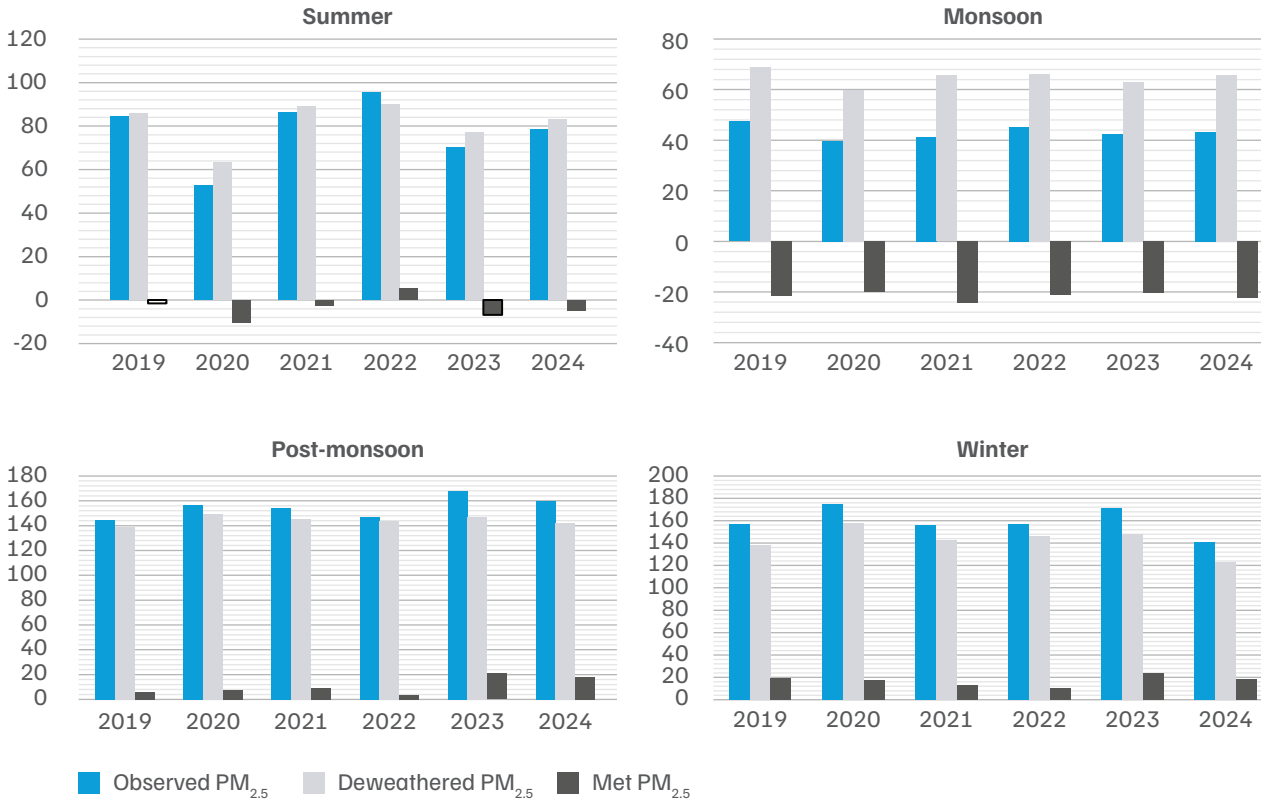
Example

To understand how emissions and meteorology interact across the year, we divided the data into four seasons: summer (March–May), monsoon (June–September), post-monsoon (October–November), and winter (December–February). When applied elsewhere, analysts can adapt the classification of seasons to reflect local seasonal conditions. For each season, the average observed concentration, average deweathered concentration, and meteorological effect (the difference between the observed and deweathered concentrations) must be calculated.

