Assessment of Changes in Air Quality in Indian Cities Since the Launch of the **National Clean Air Programme**

HEI
Health Effects Institute

A city skyline shrouded in fog

About This Report

This report adopts a robust scientific framework to assess changes in air quality across Indian cities since the inception of the National Clean Air Programme (NCAP). It examines data availability and improvements in air quality as measured by real-time particulate matter, PM_{10} and $PM_{2.5}$ between 2017-2024. This report tests available methodologies to understand air quality trends while accounting for confounding factors such as data quality and meteorology. Based on the findings, the report provides recommendations that can be applied while assessing the air quality trends and efficacy of air quality regulations in the Indian context.

How Can I Explore the Data?

A summary of data and code is available on GitHub: *https://github.com/IndiaAQ-NCAP/IndiaAQ_Assessment*.

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Executive Summary

Dust rising from the roads in Rishikesh, India

Purpose

Air pollution levels in India continue to be high, significantly impacting public health and well-being. In response, over the last two decades, India's national, state, and local governments have implemented various measures to improve air quality, including the National Clean Air Programme (NCAP) in 2019. There is a growing need to assess the effectiveness of these new policy interventions. A further impetus for program evaluation is provided by the fact that 2024 marked the end of the first phase the NCAP and its associated goal, along with coupling of fund allocation and city performance under the NCAP. While funding for air quality in cities is now partly performance-linked, no standardized guidance has been developed for assessment of year-on-year changes in air quality or analysis of pollutant trends over longer periods of time. Thus, a key question remains: how can improvements in air quality be assessed in a consistent manner across cities?

Scope

This report evaluates changes in air quality since the launch of the NCAP in 2019, with a focus on particulate matter (PM_{10} and $PM_{2.5}$). We apply multiple analytic approaches to detect trends, explicitly accounting for data completeness, seasonality, and meteorological influences. The analysis uses regulatory-grade, real-time data from government-run continuous ambient air quality monitoring stations (CAAQMS) spanning 2017–2024 , with 2017 as the NCAP baseline year and allowing us to examine conditions both before and after the programme's launch in 2019. Changes in air quality were assessed at the station level, rather than through citywide averages, because city averages can mask hyperlocal variations. For this analysis, a strict set of completeness criteria was adopted: stations had to report pollutant data for at least 18 hours each day, 23 days each month, and 11 months each year. For trend assessment, only stations with data available for at least 3 consecutive years were included.

Key Findings

The number of monitoring stations and data availability has improved since 2017.

The number of $PM_{2.5}$ monitoring stations grew by 344%—from 78 across 38 cities in 2017 to 346 in 101 cities by 2024. The number of PM_{10} monitoring stations rose 462%, from 61 in 33 cities to 343 in 102 cities. Data availability and completeness also improved: by 2024, ~82% of stations met completeness criteria, up from ~18%–22% in 2017. However, coverage remains uneven — some large cities have many stations, while others have one, and rural areas are still largely unmonitored.

Annual data availability thresholds alone are insufficient, as they can miss seasonal and peak pollution episodes.

Even with 75% data availability, gaps of more than 2 months, and in some cases up to 3 months, can occur, potentially omitting an entire season. Hence, applying granular completeness criteria (data for at least 18 hours each day, 23 days each month, and 11 months each year) can provide a more representative picture.

Compliance against annual NAAQS:

Between 2017 and 2024 the number of stations exceeding the annual NAAQS has remained largely unchanged for PM_{10}, with over 90% of stations exceeding the limit each year. In contrast, for $PM_{2.5}$ the stations exceeding the annual NAAQS decreased by 33% over the same period, with a steady rate of decline observed year after year. Nevertheless, over 60% of monitoring stations continue to exceed the annual NAAQS for $PM_{2.5}$. The Delhi National Capital Region (NCR) cluster dominates the list of the most polluted stations for both metrics, underscoring persistent regional hotspots.

The assessment of annual NAAQS exceedance days showed inconsistent results across stations and proved unreliable for capturing long-term trends.

Exceedance counts are binary and insensitive to magnitude, and at both the station and city levels they fail to provide a consistent trend.

Deseasonalization and meteorological normalization sharpen the signal.

After removing seasonal cycles, the number of stations with statistically significant trends more than doubled for both PM_{10} and $PM_{2.5}$. Meteorological normalized series increased the share of stations with statistically significant trends even further (e.g., PM_{10}: 23% → 80%; $PM_{2.5}$: 26% → 69%), revealing underlying improvements that weather variability had masked. These tools are powerful for research and accountability studies; for routine reporting, deseasonalization is simpler and more transparent.

When compared to the 2017 baseline, more than half of the stations show declining trends.

For PM_{10} levels, 66.5% of the 209 stations analyzed showed decreases, while 33.5% showed increases. For $PM_{2.5}$ levels, 67.7% of the 211 stations analyzed showed decreases, and 32.2% showed increases.

Absolute change between 2 years can be misleading.

Two-point comparisons are sensitive to anomalous baseline/final years (e.g., lockdown dip or one-off spikes). 3-year rolling averages provide more reliable signals of sustained change over time.

Station-level averages offer better representation of local variation than city-wide averages.

In cities with multiple monitoring stations, some locations improved while others worsened in the same year. Citywide averages can flatten these differences and lead to incorrect assessment of changes in air quality.

Interpretation and Attribution

The temporal overlap of national interventions (e.g., adoption of Bharat Stage (BS)-VI mission standards and expanded access to liquified petroleum gas (LPG)), state and local measures, economic dynamics, and meteorology complicate attribution of changes in air quality to the NCAP alone. Timing for fund allocation also vary widely by city. Overall, the findings indicate that the emphasis must be on tracking performance over time using consistent data and analysis methods.

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Crop residue burning in Punjab, India

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01 Introduction

20 lakh

In 2023, air pollution was the leading risk factor for deaths in India, responsible for more than 20 lakh deaths (25% of all deaths).

Air pollution is the leading risk factor for deaths in India, responsible for more than 2 million (20 lakh) deaths (25% of global air pollution deaths) in 2023 (HEI 2025). Around 68% of the population lives in areas where $PM_{2.5}$ levels exceed the annual National Ambient Air Quality Standard (NAAQS) of 40 µg/m³ (HEI 2025). Beyond the health impacts, air pollution also has serious economic impacts. Reduced productivity, work absences, and premature deaths caused by air pollution cost the Indian economy an estimated 95 billion US dollars (~₹7 lakh crore), approximately 3% of the country's gross domestic product (GDP) in 2019 (CII et al. 2021).

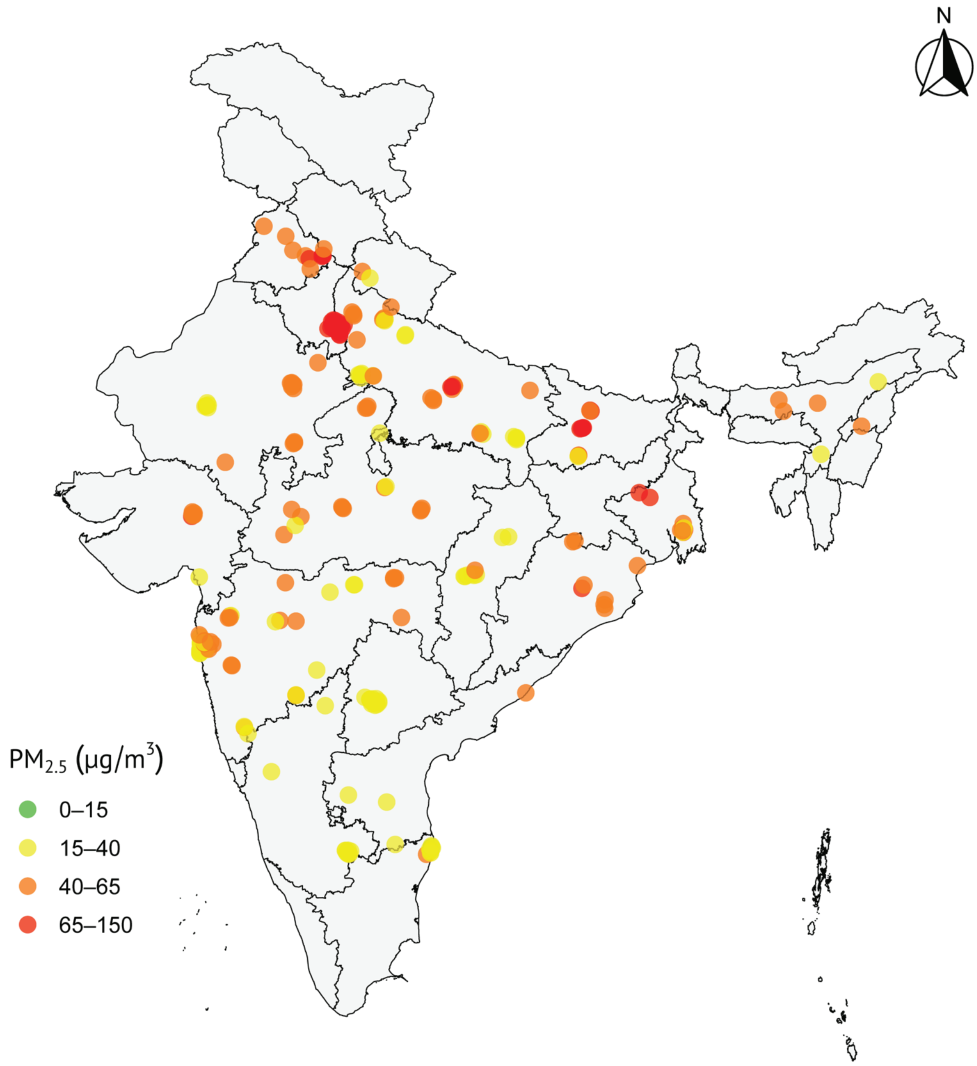


Figure 1. Annual average $PM_{2.5}$ concentrations across 95 cities in 2024.
The figure includes only the stations that met the study's completeness criteria: at least 18 hours of data each day, 23 days each month, and 11 months each year. Source: Central Pollution Control Board, India.

Air Quality Policy Landscape in India

India's air quality landscape has evolved over the years, in line with the growing recognition of air pollution as one of the major environmental and public health challenges (**Figure 2**). India's first NAAQS were introduced in 1982 for four pollutants — suspended particulate matter, sulphur dioxide, nitrogen dioxide, and carbon monoxide. Updates in 1994 and 1998 added PM_{10}, lead, and ammonia (CPCB 1994, 1998).

The 2009 revision expanded the list to include $PM_{2.5}$, ozone, arsenic, nickel, benzene, and benzo[a]pyrene (CPCB 2009). In 2021, the Central Pollution Control Board (CPCB) created a technical expert committee to review and revise the NAAQS. The revised standards are set to be released after a period of more than 15 years, although the timeline is not clear.

1981
Air (Prevention and Control of Pollution) Act

1982
Notification of National Ambient Air Quality Standards (NAAQS)

1984
National Air Quality Monitoring Programme (NAMP)

1986
Environment (Protection) Rules

1989
Motor Vehicles Rules

1991
First industry-specific emission standards (cement, iron and steel, and thermal power plants)

1994
First revision of NAAQS

1998
Formulation of Environment Pollution (Prevention and Control) Authority (EPCA)

Second revision of NAAQS

2000
Introduction of Bharat Stage Emission Standards

2003
National Auto Fuel Policy

2009
Latest revision of NAAQS

2010
Nationwide Implementation of Bharat Stage III

National Green Tribunal

National Solar Mission

2014
Swachh Bharat Mission

Directions for the installation of Continuous Emission Monitoring Systems (CEMS) in 17 categories of highly polluting industries

Unnat Chulha Abhiyan

2015
National Air Quality Index (AQI)

Revision of emission standards for thermal power plants

2016
Pradhan Mantri Ujjwala Yojana (PMUY)

2019
National Clean Air Programme (NCAP)

2020
Leapfrogging to Bharat Stage VI

2021
Formulation of Commission for Air Quality Management

Figure 2. **Timeline of air quality policy interventions in India.**

National Clean Air Programme (NCAP)

A comprehensive initiative aimed at improving air quality at the city level. It aims to reduce particulate matter levels and focuses on monitoring, emission reduction across multiple sectors, and public awareness to enhance air quality nationwide.

In January 2019, the Ministry of Environment, Forest and Climate Change (MoEFCC) launched the National Clean Air Programme (NCAP) with the goal of improving air quality; the Programme has largely focused on city-level actions. The NCAP aims to reduce PM_{10} and $PM_{2.5}$ levels and focuses on monitoring, emission reduction across multiple sectors, and public awareness to enhance air quality nationwide. Initially, the NCAP targeted a 20%–30% reduction in PM_{10} and $PM_{2.5}$ concentrations by 2024 in 102 cities. Based on directions from the National Green Tribunal, 20 additional cities were later added to the list, making it 122 cities in August 2019. In 2020, two more cities were included, bringing the total to 124. All the determined cities are called *nonattainment cities*, which have not met NAAQS for more than 5 years. In addition, 42 cities across India were identified as Million Plus Cities (population of over a million) by the 15th Finance Commission. Out of these 42 cities, 34 were already included under the NCAP, and 8 more cities were added, raising the number to 132. As part of recent redistricting, Asansol and Raniganj were combined into a single city, and Patancheru was merged with Hyderabad; this has reduced the total number of NCAP cities to 130.

In September 2022, the target was revised to reduce PM_{10} levels by up to 40% or meet national standards by 2025-26 across 130 nonattainment cities. Out of 130 cities, more than 40 million-plus cities are funded under the 15th Finance Commission Million-Plus City Challenge Fund with an air quality performance grant, and the remaining cities are funded under the MoEFCC's Control of Pollution Scheme. The 130 nonattainment cities have developed city action plans outlining source-specific actions categorized into short, medium, and long-term measures; the city action plans were approved by the CPCB (Ganguly et al. 2020). It is important to note that that the classification of nonattainment cities under the NCAP is based on the manual monitoring data from the National Air Quality Monitoring Programme, India's network of manual air quality monitors. Thus, cities that did not have operational air quality monitoring stations were not included in the classification, and those which do not meet the 104 days of monitoring data criterion were also not part of the classification. As a result, many cities with high levels of ambient air pollution, including several cities in the Indo-Gangetic Plains, are not included under nonattainment cities in NCAP.

City skyline under hazy conditions

Between financial years 2019–2020 and 2025–2026, the funds released to NCAP cities and states under the 15th Finance Commission amounted to ₹11021 crore for the 42 million-plus cities and seven Urban Agglomerations, while the remaining cities received allocations totaling ₹2395 crore (CPCB 2025). This reflects a significant variation in the allocation of funds. The years in which funds were allocated also varied across cities, indicating that the initiation of NCAP activities was not uniform across cities. Among the allocated funds, around 67% has been directed toward dust mitigation efforts, indicating that more than half of the total funding was dedicated to controlling road dust (CSE 2025).

Determination of the status of nonattainment cities, as well as estimation of improvements in air quality, is largely conducted using data from the manual monitoring stations or through integration of manual and Continuous Ambient Air Quality Monitoring Stations (CAAQMS) data. Cities are mandated to report on annual progress in air quality improvements for demonstrating progress to secure air quality funding under the NCAP and the 15th Finance Commission and for the annual Swachh Vayu Survekshan (SVS) rankings based on cities' efforts to improve air quality. The evaluation performance criteria for the funding and SVS ranking are different. For allocation of funds, cities are assessed on four key factors: (1) strengthening pollution monitoring systems, (2) conducting source-wise analysis of air pollution, (3) demonstrating progress on their action plans and compliance with statutory guidelines, and (4) quantifying improvements in air quality.

For allocation of funds, cities are assessed on 4 key factors:

1. Strengthening pollution monitoring systems
2. Conducting source-wise analysis of air pollution
3. Demonstrating progress on their action plans and compliance with statutory guidelines
4. Quantifying improvements in air quality

Since 2022, the 15th Finance Commission has allocated 100% weight to the amount of air quality improvement in the city performance assessment. The SVS ranking is based on measures taken to reduce emissions from sources such as biomass burning, municipal solid waste, road dust, construction and demolition waste, vehicular emissions, industrial activities, and other sources, along with public awareness initiatives and improvements in PM_{10} concentrations. Air quality improvement is given a relatively low weight of 2.5% among all the factors.

Both the Ministry of Environment, Forest and Climate Change (MoEFCC) and Ministry of Finance (MoF) have provided guidance documents for assessing air quality improvements (**Table 1**).

A cyclist riding through a hazy street

Table 1. Guidelines for Assessment of Air Quality Improvements in Indian Cities

PARAMETER(S)	GUIDELINE FROM MOEFCC[a]	GUIDELINE FROM MOF[b]
Annual Assessment Period	April 1 to March 31	April 1 to March 31
Data	Integrated set of manual and continuous monitoring station data	As defined by MoEFCC
Metric for Evaluation of Progress	**Performance factor (P) (on total score of 100):** $P = 100 \times R(A)/R(T)$ R(A) = actual reduction in PM_{10} for the assessment year R(T) = targeted reduction of PM_{10} for the assessment year	**Combined performance factor for ranking cities:** Reduction in PM_{10} levels and Frequency of daily AQI exceedance
Other Considerations for Data Assessment	**Data adjustments:** Data unavailable for a few days can be computed using linear interpolation. However, data missing continuously for more than 30 days is not considered. **Data cleaning:** Outliers are removed using $\pm 2\sigma$ **Data exclusion:** If cities with less than 75% of data are available for particular quarter, reported data for the particular quarter is not considered for reporting.	**Reduction in PM_{10} levels:** Improvement is defined as the percentage reduction in 98th percentile value on normal days[c] vs. baseline. ≥15% reduction → "High" improvement <15% reduction → "Low" improvement **Frequency of AQI exceedance:** Measures good days[d] per year with AQI < 200 ≥15% increase in good days → "High" improvement <15% increase in good days → "Low" improvement The performance factor is assigned as follows: High reduction and High good air days → 100 Low reduction and High good air days → 75 High reduction and Low good air days → 50 Low reduction and Low good air days → 25

[a] Guidelines for release and use of funds under the National Clean Air Programme.
[b] Operational guidelines for implementation of recommendations on Urban Local Body grants [Ambient Air Quality Component]. AQI = Air Quality Index.
[c] Normal days defined by cities with meteorological department analysis.
[d] Good days = AQI < 200.

Why is the Air Quality Index (AQI) not a useful metric for evaluating changes in air quality over time?

AQI is a tool for public communication and is typically used to communicate information about the quality of the air and related health advisories to the public. The metric is not designed to quantify long-term air quality improvements.