We obtained the following results when we applied this method to assess air quality trends in Delhi. During the monsoon season, meteorological conditions improved air quality, with precipitation and higher wind speeds reducing $PM_{2.5}$ and PM_{10} concentrations. In contrast, during the post-monsoon and winter seasons, these factors contributed to higher $PM_{2.5}$ concentrations (Figure 9). More importantly, even after accounting for meteorological effects, deweathered $PM_{2.5}$ concentrations remained substantially higher during the post-monsoon and winter seasons than during the summer and monsoon seasons. This shows that severe winter air pollution episodes are not solely weather-related phenomena. Rather, meteorology acts as a multiplier of air pollution, while high emissions remain the primary driver.

> Meteorological factors can help reduce ambient $PM_{2.5}$ levels during monsoon while contributing to worse air quality during winter.

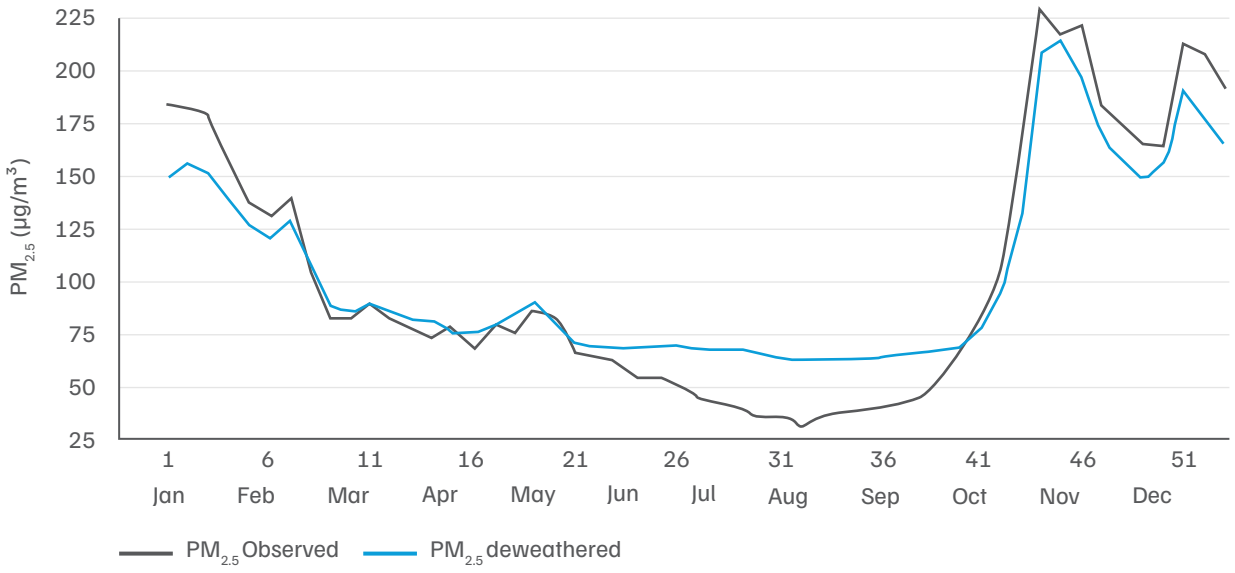
Figure 9. Meteorology can reduce $PM_{2.5}$ by up to 33 per cent during the monsoon but increase it by ~12 per cent during winter in Delhi.



Source: Authors' analysis

The meteorological effect (Met Effect) represents the contribution of meteorological conditions to ambient pollutant concentrations and is estimated as the difference between observed and deweathered concentrations.

Figure 10. A double winter peak characterises Delhi's annual $PM_{2.5}$ cycle



Source: Authors' analysis

In Figure 10, an increase in observed and deweathered $PM_{2.5}$ concentrations is noted beyond the first week of October (week 41). This can be attributed to unfavourable meteorological events during the winter weeks and anthropogenic activities—such as stubble and biomass burning for space heating—contributing to a spike in air pollution.