In India, AQI is calculated based on the maximum subindex of at least three pollutants among the eight that are regularly monitored (CPCB 2014). It represents the worst subindex of the AQI for that location. For instance, if $PM_{2.5}$ dominates the AQI and its levels improve, the AQI may still remain high due to another pollutant (e.g., ozone). Therefore, AQI does not reflect cumulative air quality improvement across all pollutants. To assess long-term trends in air quality and impact of policies such as the NCAP, it is critical to conduct analyses using pollutant concentration data. AQI can, for instance, hide the magnitude of change; for example, a decrease of 100 $\mu g/m^3$ in $PM_{2.5}$ might still fall within the same AQI band (Very Poor category: 121–250 $\mu g/m^3$). In India, AQI is calculated based on the city average. Studies have reported that the number of monitors active on a day in major cities such as Hyberabad and Bengaluru have high variance. Thus, the AQI calculated with high variance will may not be comparable and useful for policy purposes (Dammalapti and Guttikunda 2024).

Air Quality Monitoring Networks in India

Regulatory air quality monitoring in India is mandated by the Air (Prevention and Control of Pollution) Act of 1981 and is overseen by the CPCB. The regulatory monitoring network is currently composed of manual monitors under the National Air Quality Monitoring Programme (NAMP) and real-time continuous ambient air quality monitoring stations (CAAQMS). The manual monitors are set up under the National Air Quality Monitoring Programme (NAMP), and each monitor collects data for up to 104 days each year. Manual monitors work on the gravimetric principle, where particulate matter samples are collected on a filter paper that needs to be replaced periodically. As a result, observations are not available on a daily basis. The CAAQMS provide real-time air quality data at intervals ranging from 15 minutes to 1 hour. Data from this network is available on national and some state-level government portals. For both the NAMP and the CAAQMS, most stations are in urban areas, with sparse coverage in rural areas; so far, only 26 manual monitors are available in rural locations across all of India. As of July 2025, 128 NCAP cities have manual monitoring stations while 102 cities have CAAQMS (**Table 2**). Vasai-Virar and Mumbai in Maharashtra are two cities that do not have manual monitoring stations. Of note, there were three manual monitoring stations in Mumbai until October 2024. In addition, there are a variety of reference grade monitors run by research and academic institutions, as well as a number of low-cost sensor networks across the country (**Figure 3**).

AIR QUALITY MONITORING SYSTEMS[a]

Regulatory Compliance[b]

Manual Monitors

National Air Quality Monitoring Programme (NAMP)

State Ambient Air Quality Monitoring Programme (SAMP)

Resolution

Spatial
1018[c] monitors in 437 city/town/village

Temporal
24-hour average data for 104 days in a year

Real-time Monitors

Continuous ambient air quality monitoring (CAAQMS) by CPCB and SPCBs/PCC

Resolution

Spatial
562 monitors in 292 city/town

Temporal
15 minutes–1 hour

Forecasting and Early Warning

System of Air Quality and Weather Forecasting and Research (SAFAR[d])

Resolution

Spatial
42 monitors in 4 cities

Air Quality Early Warning System for Delhi

Joint Pilot Initiatives

Low-cost sensor networks (e.g., Kanpur/ Bihar)

Super site — Real-time Advanced Air Source Management Network (R-AASMAN) in Delhi

Satellite and Remote Sensing

Ocean Colour Monitor by ISRO — Aerosol Optical Depth (AOD)

Satellite-based Application for Air Quality Monitoring and Management at National Scale (SAANS)

Resolution

Spatial
1 km × 1 km

Research

Modelling Atmospheric Pollution and Networking (MAPAN) in 20 cities

Atmospheric Observatory in Sonipat

SPARTAN network in Kanpur

COALESCE network in Bhopal, Mesra, Mysuru

IGP-CARE in Hamipur

[a] The list may not be exhaustive and provides an overview of publicly available information.
[b] Numbers accessed from the PRANA portal as of November 19, 2025. From 2021, the manual monitoring data is integrated with the continuous monitoring data.
[c] This number does not include monitors under SAMP.
[d] Provides information in the form of the Air Quality Index (AQI), but individual pollutant levels are not publically available.

National Air Quality Monitoring Programme (NAMP): *https://cpcb.nic.in/manual-monitoring/*.
Continuous Ambient Air Quality Monitoring (CAAQMS) by CPCB and SPCBs/PCC: *https://airquality.cpcb.gov.in/ccr/#/login*.
System of Air Quality and Weather Forecasting and Research (SAFAR): *https://safar.tropmet.res.in/*.
Air Quality Early Warning System for Delhi: *https://ews.tropmet.res.in/*.
Ocean Colour Monitor by ISRO, Aerosol Optical Depth (AOD): *https://www.isro.gov.in/PreciseAirQualityMonitoring.html?form=MG0AV3*.
Satellite-Based Application for Air Quality Monitoring and Management at National Scale (SAANS): Available on request. Contact Dr. Sagnik Dey, Indian Institute of Technology (email: *sagnikdey.iitd@gmail.com*).

Figure 3. Air quality monitoring systems in India.

Pedestrians walking through road dust

Table 2. Status of Air Quality Monitoring Stations in India[a]

	Number of monitoring stations	
	2017	2025
Number of manual air quality monitoring stations	703	1,018
Number of CAAQMS	124	562

[a] The NCAP target is 1500 for manual stations and 150 for CAAQMS. Source: Prana Portal and CPCB official website [accessed 19 November 2025].

02 Objectives and Scope

From the above discussion, it is clear that several steps have been taken by the Indian government and a significant amount of funding has been dedicated toward air quality management. There is a strong case for estimating changes in air quality in a scientifically robust manner, and by extension, estimating possible benefits, if any. Also, funding is partially tied to the performance of the cities. Different methods adopted by different groups have shown varying results, and meteorology plays an important role in the context of pollution reduction. Moreover, there has been an increase in the availability of air quality data, and it is useful to assess how much of this data is in a usable form to identify meaningful trends over time.

This study is not intended as a performance report card for cities in terms of air quality improvement. Instead, the objective is to explore how air quality trends appear when represented using different indicators, how various analytical approaches affect the interpretation of those trends, and how the data itself behaves under different conditions.

Objectives of the assessment:

1. Assess temporal trends in the levels of $PM_{2.5}$ and PM_{10} across NCAP cities between 2017 and 2024
2. Develop a standardized and replicable framework for trend assessment in Indian cities that incorporates data quality filters, statistically sound trend detection methods, and meteorological adjustments, making it suitable for performance evaluation for the NCAP in the long term

The scope of the work is limited to the following parameters and methodological choices:

- **Time period**
  2017–2024
- **Locations**
  102 NCAP cities where CAAQMS data are available
- **Pollutants**
  PM_{10} and $PM_{2.5}$. *Note the NCAP targets are set on the basis of* PM_{10}.
- **Data type**
  Real-time data from CAAQMS is used; manual monitoring data is excluded. Furthermore, data from low-cost sensors was not used, in part because such data has not yet been used for regulatory applications in India and there remain specific quality assurance and quality control considerations.
- **Methods**
  Air quality trends are assessed using individual station averages, not aggregated city-level averages. Station-level averages are used for the assessment over citywide averages, as variations in monitor operation such as shutdowns or restarts may distort overall values. They also ensure that localized pollution patterns are accurately represented.
- Weather normalization is performed using a limited set of meteorological variables including temperature, boundary layer height, relative humidity, wind direction, wind speed, precipitation, and atmospheric pressure to account for the influence of meteorology on pollutant levels.

03 Approach

Data

Note: All analyses use CAAQMS data retrieved on April 30, 2025; counts and tables reflect this date.

Regulatory-grade, real-time air quality monitoring data from 2017 to 2024 was used for this analysis. Data for all NCAP cities was retrieved from the Central Control Room for Air Quality Management — All India repository through Earthmetry. Raw data was subject to a three-level quality check: first, abnormally high values were filtered (PM_{10}: 2,000 µg/m³; $PM_{2.5}$: 1,600 µg/m³); next, two jump tests were conducted — one within 15 minutes and another within 20 to 76 minutes; and finally, any data where $PM_{2.5}$ values exceed PM_{10} were removed.

The meteorological data was sourced from the ERA5 reanalysis dataset (Hersbach et al. 2020). The following parameters were obtained for the assessment: boundary layer height, air temperature (measured 2 m above the ground level), relative humidity (derived from temperature and dew point temperature), wind direction (10 m above the surface), wind speed (10 m above the surface), precipitation, and atmospheric pressure (surface level). All values were obtained at district level at ~31 km resolution.

Data Availability

The annual availability of data for $PM_{2.5}$ and PM_{10} data across monitoring stations for every year between 2017 and 2024 was calculated.

The percentage data availability was further categorized into thresholds of >95%, >85%, and >75% to assess how many stations met each criterion over the years. Using these categories, we also examined the variability in data availability across states and cities. Establishment of each monitor was determined based on when the data from a particular location became available, and data for the first year was excluded. This was important because several monitors began operations partway through the year, which could have an impact on the data availability as well as annual average concentrations.

Data Completeness

Data completeness was assessed through application of sequential criteria at the hourly, daily, and monthly scales.

- A day was considered valid if it had at least **18 hours** of pollutant data.
- A month was considered valid if it had at least **23 valid days**.
- A year was considered valid if it had at least **11 valid months.**

Only those stations that met this annual completeness criteria were considered for further analysis.

Furthermore, based on the annual completeness criteria, stations were grouped into three categories for detailed evaluation:

- Stations that met the annual completeness criteria for at least **5 years**
- Stations that met the annual completeness criteria for at least **3 years**
- Stations that met the annual completeness criteria for **1 to 2 years**

To conduct trend analysis, only those stations that met the data completeness criteria for at least three continuous years were considered.

Note: The completeness criteria defined here apply only to particulate matter. For other pollutants, such as gaseous pollutants, different criteria and modified analysis methods may be required. Therefore, the approach adopted in this study can be replicated only for particulate matter, not for other pollutants.

Metrics for Evaluation of Progress

For the analysis of each metric, individual station data were considered rather than city-level averages, as the number of stations meeting the annual completeness criteria varied across years. The following metrics were evaluated.

Exceedance of National Ambient Air Quality Standards (NAAQS)

The number of days in a year exceeding the 24-hour National Ambient Air Quality Standards (NAAQS) for PM_{10} (100 µg/m³) and $PM_{2.5}$ (60 µg/m³) was calculated for each monitoring station that met the data completeness criteria between 2017 and 2024.

Annual Averages

For each station, annual average concentrations of PM_{10} and $PM_{2.5}$ were calculated using daily average values between 2017 and 2024. The annual average was computed as the mean of all daily averages within the respective year.

3-Year Rolling Average

The 3-year rolling average for the period 2017–2024 was calculated by taking the mean of the annual averages for each of 3 consecutive years for all the stations meeting the completeness criteria (e.g., 2017–2019, 2018–2020).

Absolute Change in Concentration

The absolute change in concentration was calculated for the year 2024 using 2017 or the earliest available year as the base year for each station. Absolute change in concentration was estimated by subtracting the annual average pollutant concentration in the base year from the concentration in 2024.

Effect of Seasonality

The monthly data was deseasonalized using seasonal-trend decomposition with the LOESS (locally estimated scatterplot smoothing) (STL) method in the openair package in R (Carslaw and Ropkins 2012). The LOESS smoother is based on fitting a weighted polynomial regression for a given time of observation, where weights decrease with distance from the nearest neighbor. Time series of monthly mean PM_{10} and $PM_{2.5}$ for the stations that met the annual completeness criteria for at least 3 consecutive years were decomposed in trend, seasonal, and remainder components using the STL procedure. A significant slope in the monthly trend component was calculated using generalized least squares regression for each site within a 95% confidence interval with a significance level of alpha equal to 0.05.

Effect of Meteorology

A separate random forest (RF) model was built for each air quality monitoring site to predict daily PM_{10} and $PM_{2.5}$ concentrations. RF is an ensemble decision tree machine learning method. The models used a wide range of explanatory metrological variables, including temperature, precipitation, boundary layer height, relative humidity, wind direction, wind speed, and atmospheric pressure and temporal variables including Julian day and day of the week. To perform meteorological normalization, each RF model was used to predict PM_{10} concentrations 1,000 times for each day. In each prediction round, the distributions of all input variables except the trend (time) were randomly sampled without replacement and reassigned to the observations. The average of these 1,000 predictions was considered the meteorologically normalized PM_{10} or $PM_{2.5}$ concentration — representing what PM_{10} or $PM_{2.5}$ would have been under average weather conditions for each day (Grange et al. 2018).

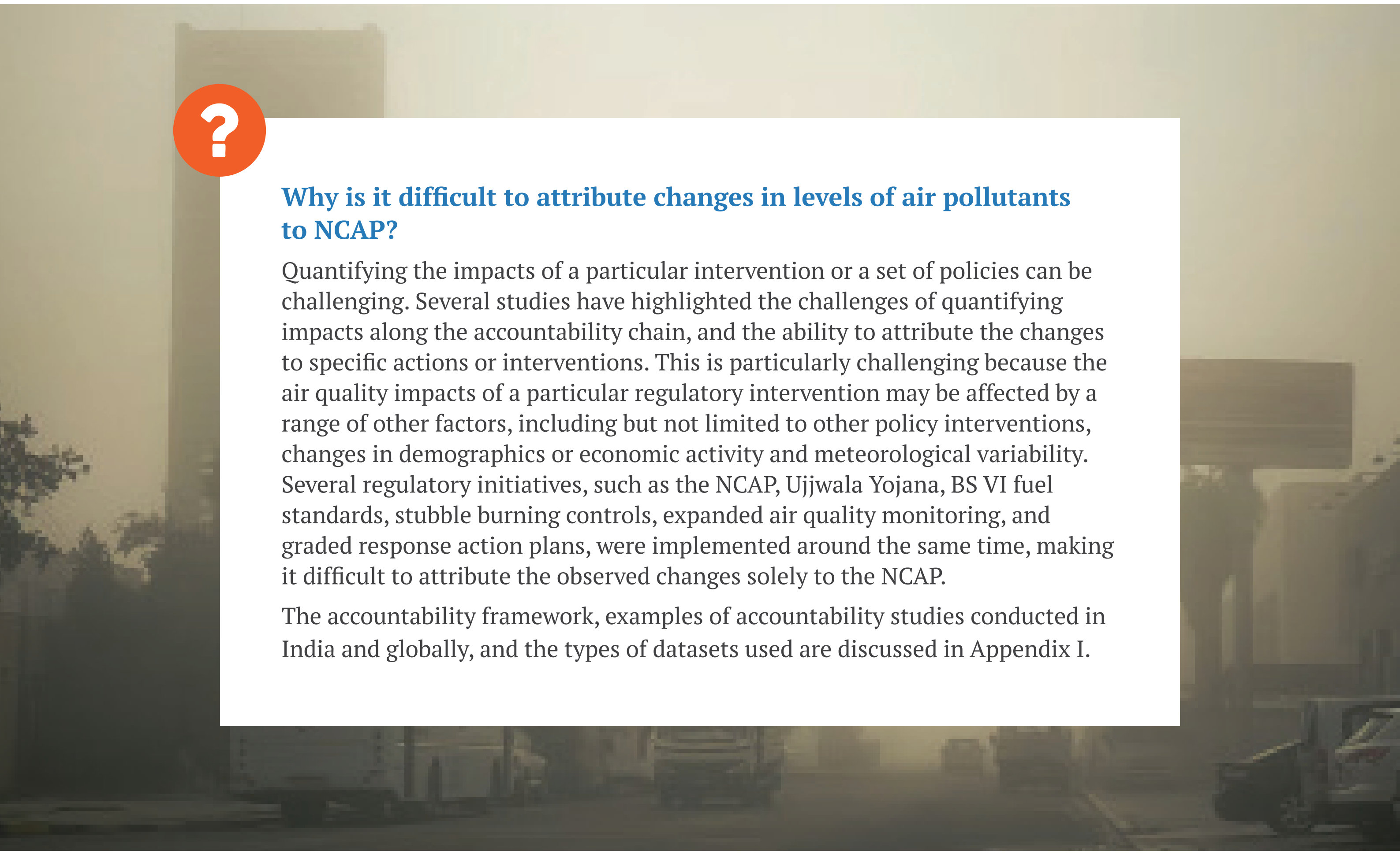
Smog-filled street in Delhi

Trend Analysis

To conduct trend assessment, only those stations that met criteria for at least 3 continuous years were included in the assessment. Nonparametric methods — the Mann-Kendall test and the Theil-Sen slope estimator — were used to assess the temporal slope (Carslaw and Ropkins 2012). The trend analysis was applied to the following time series:

1. Monthly averages without any correction (raw data)
2. Monthly averages of deseasonalized data
3. Monthly averages of meteorologically normalized data

For the Mann-Kendall test, the tau (τ) value indicates the direction of the trend (negative for decreasing, positive for increasing), while the *P* value indicates its statistical significance ($P < 0.05$ considered statistically significant). The Sen's slope estimator was used to quantify the magnitude of change over time.



Why is it difficult to attribute changes in levels of air pollutants to NCAP?

Quantifying the impacts of a particular intervention or a set of policies can be challenging. Several studies have highlighted the challenges of quantifying impacts along the accountability chain, and the ability to attribute the changes to specific actions or interventions. This is particularly challenging because the air quality impacts of a particular regulatory intervention may be affected by a range of other factors, including but not limited to other policy interventions, changes in demographics or economic activity and meteorological variability. Several regulatory initiatives, such as the NCAP, Ujjwala Yojana, BS VI fuel standards, stubble burning controls, expanded air quality monitoring, and graded response action plans, were implemented around the same time, making it difficult to attribute the observed changes solely to the NCAP.

The accountability framework, examples of accountability studies conducted in India and globally, and the types of datasets used are discussed in Appendix I.

Code Availability

Analysis was conducted using R. All the R codes used in the analysis are available on GitHub: *https://github.com/IndiaAQ-NCAP/IndiaAQ_Assessment*.

04 Findings

Availability of air quality data has improved since 2017.

> The number of ambient air quality monitoring stations has increased substantially between 2017 and 2024, and more data are being reported. However, data quality issues remain.

Expansion of air quality monitoring has been one of the key pillars of the NCAP. The NCAP aimed to establish 150 CAAQMS; 563 stations are now operational, marking progress. For context, it has been estimated that at least 4,000 CAAQMS are needed to adequately represent India's air quality both spatially and temporally — 2,800 in urban areas and 1,200 in rural areas (Ganguly et al. 2020).

Between 2017 and 2024, NCAP cities witnessed a significant expansion in the number of CAAQMS for both $PM_{2.5}$ and PM_{10} (Figure 4).

- **For $PM_{2.5}$, there was a 344% increase in the number of stations** from 78 stations across 38 cities in 2017 to 346 in 101 cities by 2024.
- **The number of PM_{10} monitoring stations has also increased rapidly** from 61 stations across 33 cities to 343 in 102 cities during the same period — an increase of 462%.

The largest number of CAAQMS have been deployed in the largest cities, including Delhi (40), Mumbai (30), Bengaluru and Hyderabad (14), Pune (13), and Ahmedabad (9), and Chennai (9). Overall, out of 130 NCAP nonattainment cities, 102 cities have CAAQMS as of April 2025. For PM_{10}, only 30 cities meet the CPCB guidelines of having at least four monitoring stations per city, while 46 cities operate with just one. This means nearly 70% of cities lack the minimum representative coverage, raising concerns about the reliability of reported air quality. Individual stations may provide timely data, but they cannot capture citywide variability. NCAP should prioritize expanding the monitoring network to meet at least the CPCB guidelines and improve the accuracy of air quality reporting.

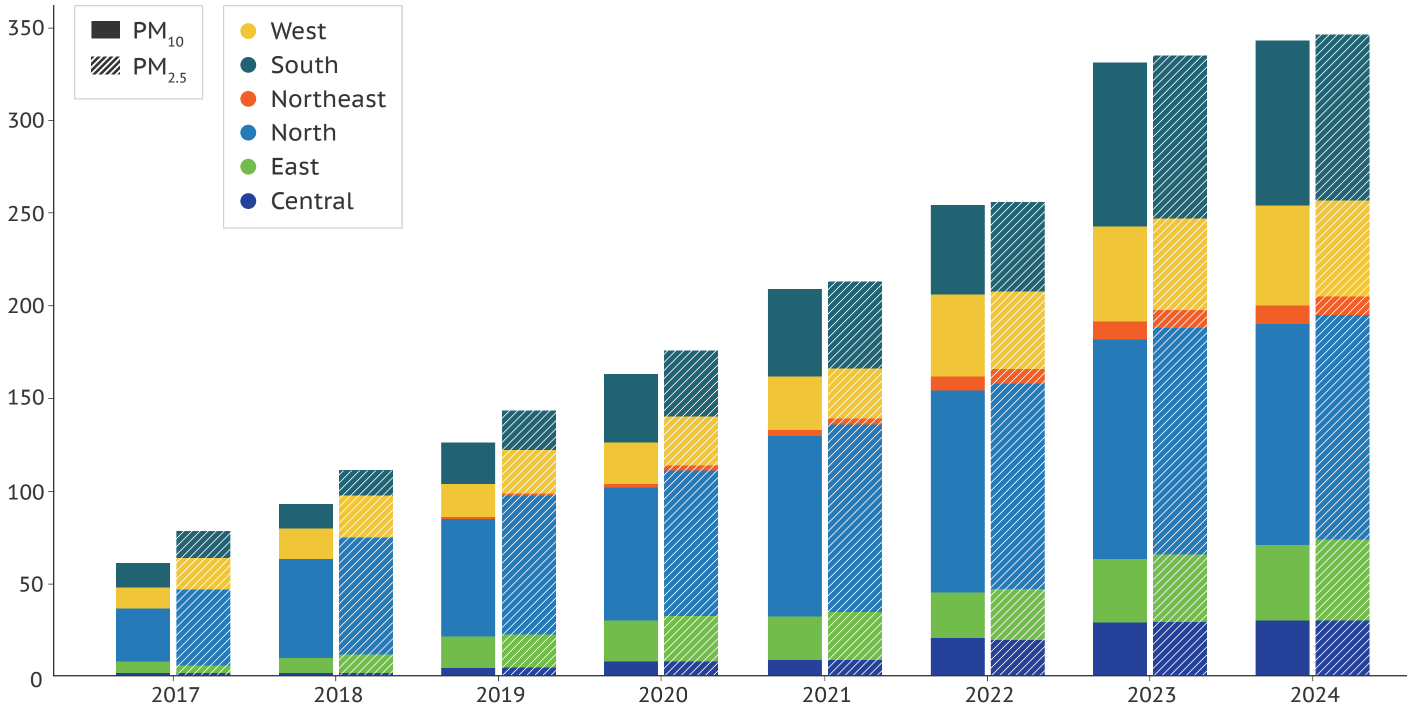


Figure 4. Number of real-time monitoring stations between 2017 and 2024.
Source: Central Control Room for Air Quality Management.

Availability of air quality data steadily increased from 2017 to 2024.

In line with increased availability of monitoring stations, data availability has improved considerably since 2017 (Table 3). In this context, data availability is defined as the percentage of days in a year that the data is available. Thus, 95% availability translates to availability of data on ~347 days in a year.

In 2017, only 10 stations met the >95% data availability criterion for PM_{10}, while 23 stations achieved >85% availability. By 2024, 253 stations met the >95% data availability criterion, showing a significant improvement. This indicates that not only has the monitoring network expanded, but data completeness has also improved. Notably, the number of stations with poor data availability (<50%) remained relatively low throughout the analysis period, with only seven stations falling into this category in 2024.

The largest annual increase in high-availability stations occurred in 2024, with 253 stations achieving >95% data availability compared to 123 stations in 2023. This rise coincides with a substantial overall increase in the number of stations in 2023. Please note that the percentage availability was calculated by excluding the year in which the monitor was installed, unless it was installed within the first 2 months of that year.

Table 3. Data Availability (in % per Year) for PM_{10} and $PM_{2.5}$ Between 2017 and 2024

NUMBER OF MONITORING STATIONS

	PM_{10}					$PM_{2.5}$				
YEAR	TOTAL	>95%	>85%	>75%	<50%	TOTAL	>95%	>85%	>75%	<50%
2017	61	10	23	29	10	78	17	35	44	9
2018	93	38	64	68	7	111	47	77	82	8
2019	126	67	86	91	2	143	85	98	104	3
2020	163	86	109	113	13	176	99	130	134	4
2021	209	89	133	150	7	213	107	146	158	3
2022	254	126	171	181	16	256	121	176	184	16
2023	331	123	195	220	8	335	129	195	219	13
2024	343	253	291	306	7	346	252	291	305	13

While data availability is increasing, the expansion of air quality monitoring stations is not uniform across states in India. Despite the growth in the national monitoring network, the number of stations varies widely across states and cities (Figure 4). Cities including Delhi and Mumbai have over 30 CAAQMS, while many large cities including Surat, Visakhapatnam, Talcher, and Srinagar have only one monitor.

Notably, although the number of monitors has increased since 2017, the addition of new cities to the monitoring network has been relatively limited. For example, several nonattainment cities including Nellore, Vadodara, Ranchi, and Raebareli do not have any CAAQMS as of April 2025. Note that several states and UTs including Lakshadweep, Goa, Arunachal Pradesh, Puducherry, Andaman and Nicobar Islands, Dadra and Nagar Haveli, Daman and Diu, Sikkim, Kerala, Mizoram, Ladakh, Tripura, and Manipur are not represented in the NCAP; this is because at the time, pollutant concentrations were not in exceedance of the Indian NAAQS.

Furthermore, there are no CAAQMS in rural areas of the country, leaving these areas entirely excluded from the real-time monitoring network.

- In 2024, PM_{10} data availability was **highest** in the states in North India, including Punjab (99.8%), Rajasthan (99.3%), Uttar Pradesh (99.2%), Chandigarh (98.99%), and in West Bengal (99%). In comparison, the states with relatively **lower data availability** include Jharkhand (59.3%) and Jammu and Kashmir (59.6%).
- The results are similar for $PM_{2.5}$; **one exception** is Jharkhand, where the availability of $PM_{2.5}$ data was lower than PM_{10} (PM_{10} = 59.3%, $PM_{2.5}$ = 44.3 %). It is important to note that in Jharkhand, $PM_{2.5}$ monitoring started functioning only from 2023 and 2024, with just two monitors in operation.

At the city level, 21 and 27 cities have been consistently reporting data since 2017 for PM_{10} and $PM_{2.5}$ respectively (Table 4). In 2024, more than 15 cities reported 100% of data in a year, and only four cities reported less than 60% of data.

A busy street packed with vehicles

Table 4. Data Availability in Cities

PM_{10}	$PM_{2.5}$
CITIES REPORTING DATA SINCE 2017	
Amritsar, Aurangabad, Bengaluru, Chandrapur, Delhi, Durgapur, Haldia, Howrah, Jaipur, Jodhpur, Kolkata, Mumbai, Nagpur, Nashik, Navi Mumbai, Noida, Pune, Solapur, Thane, Varanasi, Visakhapatnam	Agra, Ahmedabad, Amritsar, Aurangabad, Bengaluru, Chandrapur, Chennai, Delhi, Faridabad, Gaya, Hyderabad, Jaipur, Jodhpur, Kanpur, Lucknow, Mumbai, Muzaffarpur, Nagpur, Nashik, Navi Mumbai, Noida, Patna, Pune, Solapur, Thane, Varanasi, Visakhapatnam
CITIES REPORTING 100% OF DATA IN 2024	
Akola, Alwar, Angul, Asansol, Cuttack, Ghaziabad, Jalandhar, Jalgaon, Ludhiana, Patiala, Sagar, Silchar, Sivasagar, Thoothukudi, Udaipur, Visakhapatnam	Akola, Alwar, Angul, Asansol, Badlapur, Cuttack, Jalandhar, Jalgaon, Ludhiana, Patiala, Sagar, Silchar, Sivasagar, Udaipur, Ujjain, Ulhasnagar, Visakhapatnam
CITIES REPORTING LESS THAN 60% OF DATA IN 2024	
Dhanbad, Tiruchirappalli, Srinagar	Davanagere, Dhanbad, Tiruchirappalli, Srinagar

The largest year-on-year increase in CAAQMS stations for both pollutants occurred in 2023, with the number of $PM_{2.5}$ stations rising from 256 in 2022 to 335 in 2023, and the number of PM_{10} stations growing from 254 to 331. By 2024, both $PM_{2.5}$ and PM_{10} monitors had achieved similar city coverage. The increase in the number of available monitors in 2023 reflects the concerted push for increased monitoring under NCAP and the availability of a substantial funding pool. However, in December 2022, the CPCB issued an order prohibiting states from procuring CAAQMS using NCAP or 15th Finance Commission funds from international vendors. Although this restriction applies to future procurements, existing tenders were allowed to proceed. It remains to be seen how this decision will influence the future trajectory of the expansion of India's air quality monitoring network.

Data Completeness

Analysis of long-term trends in air quality depends on the availability of complete data. For example, if the data are missing during peak pollution periods, annual average concentrations may be underestimated for a given station or location. In the case of long-term trend assessments, incomplete datasets can introduce noise and bias which can mask real trends. In a few studies conducted in India, an uptime filter limit is fixed and stations that pass the criteria are included for the trend assessment (CREA 2024). It is important to apply such criteria because datasets lacking too much data may not reflect actual air quality levels.

There were stations that recorded data points for more than 90% of the days in a year; albeit with discrepancies. For example, in 2023, at the SAC ISRO satellite, Ahmedabad IITM station, data availability was reported for more than 90% of days, but for a period of more than 5 months, the levels were observed to be static (**Figure 5**).

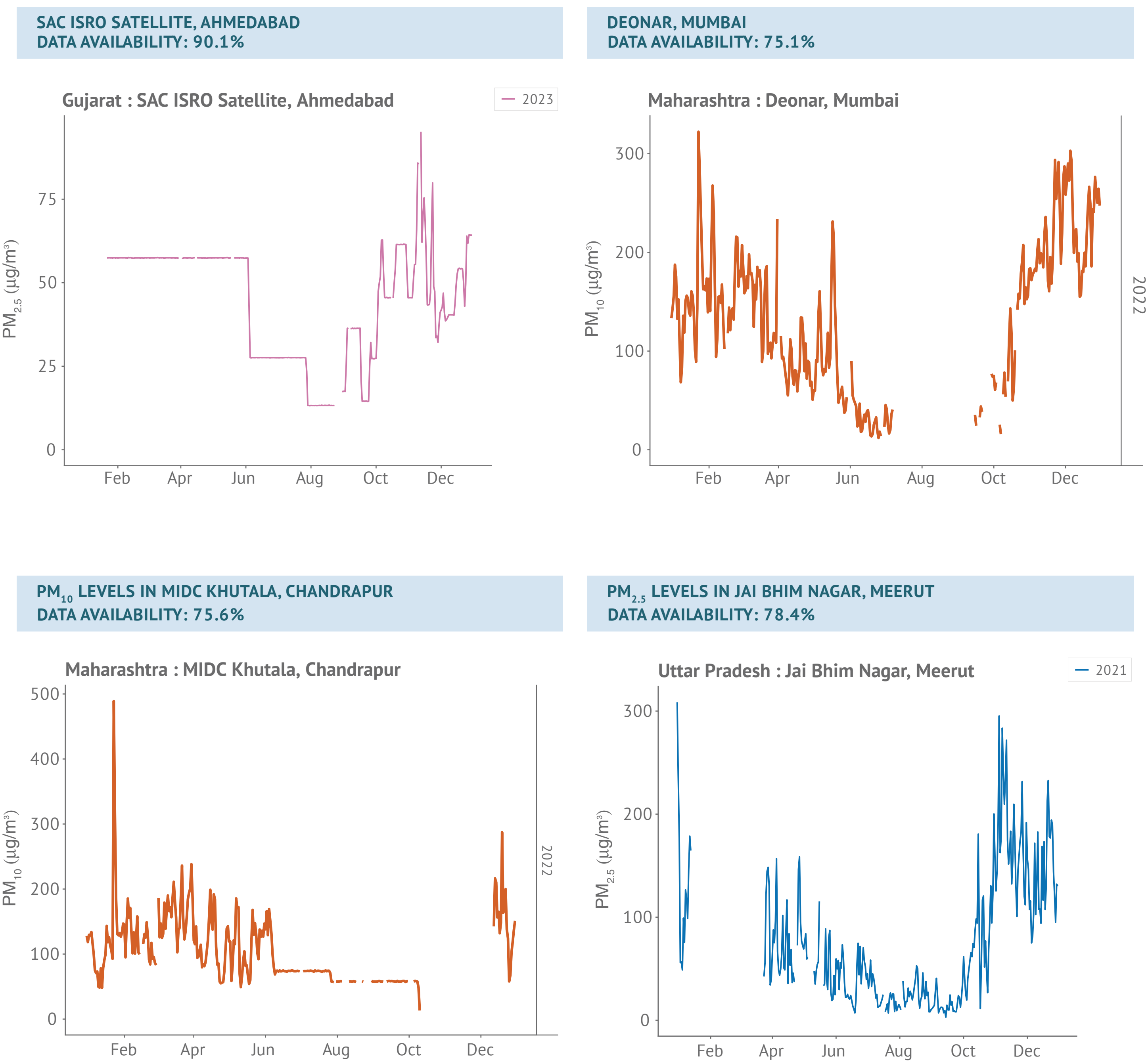


Figure 5. Examples of discrepancies in availability of PM_{10} or $PM_{2.5}$ data.

Stations passing the 75% data availability criteria were assessed because a number of studies in India adopt this threshold to estimate changes in air quality (CREA 2024; CREA 2023; Climate Trends & Respirer Living Sciences 2024). This calculation is based on the total number of days in a year and does not account for hourly or monthly availability (i.e., data is available for approximately 274 days in a standard year).

Out of the 343 and 346 stations that monitored PM_{10} and $PM_{2.5}$, respectively, in 2024, 306 and 305 stations met the 75% data availability criteria. Trend plots provided in Figure 5 represent the stations with 75% data availability; note that data is missing for more than 2–3 months, potentially missing data for an entire season.

Considering the potential drawbacks of assuming annual availability of data, including loss of granularity, for our analysis, a strict set of criteria was adopted for availability of data on a monthly, daily, and hourly basis. For inclusion in the analysis, stations had to report PM data for at least 18 hours each day, 23 days each month, and 11 months each year. In fact, once these stringent criteria were applied, the number of stations was considerably reduced (**Figure 6**).

However, note that the total number of stations meeting the annual completeness criteria for both $PM_{2.5}$ and PM_{10} has steadily increased from 2017 to 2024 (**Figure 6**).

- **Data completeness improved**, with $PM_{2.5}$ rising from 21.8% in 2017 to 81.5% in 2024, and PM_{10} increasing from 18.0% to 81.9% over the same period.
- In most cases where data was removed for a particular year, it was typically due to **the establishment of the monitoring station.**

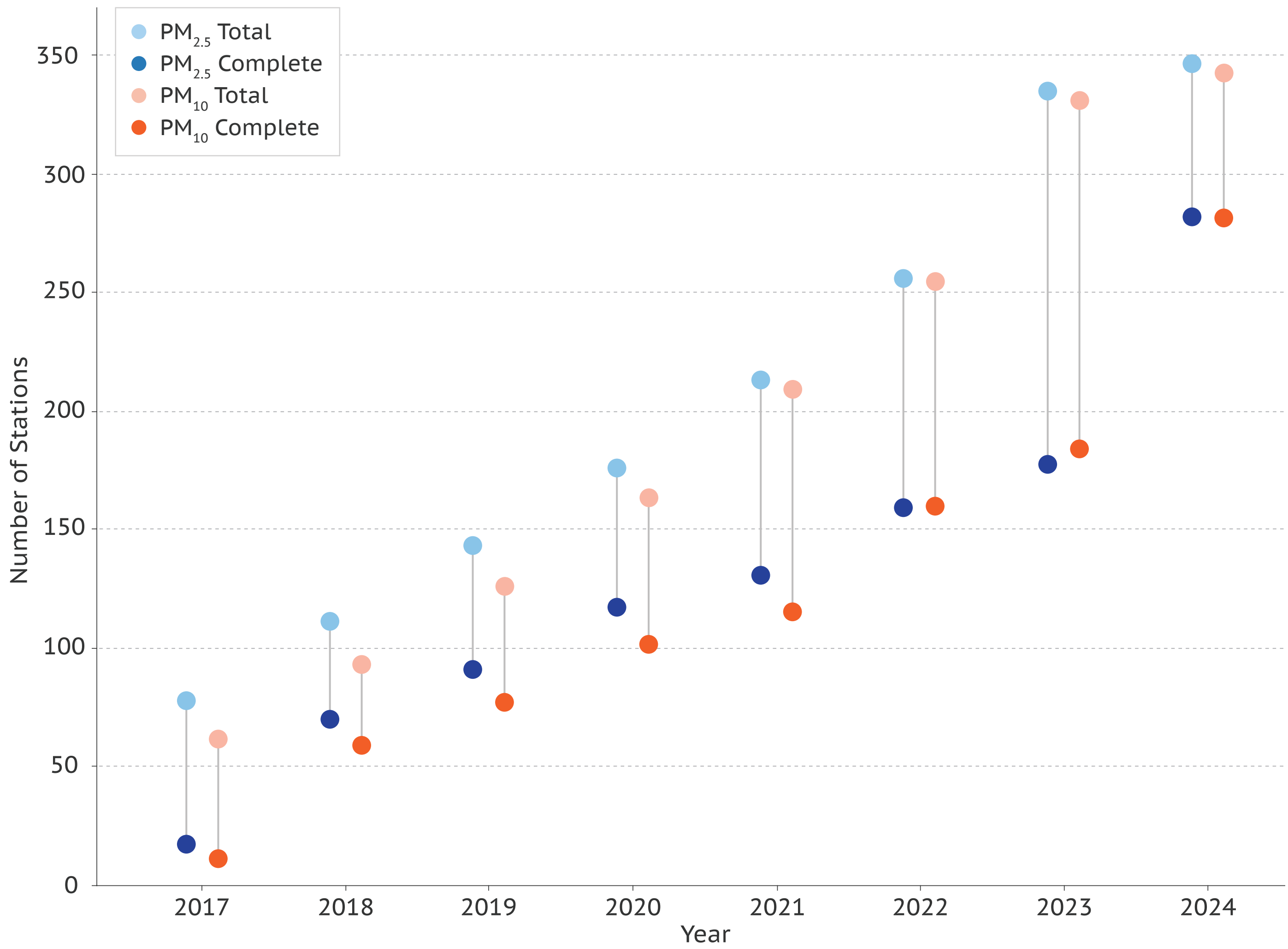


Figure 6. Total number of stations and those that meet the annual completeness criteria.
Stations labeled as "complete" in the figure indicate those that met the annual data completeness criteria as defined for this analysis.