Box 3. Case study from COVID-19

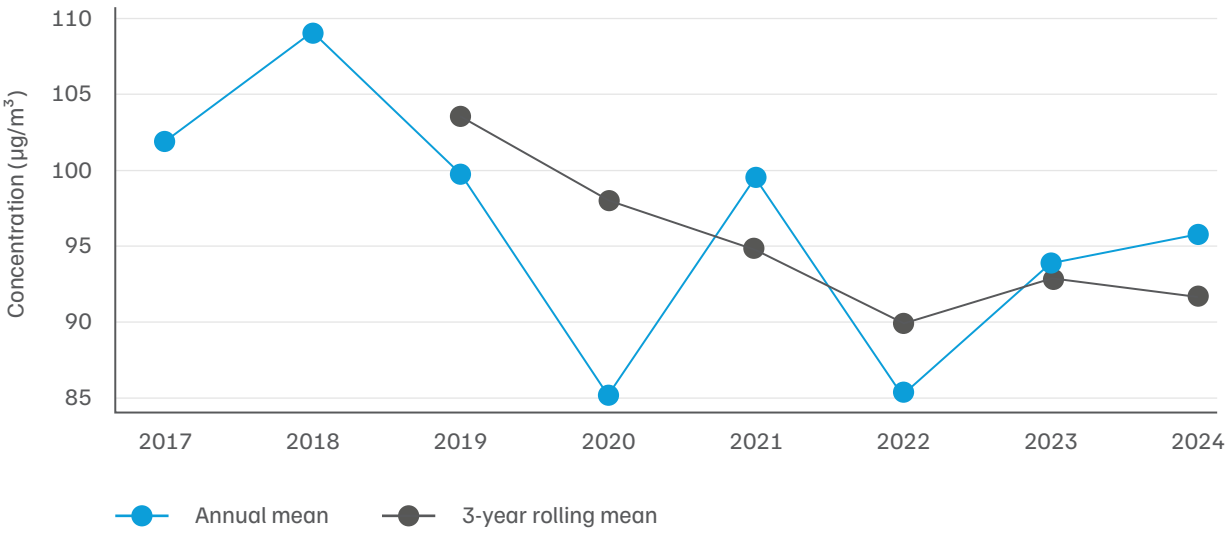
The COVID-19 pandemic lockdown in 2020 provides an effective case study for analysing the impact of a sudden event. During the Government of India's nationwide restrictions, transport activity declined, construction slowed, and various industries were forced to shut down temporarily. In Delhi, $PM_{2.5}$ concentrations decreased by 32 µg/m^3 between March and May 2020 compared with the same period in 2019, while deweathered $PM_{2.5}$ concentrations declined by 22 µg/m^3. The considerable reduction persisted even after accounting for meteorological factors, indicating that it was primarily driven by the lockdown-induced decline in anthropogenic activities. However, it is important to note that the reduction in concentrations during the lockdown period was reversed during the post-monsoon and winter seasons of 2020. Further, a peak was observed in deweathered $PM_{2.5}$ concentrations during the winter season of 2020–21, possibly reflecting the relaxation of restrictions and the subsequent resumption of economic activities. For further information, please refer to Verma et al. (2025).

4. Comparison of the analytical approaches used for trend assessment

This section uses Mandir Marg in Delhi as a case study to apply all three methods and evaluate the overall trends and insights emerging from each analysis. These methods are independent assessment approaches that may be applied individually depending on the study objectives and data availability; they are not intended to be used sequentially.

As seen in Figure 11a, fluctuations are sharper with annual averages than with rolling means (i.e., averaging over three years at a time). Broadly speaking, a rolling mean provides a clearer picture of long-term trends. The downward trend in the rolling mean indicates a slow but steady improvement in air quality at the sample site. However, annual fluctuations highlight that short-term factors, such as weather conditions or events such as lockdowns, still strongly influence pollution levels.