For further analysis, we divided the stations into three categories:

1. Stations that met the annual completeness criteria for at least 5 years
2. Stations that met the annual completeness criteria for at least 3 years
3. Stations that met the annual completeness criteria for 1 to 2 years

After applying these criteria, there was a significant reduction in the number of stations and cities that could be considered for the final trend assessment (Figure 7).

- In the PM_{10} dataset, out of **92 stations across 42 cities** with at least 5 years of data, 29 were in Delhi. The other 31 cities each had only one monitoring station with consistent 5-year data.
- For $PM_{2.5}$, **102 stations across 40 cities** had data for at least 5 years. Each of the remaining 27 cities had only one station with consistent data for at least 5 years.
- A total of **83 stations across 34 cities** had both PM_{10} and $PM_{2.5}$ data for at least 5 years, while 9 stations in 8 cities had only PM_{10} data and 19 stations in 12 cities had only $PM_{2.5}$ data. Mandir Marg, New Delhi, is the only station that had both PM_{10} and $PM_{2.5}$ data continuously for all 8 years between 2017 and 2024.

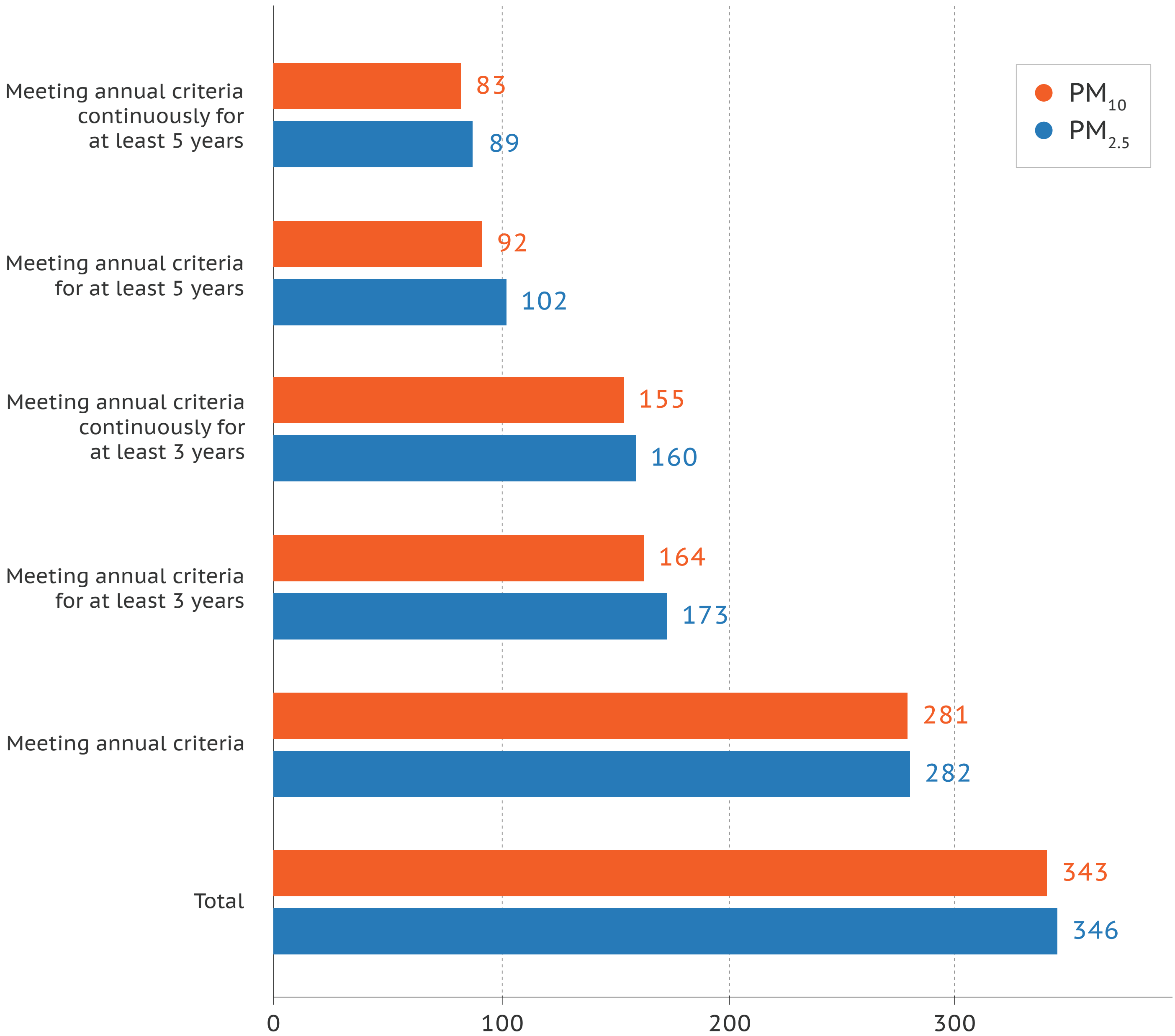


Figure 7. Number of monitoring stations under various data criteria.

Testing of Scenarios

To quantify changes in air quality during the NCAP implementation period, we tested the data in a variety of ways. Note that all analyses were conducted for real-time PM_{10} and $PM_{2.5}$ concentration data, and AQI was not used as a metric for the assessment.

Compliance with Annual NAAQS

Between 2017 and 2024, the number of stations exceeding the annual NAAQS has remained largely unchanged for PM_{10}, with over 90% of stations exceeding the limit each year. In contrast, for $PM_{2.5}$ the stations exceeding the annual NAAQS decreased by 33% over the same period, with a steady rate of decline observed year after year (**Table 5**).

The NCAP aims to reduce PM_{10} and $PM_{2.5}$ levels by 40% or ensure compliance with the national ambient air quality standard by 2025–2026. In 2024, out of 281 air quality monitoring stations across India that met data completeness criteria, 258 stations — approximately 91% — recorded annual average PM_{10} concentrations exceeding the national limit of 60 µg/m³. Note that the data were not averaged across the city for this analysis.

- In 2024, the **most polluted station** in the country was Jahangirpuri in Delhi, which recorded an annual average PM_{10} level of 276.1 µg/m³.
- All of the top 20 most polluted stations were located in **Delhi-NCR** with 95% (19 stations) situated within Delhi.
- Other highly polluted locations included stations in Patna-Muradpur (203.7 µg/m³), Samanpura (197.4 µg/m³), DRM Office Danapur (162.8 µg/m³), and Rajbansi Nagar (155.2 µg/m³).
- A high PM_{10} level was also reported from the Central Academy for SFS in Byrnihat, Meghalaya (162.7 µg/m³).
- Only about **8.2% of the stations** (23 out of 281) reported annual averages below 60 µg/m³. The lowest PM_{10} concentration was observed at Mahatma Basaveswar Colony in Kalaburagi, with an annual average of 38.6 µg/m³. Among these, notable stations included ESD Banaras Hindu University in Varanasi (42.5 µg/m³), Civil Lines in Bareilly (46.5 µg/m³), Velachery Residential Area in Chennai (47.0 µg/m³), Lal Bahadur Shastri Nagar in Kalaburagi (48.2 µg/m³), and Maldahiya in Varanasi (49.2 µg/m³).
- Within the Indo-Gangetic Plain, only three cities — Bareilly, Agra, and Varanasi, all in Uttar Pradesh — had stations reporting PM_{10} levels within the national limit, underscoring the severe and widespread air quality challenges in this densely populated region.

Table 5. Number of Stations with Annual NAAQS Exceedance Between 2017 and 2024

	PM_{10}		$PM_{2.5}$	
YEAR	TOTAL NUMBER OF STATIONS	NUMBER OF STATIONS ABOVE ANNUAL NAAQS (%)	TOTAL NUMBER OF STATIONS	NUMBER OF STATIONS ABOVE ANNUAL NAAQS (%)
2017	11	10 (91%)	17	16 (94%)
2018	59	57 (96%)	70	63 (90%)
2019	77	76 (99%)	91	75 (82%)
2020	101	97 (96%)	117	90 (77%)
2021	115	113 (98%)	131	104 (79%)
2022	160	156 (98%)	159	130 (82%)
2023	184	174 (95%)	178	132 (76%)
2024	281	258 (92%)	282	173 (61%)

A greater number of stations met the annual average target for $PM_{2.5}$ in 2024 compared to PM_{10}.

Although $PM_{2.5}$ is not included in the revised NCAP target, some progress has been made with respect to $PM_{2.5}$.

- In 2024, out of 282 monitoring stations, 173 stations — or approximately **61.4%** — did not meet the annual data ambient air quality standard for $PM_{2.5}$ (40 µg/m³).
- The highest annual average $PM_{2.5}$ concentration was recorded at **Jahangirpuri, Delhi**, with a level of 125.8 µg/m³.
- Among the top 25 most polluted stations for $PM_{2.5}$, **all were located in Delhi** except for one: Central Academy for SFS, Byrnihat (Meghalaya), which reported 114.8 µg/m³. However, this is the only monitoring station in the city, and may not represent the city's overall air quality. This underlines the need for cautious interpretation of data from cities with only one monitoring site. A decline in $PM_{2.5}$ levels was observed at this station between 2023 and 2024 (Figure 8).
- The lowest annual average $PM_{2.5}$ level was recorded at Kodungaiyur, Chennai, with just 12.6 µg/m³. Other stations reporting $PM_{2.5}$ levels below 20 µg/m³ included: Civil Lines, Bareilly (15.1 µg/m³), Mahatma Basaveswar Colony, Kalaburagi (15.5 µg/m³), ESD Banaras Hindu University, Varanasi (15.6 µg/m³), Urja Nagar, Korba (17.7 µg/m³), Bhelupur, Varanasi (18.3 µg/m³), Deen Dayal Nagar, Sagar (18.5 µg/m³), and Borivali East, Mumbai (19.5 µg/m³).

The assessment of annual NAAQS exceedance days showed inconsistent results across stations and proved unreliable for capturing long-term trends. Some states use change in the number of NAAQS exceedance days based on the 24-hour NAAQS threshold as a metric to evaluate progress (DoE 2024). Here, it was observed that the annual average number of NAAQS exceedance days for all complete stations showed a decreasing trend, whereas the average for stations with more than 5 years of data showed an increasing trend. This contradiction does not provide a reliable picture of air quality improvement or deterioration for PM_{10} and reinforces the notion of exceedance days being a poor metric.

To investigate further, individual stations were analyzed to check for any consistent trends (Figure 9). In states such as Delhi, Punjab, and Maharashtra, the data exhibited high variability and no clear trend. Similarly, in Rajasthan, Telangana, and West Bengal, most stations did not show any consistent direction. Similar patterns were observed for the number of $PM_{2.5}$ NAAQS exceedance days in states such as Delhi and Andhra Pradesh, while a steady decline was noted at stations in Gujarat and Uttar Pradesh (Figure 10). However, the number of NAAQS exceedance days are not a reliable metric for assessing change over time, as they do not capture the magnitude of improvement or deterioration in air quality.

To better understand the limitations of this metric, it is important to consider how exceedance days are defined and why they may fail to capture meaningful changes in pollution levels over time. Exceedance days are calculated based on whether pollutant concentrations exceed a fixed threshold (e.g., 100 µg/m³ for PM_{10}). A day with 101 µg/m³ counts the same as a day with 250 µg/m³ — making it a binary indicator that ignores the severity of pollutant concentrations. As a result, this metric can obscure gradual improvements or declines and may be overly sensitive to short-term fluctuations or local anomalies.

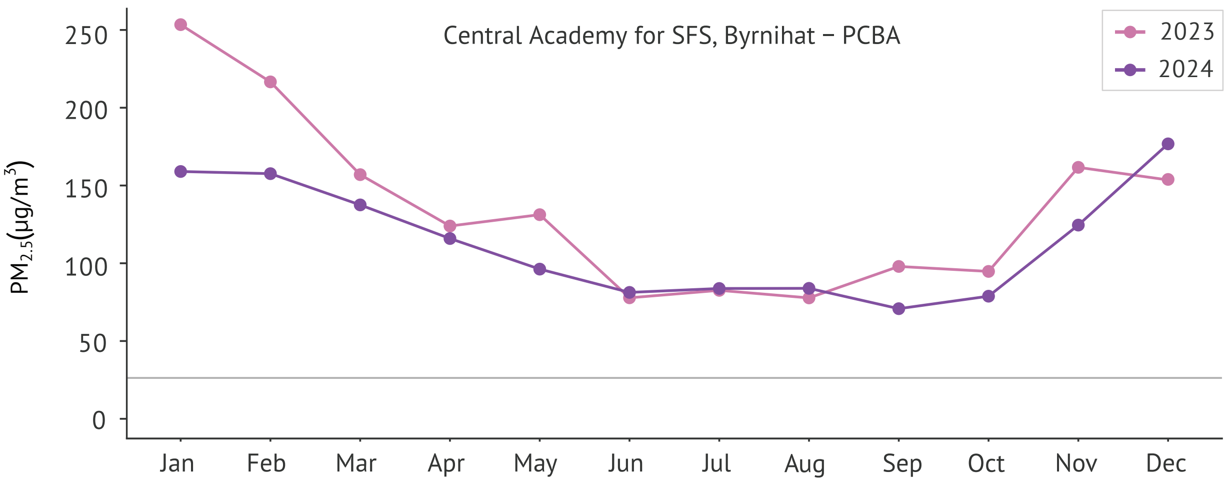


Figure 8. Levels of $PM_{2.5}$ in Byrnihat, Meghalaya in 2023 and 2024.

For most stations, the number of NAAQS exceedance days for $PM_{2.5}$ was fewer than the number of exceedance days for PM_{10}. Between 2017 and 2024, more than 96% of monitoring stations recorded fewer NAAQS exceedance days for $PM_{2.5}$ compared to PM_{10}. This indicates that PM_{10} exceedances were more prevalent across most locations. In the relatively few locations where the number of $PM_{2.5}$ exceedance days surpassed PM_{10}, the differences were typically modest. However, in many cities — including Mumbai, Bengaluru, Hyderabad, Varanasi, Allahabad, and Solapur — the number of PM_{10} exceedance days exceeded those of $PM_{2.5}$ by substantial margins, indicating a strong and persistent presence of coarse dust and larger particulate matter in urban air. For instance, a source apportionment study conducted in Bengaluru showed that soil dust emerged as the top contributor to PM_{10} with a 51% share. Similarly, in other cities such as Hyderabad, more than 60% of PM_{10} consisted of road dust (CSTEP 2022; Guttikunda et al. 2013). Notably, recent assessments of NCAP spending have shown that a large share of funds has been directed toward dust control measures, which primarily target PM_{10} sources (CSE 2025). While this focus appears aligned with the exceedance trends, the consistently high PM_{10} levels across cities also raises questions about the effectiveness of such interventions.

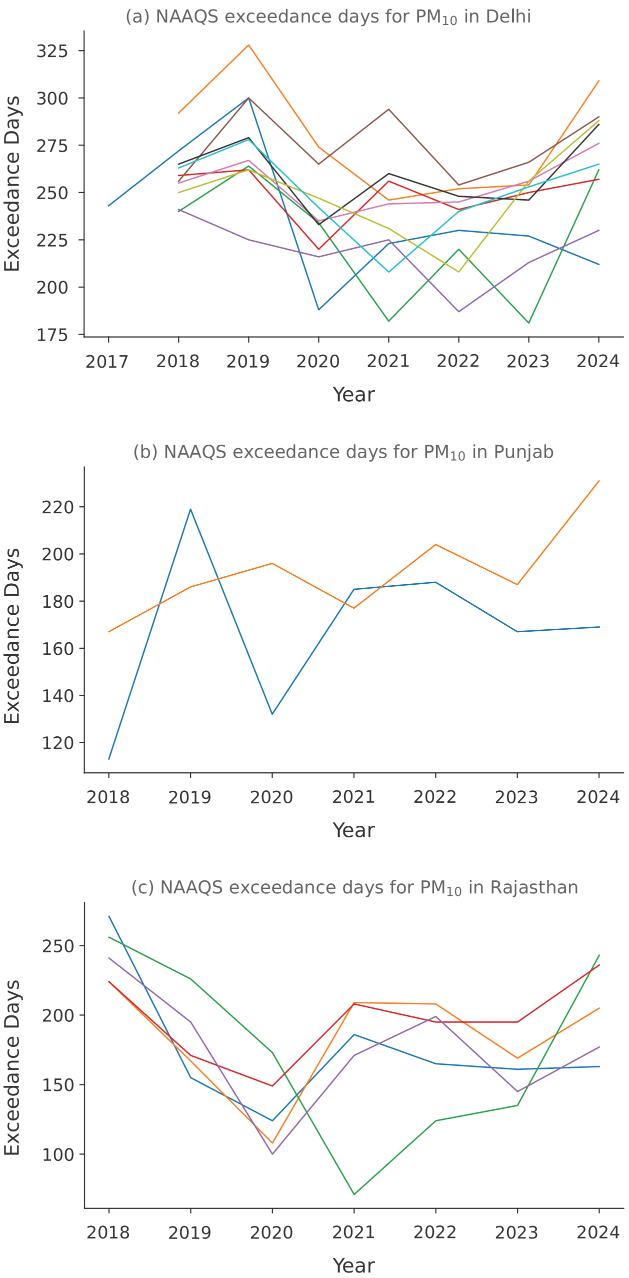


Figure 9. The number of NAAQS exceedance days for PM_{10} for a monitoring station with 7 or more years of data in Delhi, Punjab and Rajasthan.
Each line represents the NAAQS exceedance days for PM_{10} for a monitoring station.

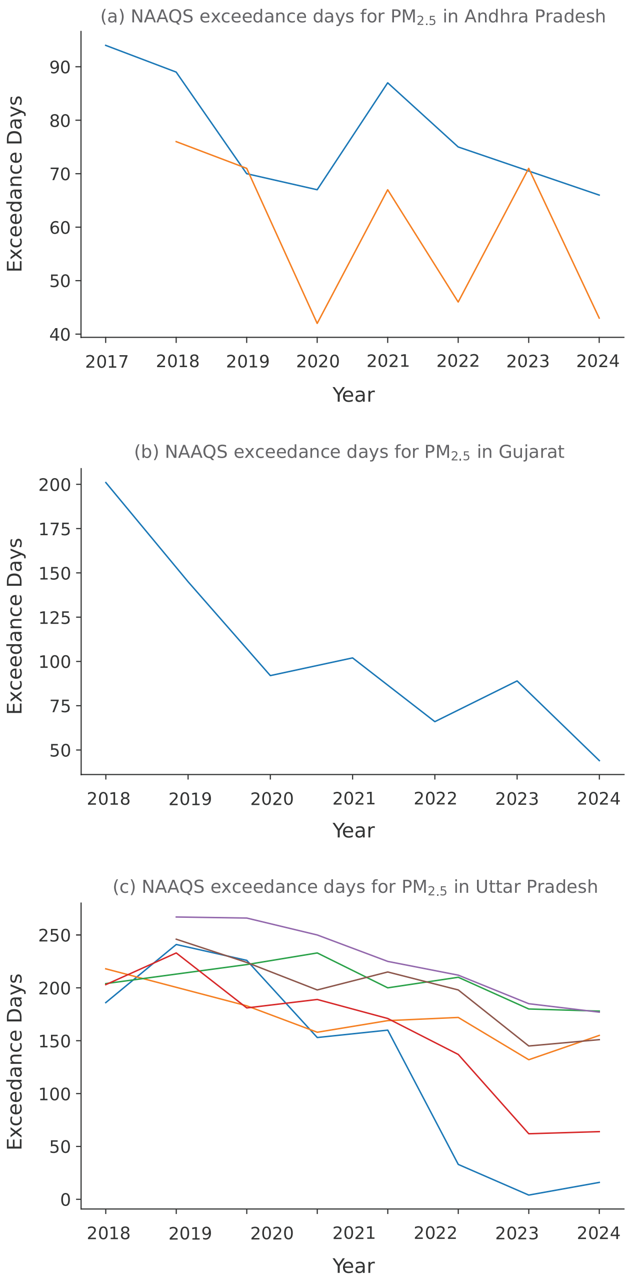


Figure 10. The number of NAAQS exceedance days for $PM_{2.5}$ for a monitoring station with 7 or more years of data in Andra Pradesh, Gujarat and Uttar Pradesh.
Each line represents the number of NAAQS exceedance days for $PM_{2.5}$ for a monitoring station.

Absolute Change in Pollutant Concentration

A total of 99 cities had complete annual data for PM_{10} for at least 1 year between 2017 and 2024. The distribution of cities based on the years for which they had complete data is as follows: 9 cities for 2017–2024, 21 for 2018–2024, 7 for 2019–2024, 10 for 2020–2024, 5 for 2021–2024, 10 for 2022–2024, 13 for 2023–2024, 23 for 2024 only, and 1 city for 2018 only. The NCAP has identified 2017 as the baseline year to evaluate changes in air quality (details in Appendix II). For estimating the absolute change in PM levels, station averages were used because the number of monitoring stations meeting the completeness criteria was not consistent across all years.

Among the 209 stations analyzed for absolute change in PM_{10} levels, 66.5% showed a decreasing trend, while 33.5% showed an increasing trend, meaning roughly two-thirds of the stations recorded a decline in PM_{10}, a sign of improvement in air quality. Of the total $PM_{2.5}$ monitoring stations analyzed (n = 211), approximately 67.7% showed a decreasing trend, while about 32.2 % showed an increasing trend. Among the stations that showed a declining trend for both PM_{10} and $PM_{2.5}$, the highest reduction in 2024 was observed at Ardhali Bazar, Varanasi, with a 75% decline in PM_{10} compared to the baseline year. For $PM_{2.5}$, the same station also recorded the highest decline, at 78%. **Figures 11 and 12** present the top 20 stations with the highest PM_{10} and $PM_{2.5}$ reductions. Earlier studies conducted in NCAP cities have reported there is similar improvement in AQI values associated with PM_{10} reductions, but these gains do not translate into an overall improvement in urban or regional air quality. Trends in regional gaseous pollutant concentrations and national fuel consumption patterns suggest that emissions from fossil fuel combustion continue to rise at business-as-usual rates, largely unaffected by targeted interventions (Guttikunda et al. 2025).

Figure 11.
Absolute change in PM_{10} from earliest year data was recorded to 2024.

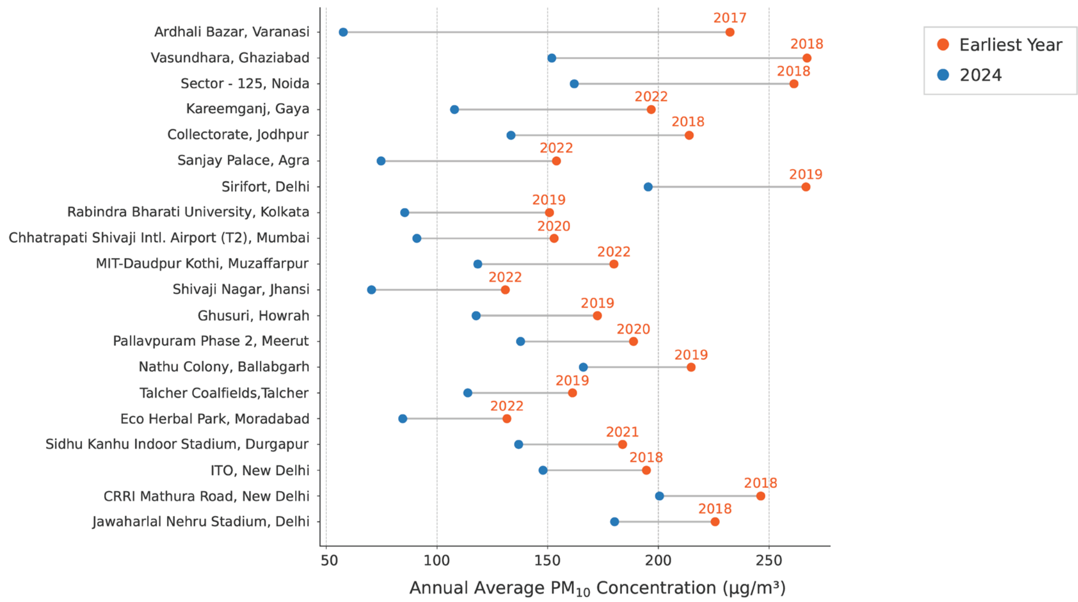
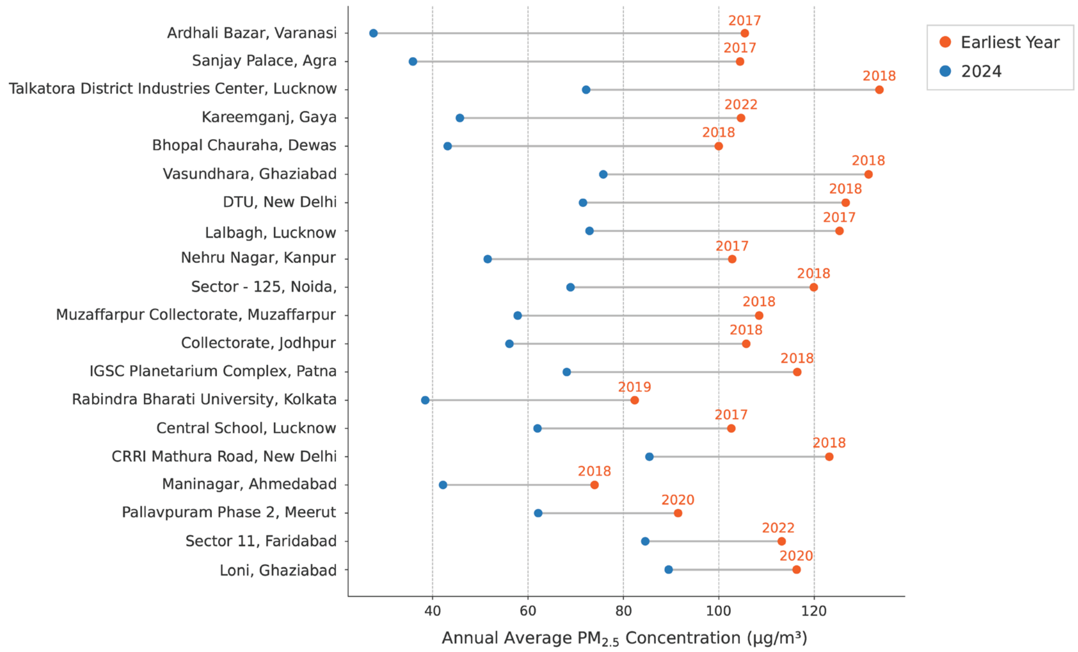


Figure 12.
Absolute change in $PM_{2.5}$ from earliest year data was recorded to 2024.



However, absolute change between 2 years can be misleading. Absolute change as a metric does not take into account the variability and fluctuations over time, making it potentially misleading. A single unusually high or low value in either the baseline or final year can distort the actual pattern of change (**Figure 13**). For instance, a city may show steady improvement across several years but then experience a spike in pollution in the final year — this would mask the overall progress if only the start and end points are compared. Conversely, a city might worsen for most of the period and show a sudden drop in the final year, creating the illusion of sustained improvement. This kind of two-point comparison fails to capture the underlying trend or the consistency of change. For examples, across most stations in Hyderabad, there was a strong and sudden dip in pollutant concentrations in 2024 (**Figure 14**).

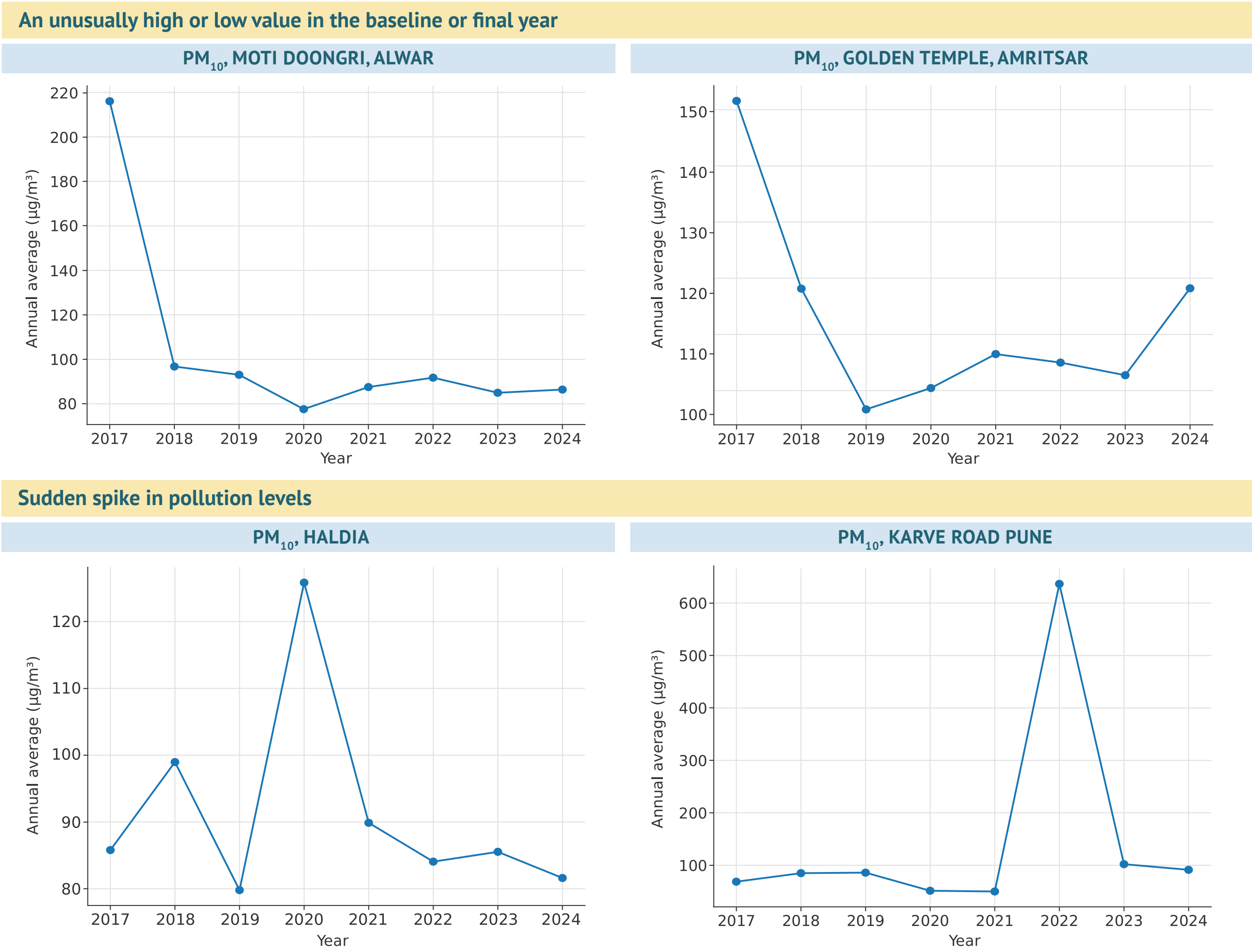


Figure 13. Stations showing unusually high or low values.

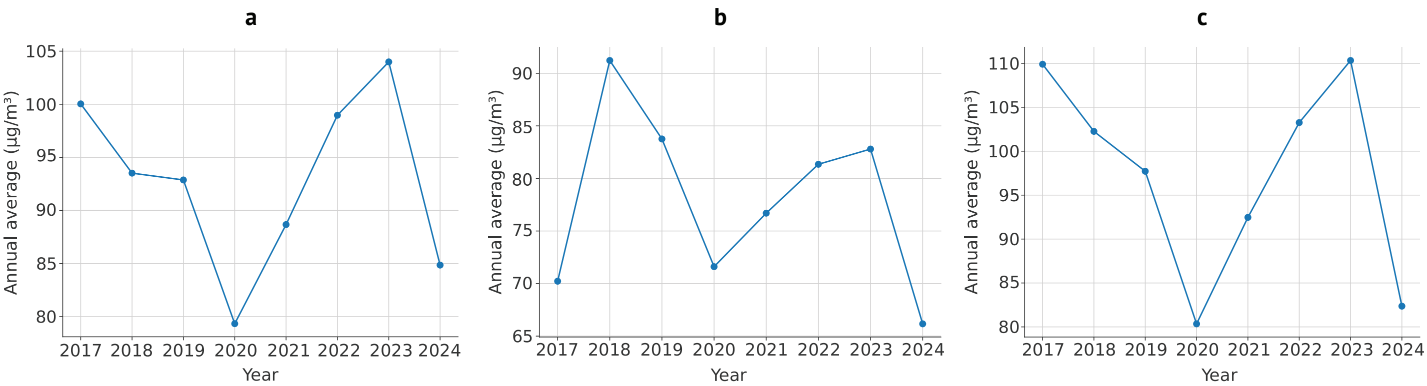


Figure 14. PM_{10} trends in stations in Hyderabad: a) IDA Pashamylaram, Hyderabad, b) Central University, Hyderabad, and c) Bollaram Industrial Area, Hyderabad.

City means can mask divergent station trends; use station-level metrics for performance. Out of 39 cities that had more than one station with data for at least 5 years, 92 stations were included for the assessment of PM_{10} city-station average difference. In total, there were 553 station-year pairs. To assess consistency between city-level and station-level annual PM_{10} concentrations, we calculated the percentage difference between each station's annual average and its corresponding city average for the same year. A station was identified as an outlier if this difference exceeded 20% and an additional threshold was set at 40% to indicate stronger deviation. Percentage differences between 10% to 25% are commonly used in data validation practices to detect anomalies (US EPA 2021). Out of 553 station-year pairs analyzed, 443 (~80%) were within ±20% of their corresponding city-level PM_{10} averages, indicating a strong overall alignment between station and city values. However, 110 records (20%) exceeded this threshold. In 2019 in Delhi, 27 stations met the annual completeness criteria and only 16 (~59%) were within the 20% deviation range, highlighting increased variability in cities with extensive monitoring coverage. On the other hand, the highest deviations (>50%) were observed in Nashik, Visakhapatnam, Meerut, and Guwahati. It is important to note that all cities with only two stations met the criteria for at least 5 years, suggesting that limited spatial coverage can also lead to discrepancies.

Note the placement of the two monitors in Meerut in **Figure 15**. The difference in variability in terms of percentage exceeds 50%, and these monitors are approximately 5 km apart. The Ganga Nagar, Meerut monitor is in a relatively green area, whereas based on Google Earth observations, the Jai Bhim Nagar monitor is in a commercial cluster. Although the monitors are not too far from each other, averaging the values of both stations would not be appropriate as they represent distinct local environments. These findings underscore that both too few and too many stations can contribute to large station-to-city average differences, and that representativeness of station placement is as critical as coverage. This highlights that station-level averages, particularly from well-sited and complete stations, may offer a more accurate reflection of local air quality conditions than aggregated city-level values, which can mask important spatial variability.

Figure 15. Locations of Air Quality Monitoring Stations in Meerut. (Image taken on November 14, 2025.)

Such variability can also be observed when looking at the change in pollution levels between the 2 years. For example, **Figure 16** shows the change in $PM_{2.5}$ levels between 2023 and 2024 in the stations in Delhi that satisfy the completeness criteria for both years. In the figure, some stations show an increase in pollution while others show a decrease, even within the same city. These contrasting trends would be lost in a citywide average, which might misleadingly suggest that there is no change or a minor overall improvement. Under the NCAP, interventions by urban local bodies are designed and implemented at the local level. With that in mind, using station-level data can be a useful way to design localized interventions and monitor the true effectiveness of air quality actions under programs such as the NCAP.

The data indicate that a long-term trend assessment for a city should be based on a network of representative monitoring stations. Indian urban landscapes are highly diverse, encompassing a mix of land-use types with overlapping residential, commercial, industrial, and transport activities (Dammalapti and Guttikunda 2024). The design of a representative monitoring network should include spatially distributed stations rather than rely on a fixed-radius buffer approach. These stations should also be evaluated for data completeness and their ability to support long-term trend assessments. Representative stations can be selected based on factors such as population exposure, emission source influence, background levels, 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.