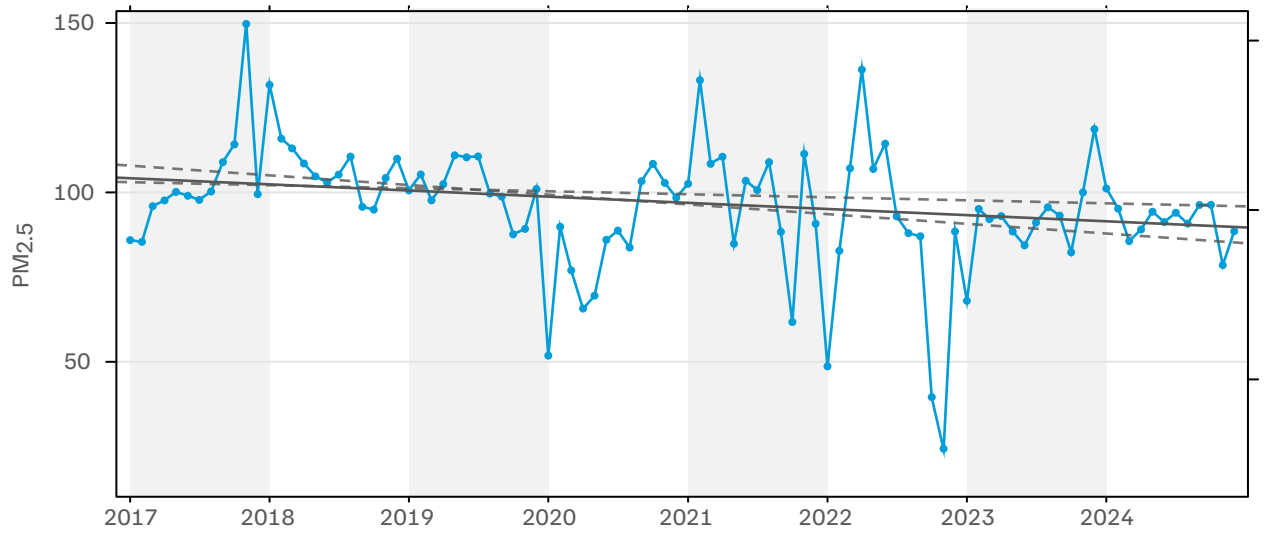
Figure 11a. Annual mean and three-year rolling average of $PM_{2.5}$ concentrations at Mandir Marg, New Delhi (2017–24)



Source: Authors' analysis

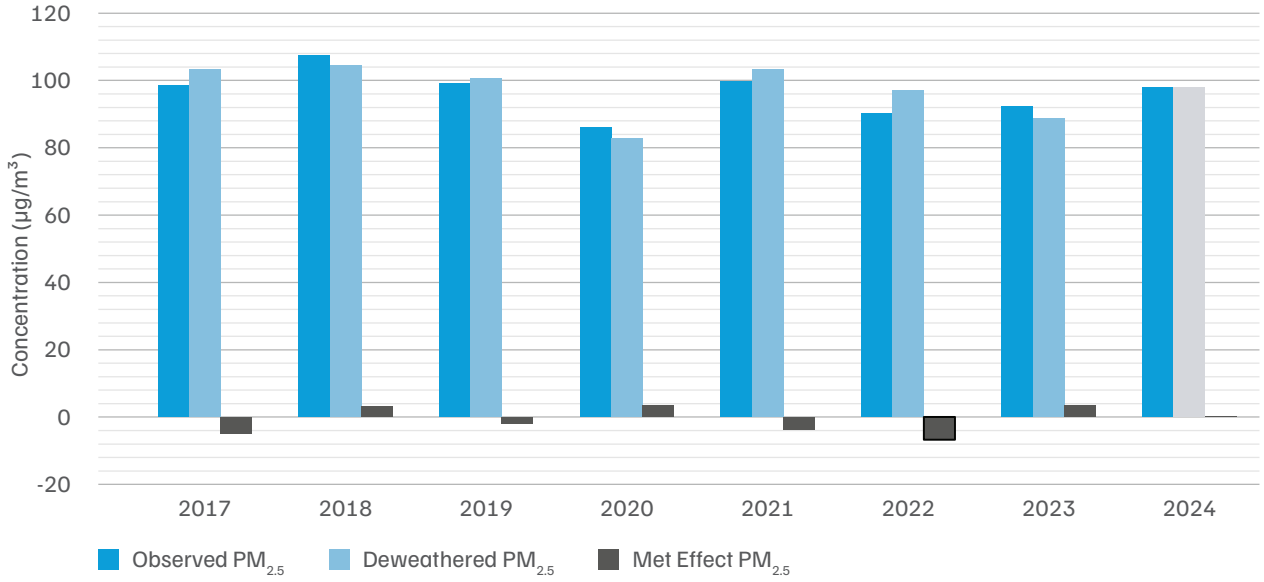
Figure 11b shows the trend plots of deseasonalised data, analysed using the Mann–Kendall test and Theil–Sen slope estimator. In this case, the slope of −1.8 µg/m³/year with confidence interval [−2.9, −0.9] shows a statistically significant decline in $PM_{2.5}$ concentrations during 2017–24. This indicates a downward trend in $PM_{2.5}$ levels at this site. This helps distinguish long-term structural changes from predictable seasonal variability. However, this method does not fully account for meteorological influences or irregular episodic events.