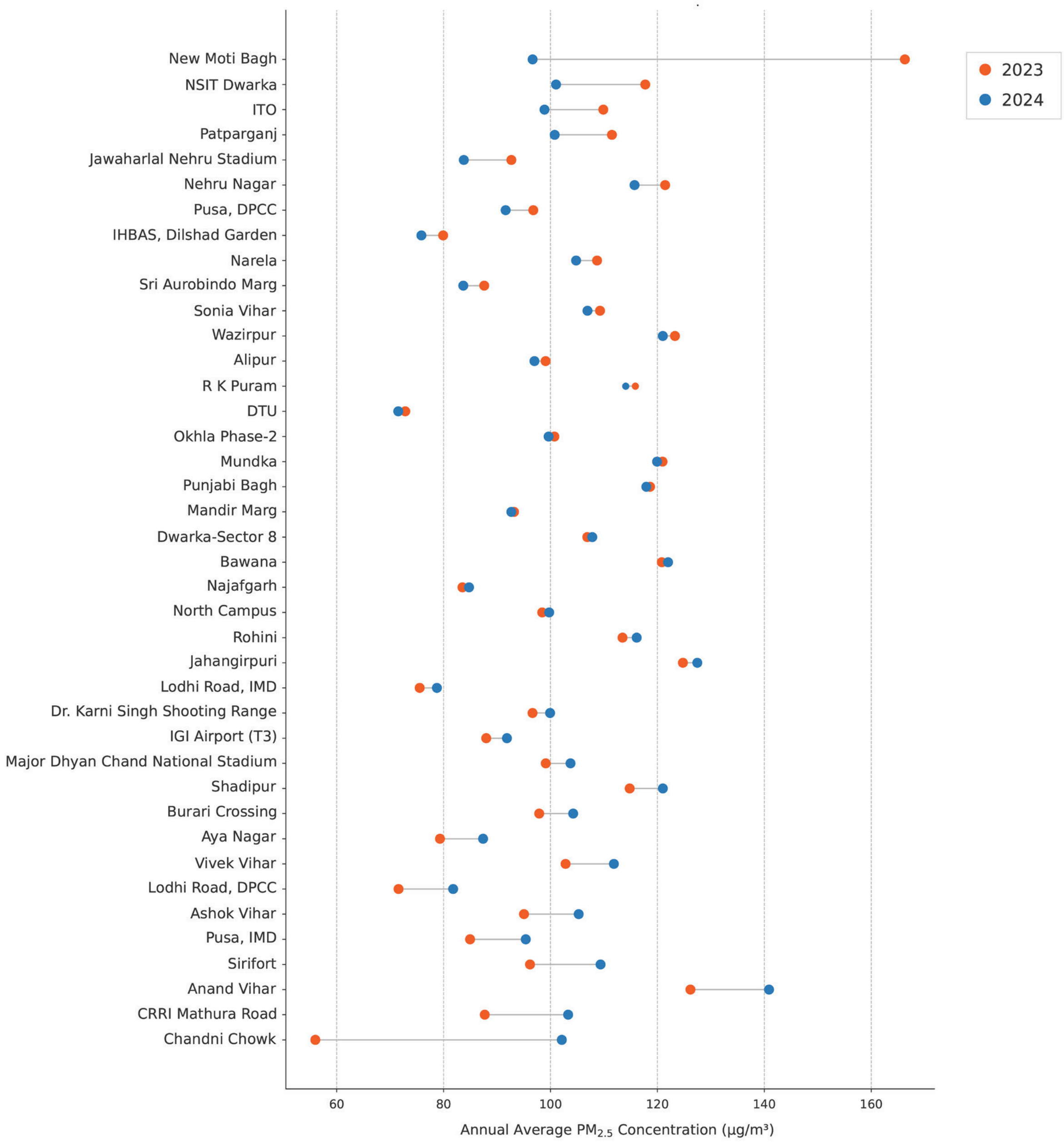


Figure 16. **Change in $PM_{2.5}$ level between 2023 and 2024 in Delhi.**

Annual Average Versus 3-Year Rolling Average

The trend analysis was influenced by the selection of stations and their data availability over time. Figures 17–19 present the annual average concentrations of PM_{10} and $PM_{2.5}$ using three sets of monitoring stations: those that meet the annual completeness criteria for any number of years, those with data for at least 3 years, and those with data for at least 5 years. The broader set of stations show a clear declining trend, while the long-term stations display no significant trend. This contrast may be due to newer stations being installed in relatively cleaner areas, leading to an apparent overall decline that does not necessarily reflect widespread improvement in air quality. Stations with fewer years of data often cover more recent periods, which may genuinely reflect improvements from recent pollution control efforts. In comparison, long-term stations capture both earlier, more polluted years and cleaner recent years, resulting in a more stable average over time.

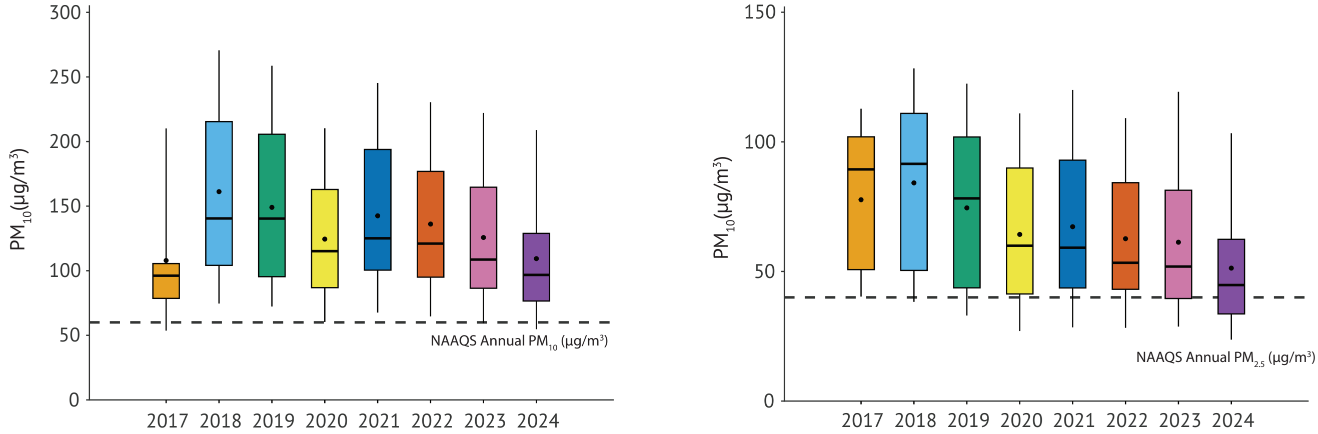


Figure 17. **Annual average PM_{10} (left) and $PM_{2.5}$ (right) for stations meeting completeness criteria for any year between 2017 and 2024.**

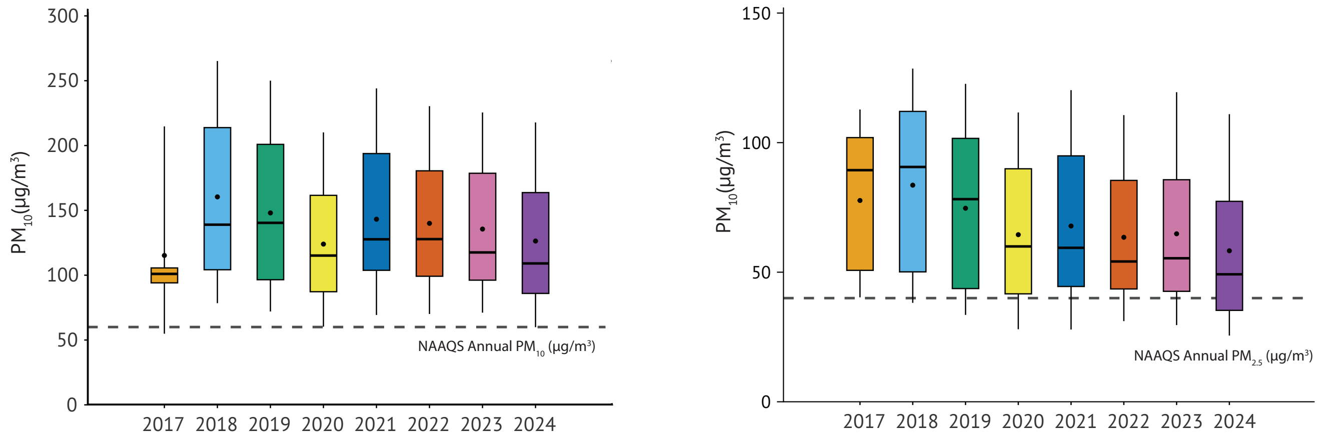


Figure 18. **Annual average PM_{10} (left) and $PM_{2.5}$ (right) from stations with at least 3 years of complete data between 2017 and 2024.**

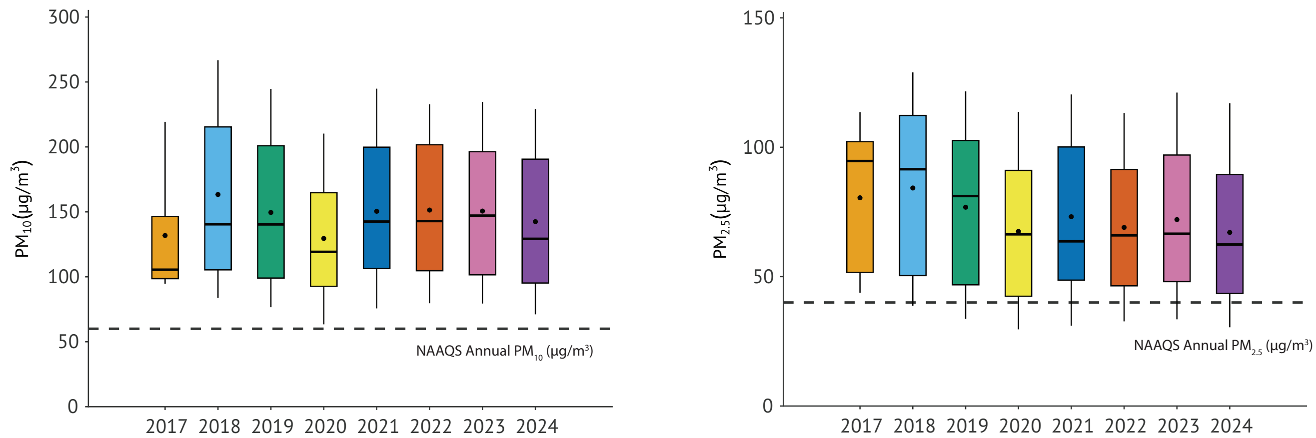


Figure 19. **Annual average PM_{10} (left) and $PM_{2.5}$ (right) from stations with at least 5 years of complete data between 2017 and 2024.**

When looking at the rolling averages, out of 39 cities with stations having at least 5 years of complete PM_{10} data, most of the stations in Varanasi, Kolkata, Ghaziabad, Jalandhar, Meerut, and Mumbai show a consistent decreasing trend. Stations in Dewas, Nashik, Mandi Gobindgarh, Patna, and Chandigarh show a consistent increasing trend. In the case of $PM_{2.5}$, stations in Varanasi, Kolkata, Dewas, Jodhpur, Mumbai, Lucknow, and Kanpur show a decreasing trend, and those in Asansol, Amritsar, Mandi Gobindgarh, and Chandigarh show an increasing trend. Dewas in Madhya Pradesh is the only city where, in the same station, the rolling average is increasing for PM_{10} and decreasing for $PM_{2.5}$. The consistent decreasing trend indicates that the 3-year rolling average smooths short-term fluctuations; a steady decline suggests real, long-term improvement in air quality, and a sustained increase indicates a worsening trend — pollution is not just spiking in 1 year but is persistently high or rising over multiple years.

Annual averages are useful; however, they are volatile and trends can change sharply due to unusual events such as lockdowns or weather patterns or local activities such as construction. The 3-year rolling average can smooth out the short-term spikes or dips and provide realistic trends. For example, in Golden Temple, Amritsar (**Figure 20**), the annual average has peaks in 2018 and 2024, with lower values in between. The rolling average smooths the curve and shows a gentle upward trend toward 2024. This rolling average filters out the noise from end-year (2024) peaks and shows a gradual increase; hence, the rise in 2024 may be part of the trend rather than a one-off observation.

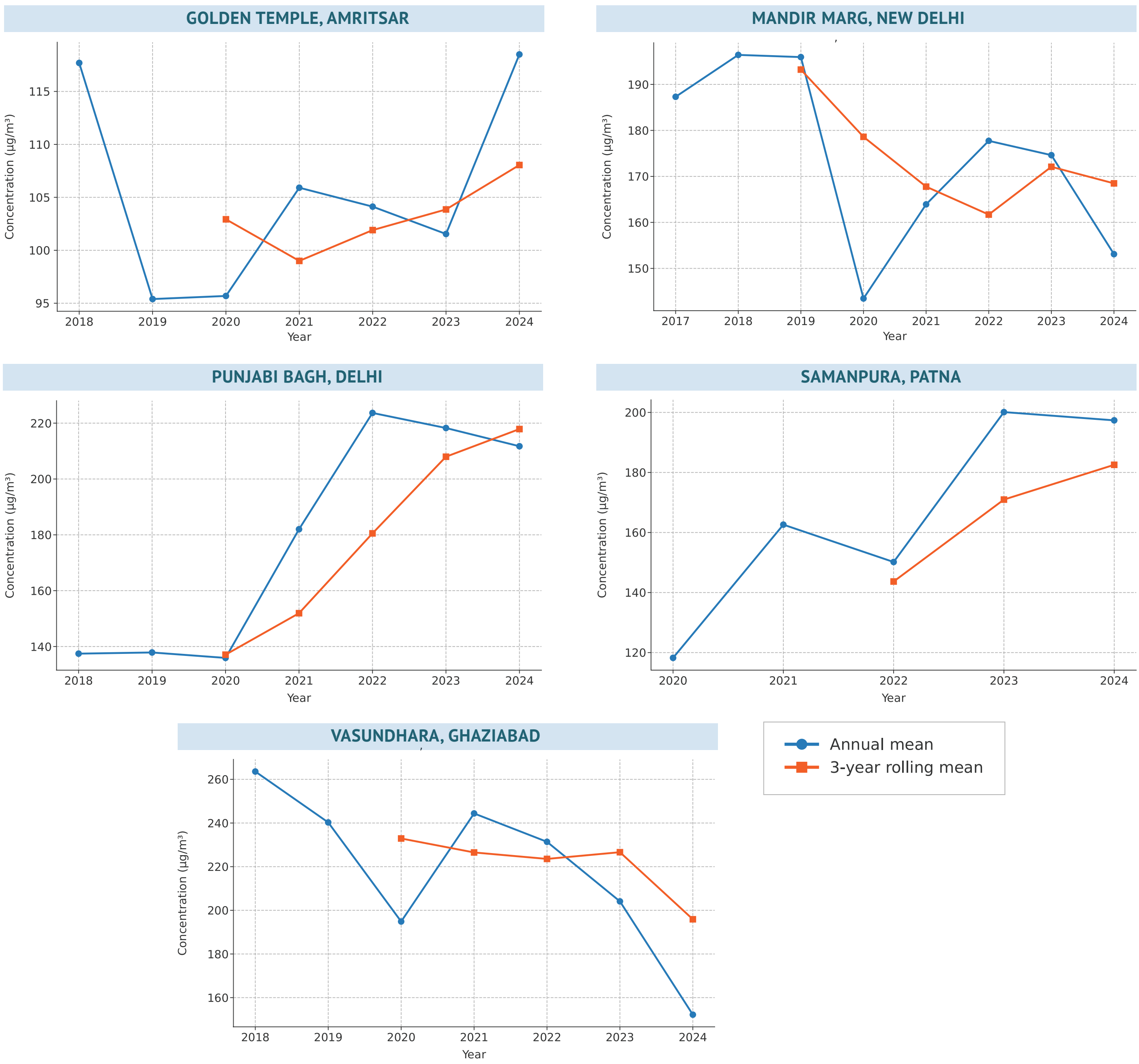


Figure 20. **PM_{10} (µg/m³) annual average versus rolling average for select locations.**

In the analysis of annual versus 3-year rolling averages, two distinct patterns emerge:

- When the annual average is higher than the rolling average, it often indicates a **potential worsening trend**, as recent pollution levels have increased compared to the previous years. This pattern is evident in stations such as Punjabi Bagh, Delhi, and Samanpura, Patna, where the annual PM_{10} levels in recent years rise more sharply than the rolling mean, suggesting a developing **upward trend in pollution.**
- Conversely, when the **rolling average is higher than the annual average**, it reflects a recent improvement – the current year's pollution levels have decreased, but past high values still elevate the rolling average. This is seen in stations like Vasundhara, Ghaziabad (2024) and Mandir Marg, New Delhi (2024), where the 2024 annual averages drop below the rolling mean, indicating a possible positive shift. These comparisons demonstrate how the **rolling average helps balance short-term fluctuations** and provides a clearer understanding of sustained changes over time.

The use of a 3-year rolling average is also effective in smoothing out anomalies caused by events such as the COVID-19 lockdown. In 2020, a temporary reduction in air pollution was observed in many cities. For instance, Mandir Marg, New Delhi, and Vivek Vihar, Delhi, show a sharp dip in annual PM_{10} in 2020. However, the rolling average did not drop, thereby providing a more stable view of the overall trend.

A foggy highway with cars driving on it

Effect of Seasonality

Trend assessment using the Mann-Kendall test and the Theil-Sen slope estimator was calculated using both raw data and deseasoned data for stations with at least 3 years of continuous data. Deseasoning led to large increases in statistically significant trends (Table 6). For both PM_{10} and $PM_{2.5}$, the proportion of stations with statistically significantly increasing and decreasing trends more than doubled after removing seasonal effects. Deseasoning the raw data helps to isolate the underlying long-term trends by removing seasonal effects (e.g., winter spikes and monsoon dips), making it easier to detect the true direction and strength of the trend.

Table 6. Trend Summary: Stations with ≥3 Years of Continuous Data (Raw vs. Deseasoned Data)

SCENARIO	NUMBER OF STATIONS	
	Increasing Trend	Decreasing Trend
PM_{10} (N = 155)		
Raw data	51 (10[a])	104 (25[a])
Deseasoned	54 (32[a])	101 (63[a])
$PM_{2.5}$ (N = 160)		
Raw data	42 (5[a])	118 (36[a])
Deseasoned	50 (33[a])	110 (87[a])

[a]*Indicates statistically significant trend.*

For example, **Figure 21** shows PM_{10} and $PM_{2.5}$ trends for a station in Kolkata. Significant seasonal variation is observed, with significantly higher levels during the winter months. Numerous studies in northern Indian cities report strong seasonal $PM_{2.5}$ variation, with peaks in postmonsoon and winter and lows during the monsoon or premonsoon (Mogno et al. 2021; Tiwari et al. 2013). When the data are deseasoned (**Figure 23**), a steeper true decline can be observed for both PM_{10} and $PM_{2.5}$ compared to what the raw data suggest (**Figure 22**).

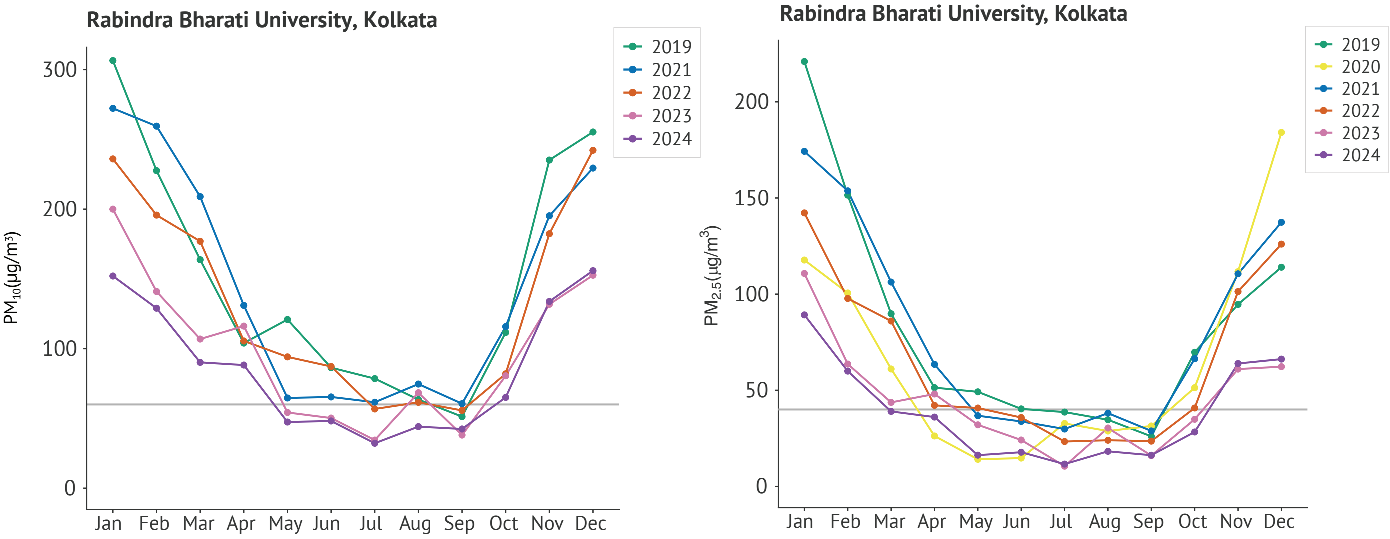


Figure 21. **PM_{10} (a) and $PM_{2.5}$ (b) levels at Rabindra Bharati University, Kolkata.**

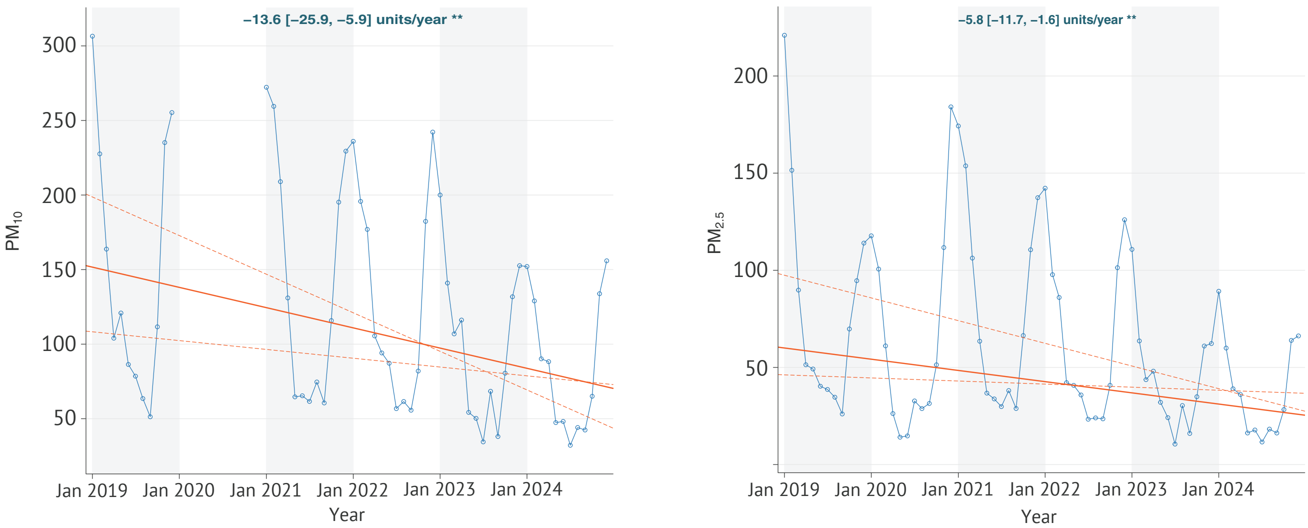


Figure 22. **Trend plots for PM_{10} (a) and $PM_{2.5}$ (b) levels at Rabindra Bharati University, Kolkata, raw data.** ** $P < 0.01$.

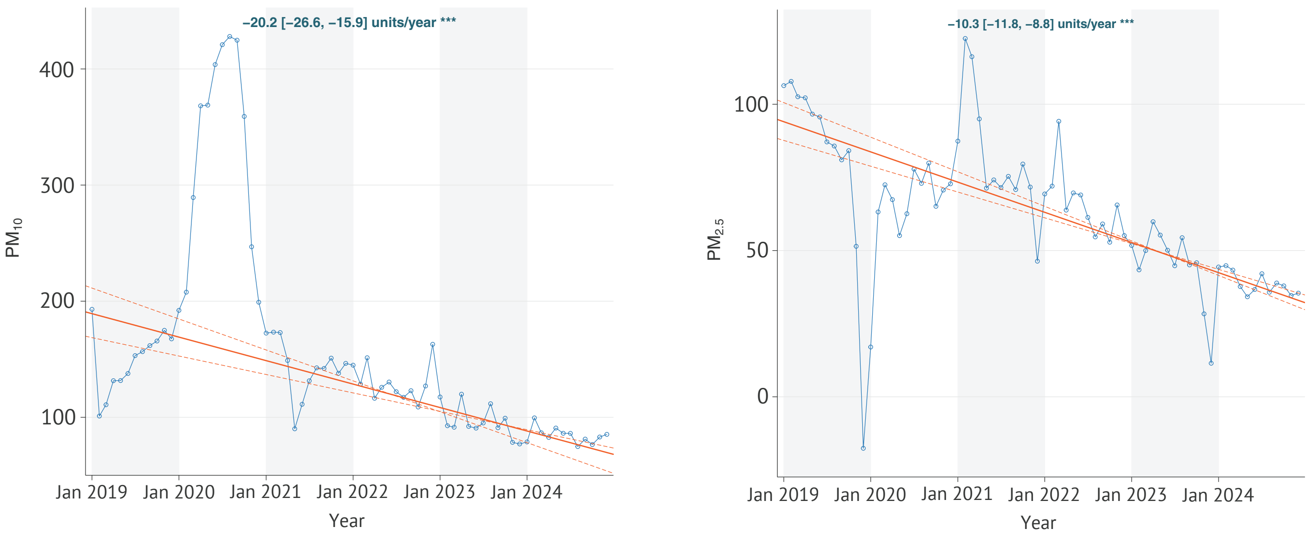


Figure 23. **Trend plots for PM_{10} (a) and $PM_{2.5}$ (b) levels at Rabindra Bharati University, Kolkata, deseasoned data.** *** $P < 0.001$.

The effect was significant not only in the places where the seasonal variation is prominent but also in regions such as South India where there is minimal seasonal variation. The level of pollution is higher during the winter months (**Figure 24**). Deseasoned PM_{10} trend plots showed a strong, statistically significant declining trend compared to the raw data where the trend is unclear (**Figure 25**).

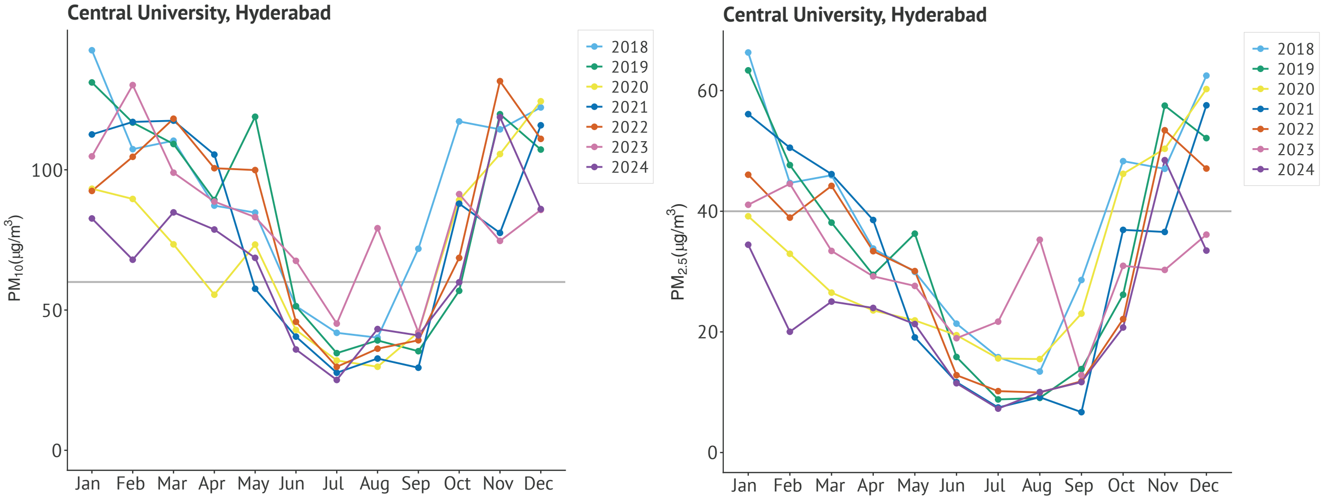


Figure 24. **PM_{10} (a) and $PM_{2.5}$ (b) levels at Central University, Hyderabad.**

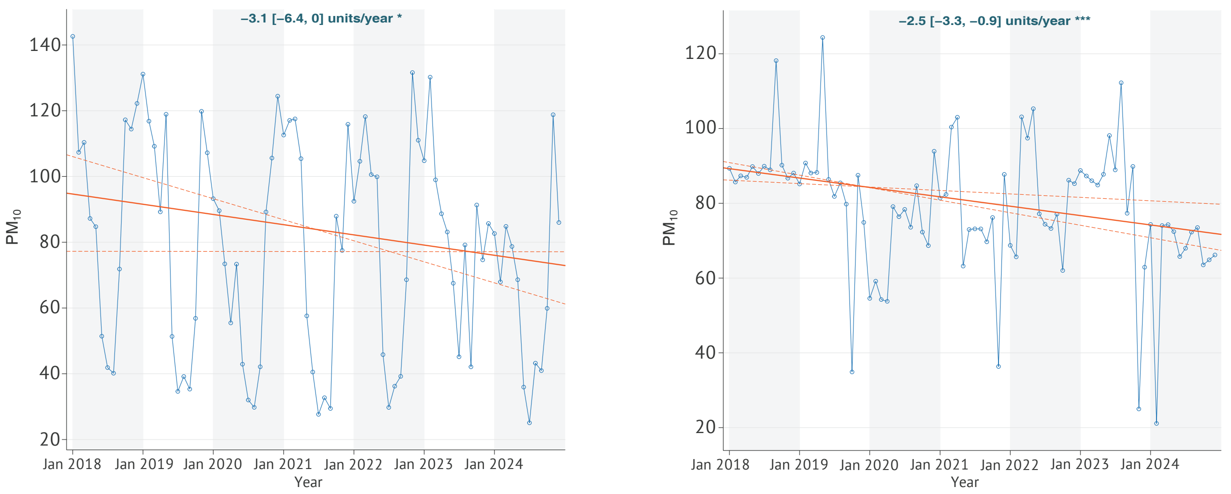


Figure 25. **Trend plots for PM_{10} levels at Central University, Hyderabad; (a) raw data, and (b) deseasoned data.** $^{*}P < 0.05$ and $^{***}P < 0.001$.

Figure 26a shows monthly $PM_{2.5}$ trends at a monitoring station in Varanasi. From 2017 to 2021, there is a clear seasonal pattern and a presence of strong peaks due to winter and troughs in between due to monsoons and summer. From 2022 onward, the seasonal fluctuation largely disappears, and the values remain relatively low and stable with no clear peaks. Natural processes such as weather do not typically stop fluctuating abruptly, especially in cities in the Indo-Gangetic Plains; it is unclear what may have caused this. Both raw (**Figure 26b**) and deseasoned data (**Figure 26c**) show highly statistically significantly decreasing trends over time and thus seasonality does not drive or distort the overall trend.

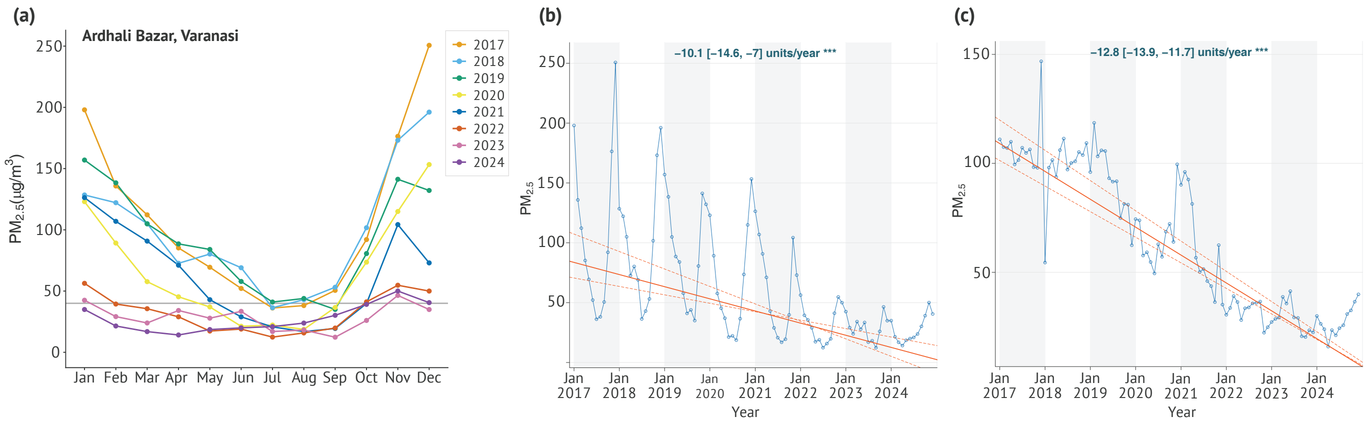
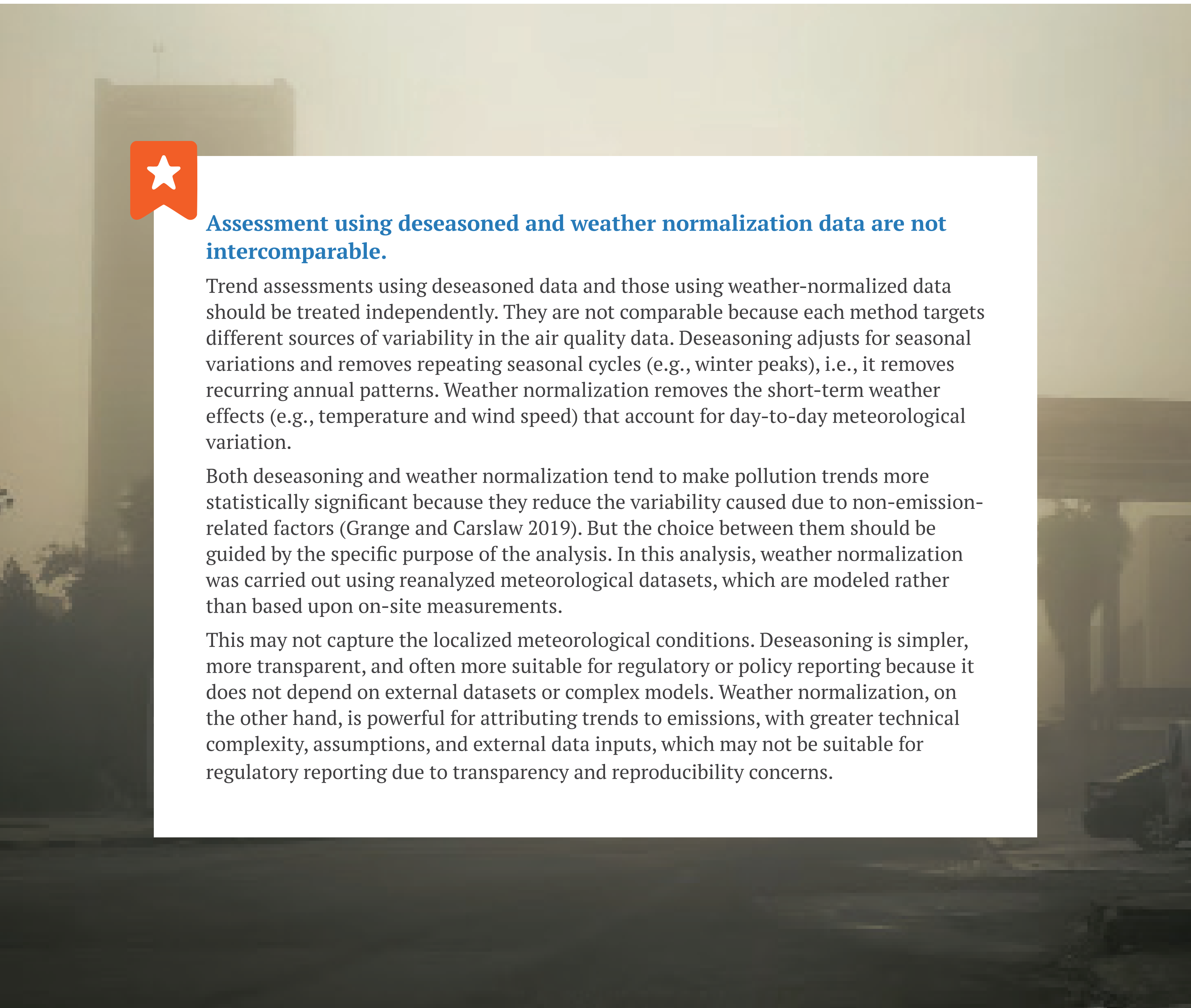


Figure 26. **(a) $PM_{2.5}$ levels at Ardhali Bazar, Varanasi, and trend plots for $PM_{2.5}$ levels at Ardhali Bazar based on (b) raw data, and (c) deseasoned data.** $^{***}P < 0.001$.