Figure 11b. Deseasonalised $PM_{2.5}$ trends at Mandir Marg, New Delhi (2017–24), ***p<0.001



Source: Authors' analysis

Figure 11c. $PM_{2.5}$ at Mandir Marg shows no consistent decline over 2017–2024



Source: Authors' analysis

Figure 11c shows the annual averages for observed and deweathered $PM_{2.5}$, along with the meteorological effect derived through meteorological normalisation. Here, the observed concentration of $PM_{2.5}$ shows a decreasing trend of −1.10 µg/m³/year, although it is statistically insignificant ($p = 0.315$). Similarly, the deweathered concentration registers a weak trend of −1.27 µg/m³/year, which is also statistically insignificant ($p = 0.323$). The meteorological effect likewise does not show any significant trend (0.18 µg/m³/year; $p = 0.797$). Here, the observed declines are partly influenced by meteorological factors in some years. The deweathered $PM_{2.5}$ concentrations do not exhibit a strong long-term decline, so there is limited evidence of a sustained emission-driven reduction over the study period. The most pronounced emission-related reduction appears around 2020, but it was not maintained consistently afterwards and was likely associated with the COVID-19 lockdowns (Box 3).

A limitation of the deweathering method is its dependence on additional data sets, including modelled reanalysed meteorological data sets, which may not capture local meteorological conditions. This limitation can be mitigated by using meteorological observations recorded at co-located weather monitoring stations alongside real-time air quality monitors.

5. Conclusion

India has made significant efforts to enhance its air quality monitoring networks, resulting in the generation of a significant amount of data on ambient air pollution levels. The next step is to create and implement methods to analyse and interpret these data to evaluate progress towards air quality goals. There is a strong need for a scientifically robust framework for air quality trend assessment in Indian cities that describes methods for data cleaning and analysis. Seasonal and meteorological conditions influence air quality trends in Indian cities. Hence, comprehensive statistical approaches are needed to account for these influences on pollutant concentrations.

These approaches can provide a more robust assessment of the effectiveness of emission-reduction programmes. Each method discussed in this brief, namely the three-year rolling average, deseasonalisation, and deweathering, serves a unique purpose in air quality assessment and should be applied appropriately, with clear guidance on its correct and effective use. This document can serve as a practical framework for conducting a scientifically robust long-term trend assessment of particulate matter in India.

Acronyms

AQI	air quality index
BLH	boundary layer height
CAAQMS	continuous ambient air quality monitoring station
CAQM	Commission for Air Quality Management in National Capital Region and Adjoining Areas
CPCB	central pollution control board
CTMs	chemical transport models
GBDT	gradient-boosted decision trees
LOESS	locally estimated scatterplot smoothing
MAE	mean absolute error
MAPE	mean absolute percentage error
MBE	mean bias error
MoEFCC	Ministry of Environment, Forest and Climate Change
MoF	Ministry of Finance
MSL	mean sea-level pressure
MTPR	mean total precipitation rate
NAAQS	National Ambient Air Quality Standards
NCAP	National Clean Air Programme
PM	particulate matter
RH	relative humidity
RMSE	root mean squared error
SSR	surface solar radiation
STL	seasonal and trend decomposition using LOESS
T2M	two-metre temperature
TCC	total cloud cover
US EPA	United States Environmental Protection Agency
UTC	coordinated universal time
WD	wind direction
WS	wind speed

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