Most stations in Delhi showed a decrease in pollutant levels after deseasoning, although the magnitudes of these decreases remain small compared to the high baseline concentrations. A total of 27 stations in Delhi had data for at least 5 years. Using raw data for PM_{10}, 21 out of 27 stations showed a decreasing trend in pollutant levels, with the decrease ranging from −0.3 to −9.7 μg/m³/year. The increase in PM_{10} levels were higher in two stations: Punjabi Bagh (16.1 [6.9, 26.5] μg/m³/year) and R.K. Puram (13.1 [4.5, 23.9] μg/m³/year). For $PM_{2.5}$, 24 out of 30 stations showed a decreasing trend, ranging from −0.12 to −7.1 μg/m³/year. It is important to note that in most cases the rise or decline was not statistically significant. The trends were significant when using deseasoned data compared to raw data. For PM_{10}, 19 stations showed decreasing trends, with the highest decrease in Jawaharlal Nehru Stadium, Delhi (−7.5 [−10.1, −4.0] μg/m³/year). For $PM_{2.5}$, 22 stations showed decreasing trends and eight stations showing increasing trends. Similar to PM_{10}, the increasing trend was highest in Punjabi Bagh (3.6 [2.4, 5.0] μg/m³/year) and R.K. Puram (6.9 [3.3, 9.8] μg/m³/year). Overall, more stations showed a decreasing trend. Earlier studies using the deseasoning approach have also shown similar trends for PM_{10} between 2015 and 2022, such as a decreasing trend of 7.6 μg/m³/year (Chetna et al. 2024). The same study showed a decreasing trend of 1.4 μg/m³/year for $PM_{2.5}$ between 2007 and 2021 (Chetna et al. 2023).



Assessment using deseasoned and weather normalization data are not intercomparable.

Trend assessments using deseasoned data and those using weather-normalized data should be treated independently. They are not comparable because each method targets different sources of variability in the air quality data. Deseasoning adjusts for seasonal variations and removes repeating seasonal cycles (e.g., winter peaks), i.e., it removes recurring annual patterns. Weather normalization removes the short-term weather effects (e.g., temperature and wind speed) that account for day-to-day meteorological variation.

Both deseasoning and weather normalization tend to make pollution trends more statistically significant because they reduce the variability caused due to non-emission-related factors (Grange and Carslaw 2019). But the choice between them should be guided by the specific purpose of the analysis. In this analysis, weather normalization was carried out using reanalyzed meteorological datasets, which are modeled rather than based upon on-site measurements.

This may not capture the localized meteorological conditions. Deseasoning is simpler, more transparent, and often more suitable for regulatory or policy reporting because it does not depend on external datasets or complex models. Weather normalization, on the other hand, is powerful for attributing trends to emissions, with greater technical complexity, assumptions, and external data inputs, which may not be suitable for regulatory reporting due to transparency and reproducibility concerns.

Effect of Meterology

The raw data was subjected to weather normalization for stations with at least 3 years of continuous complete data. The number of statistically significant trends (marked with [a]) in **Table 7** increased substantially after weather normalization for both PM_{10} and $PM_{2.5}$. In the case of PM_{10} with raw data, only 22.6% of stations showed significant trends. After weather normalization, the percentage of stations showing significant trends in PM_{10} levels rose to 80%, with a major jump in the decreasing trend (from 16.1% to 54.2%). Similarly, in the case of $PM_{2.5}$ with raw data, only 25.6% of stations showed significant trends. After weather normalization the percentage rose to 69.4%, especially in decreasing trends (from 22.5% to 64.4%). Although the total number of stations remained constant in both cases, the proportion of statistically significant trends increased drastically after weather normalization. It is evident that weather was masking the true improvement and normalization reveals a clearer pattern.

Industrial stack emissions

Table 7. Trend Summary: Stations with ≥3 Years of Continuous Data (Raw vs. Weather Normalized Data)

SCENARIO	NUMBER OF STATIONS	
	Increasing Trend	Decreasing Trend
PM_{10} (N = 155)		
Raw data	51 (10[a])	104 (25[a])
Weather normalized	56 (40[a])	99 (84[a])
$PM_{2.5}$ (N = 160)		
Raw data	42 (5[a])	118 (36[a])
Weather normalized	42 (28[a])	118 (103[a])

[a]*Indicates statistically significant trend.*

Removing weather effects reveals a clearer underlying trend.

Trend analysis using weather-normalized data shows a clear trend when compared to the trends estimated using raw data. For example, **Figure 27** shows the trend plots for $PM_{2.5}$ at the Moti Doongri station in Alwar, Rajasthan, using raw data and weather-normalized data. The raw data shows a declining trend (−1.6 [−3.3, 0.6] µg/m³/year) with uncertainty. The weather-normalized data shows a statistically significant declining trend (−0.3 [−0.5, −0.1] µg/m³/year), although it is smaller in magnitude when compared to raw data. It is clear that a declining trend in $PM_{2.5}$ at Moti Doongri is real and is not driven by weather. Weather normalization reduces variability and shows long-term improvement in air quality at this station. **Figure 28** shows the trend plots for PM_{10} at Railway Colony, Guwahati station using raw data and weather-normalized data. The trend is slightly upward but with a wide confidence interval, so it is hard to conclude if the trend is upward or downward. The data is dominated by strong seasonal peaks (blue lines), which masks the underlying pattern. With weather normalization the decline becomes significant. In both Alwar and Guwahati these are the only stations that have data for at least 5 years.

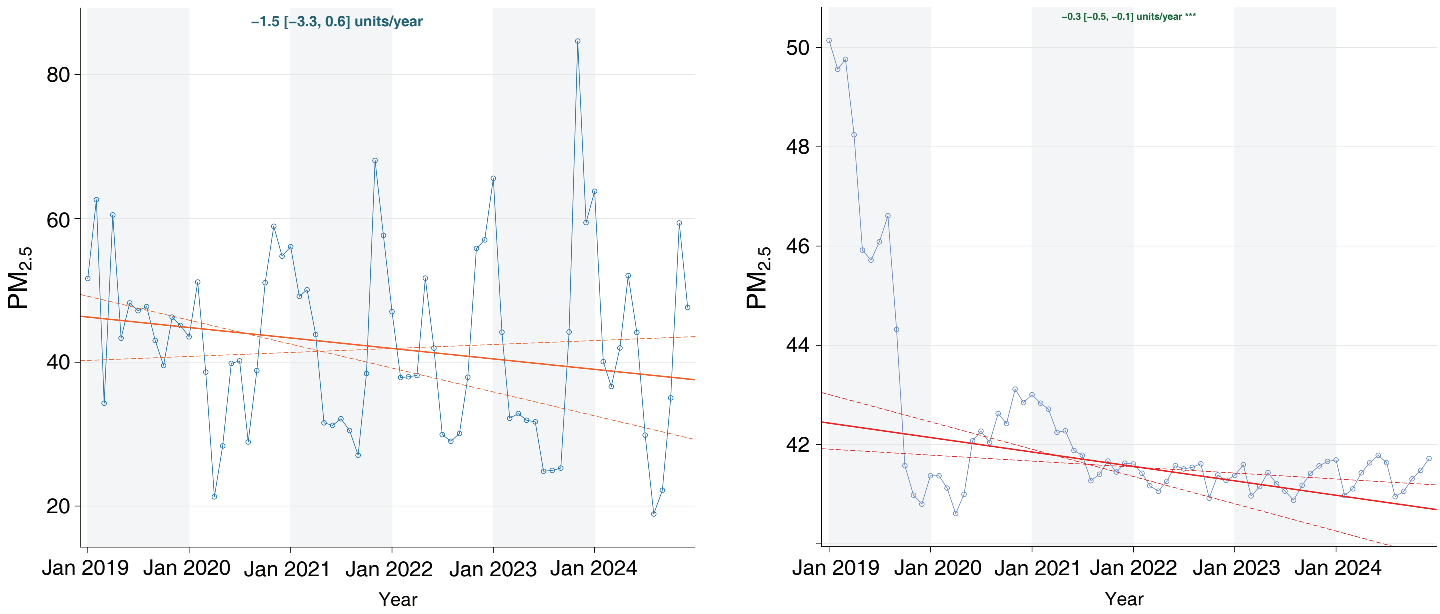


Figure 27. Trend plots for $PM_{2.5}$ at Moti Doongri station, Alwar, using raw (a) and weather-normalized (b) data. ****P* < 0.001.

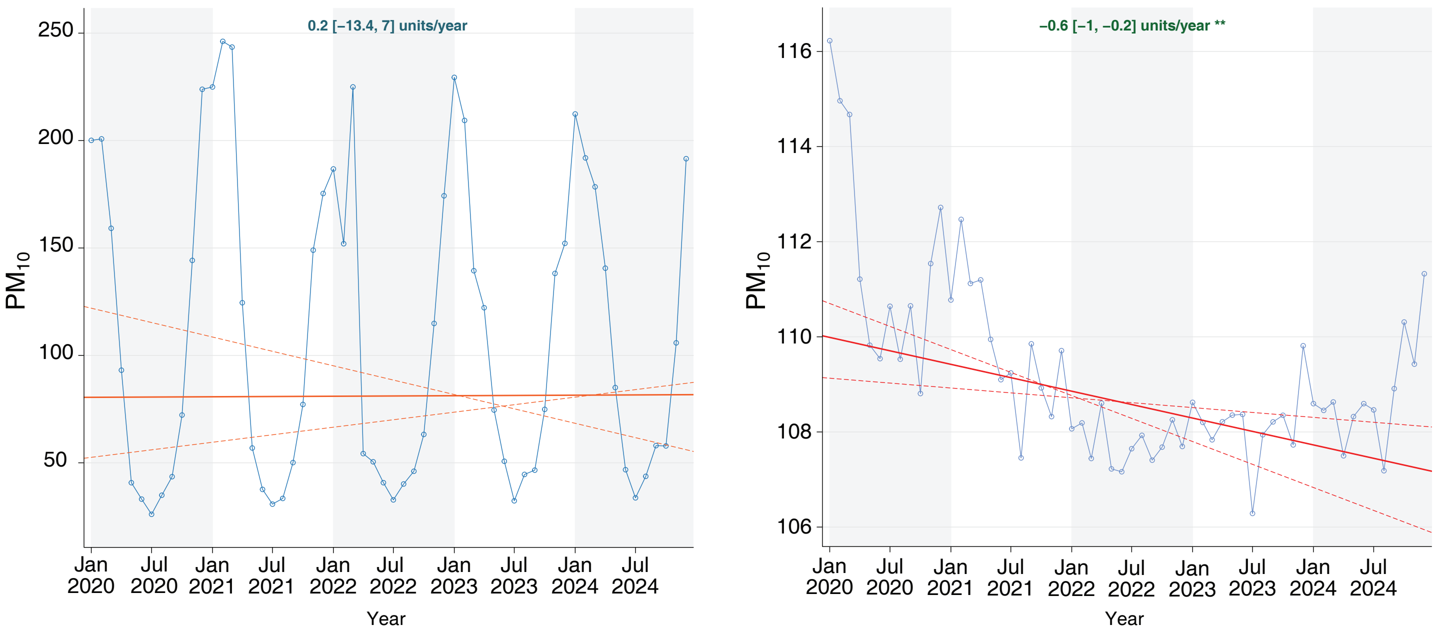


Figure 28. Trend plots for PM_{10} at Railway colony, Guwahati station using raw (a) and weather normalized (b) data. ***P* < 0.01.

We are using Kolkata as an example of a city with multiple stations having at least 3 years of data. In Kolkata there are four stations with at least 5 years of PM_{10} data and two stations with at least 3 years of PM_{10} data — six total. After weather corrections all four stations with at least 5 years of data show a declining trend. In the 3-year category, one station showed a very strong decline, and one showed a very slight increasing trend (**Table 8**). Overall, five out of six stations showed a declining trend, and the weather-normalized trends are highly significant. Hence, it is evident in this city weather plays a substantial role in short-term variations in PM levels and without normalizing for weather these changes can give a misleading impression of air quality trends. A similar trend was observed for $PM_{2.5.}$

Table 8. Rate of Change in PM_{10} and $PM_{2.5}$ Trends at Monitoring Stations in Kolkata

	PM_{10} (µg/m³/year)		$PM_{2.5}$ (µg/m³/year)	
	Raw	Weather Normalized	Raw	Weather Normalized
BALLYGUNGE	1.0 [−12.1, 10.5]	−1.1 [−1.6, −0.6]	1.0 [−6.1, 6.4]	−0.2 [−0.7, 0.0]
BIDHANNAGAR	0.7 [−8.2, 8.1]	−0.9 [−1.6, 0.5]	0.4 [−5.0, 4.4]	−0.3 [−0.6, 0.5]
FORT WILLIAM	2.6 [−9.5, 10.7]	1.4 [1.0, 1.7][a]	0.8 [−5.8, 5.0]	0.0 [−0.6, 1.6]
JADAVPUR	0.6 [−9.9, 8.4]	−1.2 [−1.7, 0.1][a]	0.1 [−5.4, 4.4]	−1.3 [−1.7, −0.1][a]
RABINDRA BHARATI UNIVERSITY	−13.6 [−25.9, −5.9][a]	−11.0 [−13.5, −9.9][a]	−5.8 [−11.7, −1.6][a]	−5.7 [-6.5, −4.9][a]
RABINDRA SAROBAR	−3.5 [−12.7, −2.2]	−4.4 [−5.0, −3.9][a]	0.6 [−4.5, 3.2]	−0.7[−0.9, −0.6][a]
VICTORIA	1.6 [−7.0, 6.4]	0.7 [0.3, 1.2][a]	−1.0 [−5.9, 2.1]	−0.7 [−0.9, −0.5][a]

[a]*Indicates statistically significant trend.*

- Overall, most cities with **complete long-term data** indicate a **declining trend in PM_{10} levels.** Across stations with at least 5 years of data (*n* = 83), 44 showed a statistically significant decline in PM_{10} levels, while 24 showed a significant increase.
- At the city level, several cities **with only one monitoring station and at least 5 years of data** — including Ahmedabad, Chandrapur, Faridabad, Guwahati, Jabalpur, Jodhpur, Patiala, Rajamahendravaram, and Varanasi — exhibited a significant declining trend in PM_{10}.
- Among cities with **multiple stations with at least 5 years of complete data**, all stations in Ghaziabad, Howrah, Hyderabad, Kolkata, Meerut, Mumbai, and Noida showed a strong and consistent decline.
- In **Delhi**, of the 27 stations evaluated, 15 showed a statistically significant decrease in PM_{10}, six showed an increase, and the rest had no strong trend.
- However, some cities showed the **opposite pattern**. Strong increasing trends were observed in cities such as Amritsar, Asansol, Bengaluru, Chandigarh, Dewas, Khanna, Kota, Ludhiana, Mandi Gobindgarh, Nashik, and Thane. All these cities have only one complete long-term monitoring station. All stations with complete data in Jaipur and Patna also showed increasing trends in PM_{10} levels.

In the case of $PM_{2.5}$, out of 89 stations with at least 5 years of data, 54 showed a strong declining trend, while 19 showed an increasing trend.

- At the city level, monitoring stations in Ahmedabad, Alwar, Faridabad, Jabalpur, Jalandhar, Jodhpur, Varanasi, and Visakhapatnam — all of which have **only one station with long-term data** —exhibited a strong decline in $PM_{2.5}$ levels.
- Among cities **with multiple stations and at least 5 years of complete data**, all stations in Ghaziabad, Howrah, Hyderabad, Kolkata, Mumbai, and Noida showed a consistent and statistically significant decline. In Delhi, 21 stations showed a declining trend, while four showed an increasing trend.
- In contrast, **strong increases** in $PM_{2.5}$ levels were observed in several cities, including Amritsar, Asansol, Chandigarh, Chandrapur, Khanna, Kota, Ludhiana, Mandi Gobindgarh, Nashik, and Thane.

Recommended Metrics for Annual Performance Tracking

DATA

Both manual and real-time data are valuable for assessing air quality trends, but the two must be evaluated independently. The sampling frequency, measurement principles, and analysis procedures differ significantly; manual monitoring typically involves 24-hour integrated samples collected on specific days, while continuous monitoring provides high-resolution real-time measurements. Because of these methodological differences, the datasets are not directly comparable and should not be combined. Averaging manual and real-time data across a city introduces further problems. Such averaging masks local variability and dilutes station-specific signals that are critical for understanding pollution dynamics. Therefore, station-level analysis is essential, and city-level averages, especially those that mix manual and real-time data, are not an appropriate metric for evaluating trends or compliance.

METRICS FOR PERFORMANCE TRACKING

It is important to note that AQI exceedance and NAAQS exceedance are not appropriate metrics for performance review (see pages 11 and 25). For annual performance review, a network of representative stations should be formed for long-term trend assessment. In cities with multiple stations, this can be done using the designated representative monitors. In cities with only a single station, it is important to expand the monitoring network and designate monitors for long-term trend assessment; until then, the single station may be used provisionally.

The next step is to check whether the station meets the completeness criteria. If the station has only 2 years of data, the absolute change between the 2 years can be assessed. If the station has more than 3 years of data, 3-year rolling averages can be used to evaluate trends and performance.

05 Conclusions

PM levels are decreasing in most locations.

A number of monitoring stations among 102 NCAP cities show a clear decline in PM_{10} and $PM_{2.5}$ levels between 2017 and 2024. This is a strong and encouraging signal that air quality is improving — not just temporarily due to favorable weather conditions. The findings also reveal that seasonal variation and meteorological influences significantly shape air quality trends in Indian cities. While such corrections may not be necessary for routine reporting, they are crucial for studies examining changes in long-term pollutant concentrations or effectiveness of interventions.

Note that the study did not include an audit of individual monitoring stations to verify whether changes in pollutant levels were influenced by shifts in instrument calibration, relocation of monitors, or other operational factors. This is a limitation of the study, as such changes could affect the interpretation of trends.

Attributing to the NCAP is difficult.

While air quality improvements have been observed in recent years, attributing these changes solely to the NCAP is challenging. A number of major interventions — such as leapfrogging from BS-IV to BS-VI, the implementation of Pradhan Mantri Ujjwala Yojana, and various state and local policies — were introduced during a similar period. In addition, in most cities NCAP funds were allocated and released at vastly different points in time, making it even harder to draw a direct link between the programme and observed trends, at least in the current time frame.

Reductions in $PM_{2.5}$ can drive real air quality and public health gains.

Looking ahead, $PM_{2.5}$ should be prioritized when assessing air quality progress, as even small changes in $PM_{2.5}$ levels have a significant impact on public health. Of note, the number of days with NAAQS exceedance for $PM_{2.5}$ is much lower than for PM_{10}. Moreover, long-term trend analysis shows that $PM_{2.5}$ levels are declining at many monitoring stations, a positive sign of progress. Given its stronger link to health outcomes and its consistent improvement, $PM_{2.5}$ can be given greater focus in both monitoring and policy efforts.

A cyclist navigating a fog- and dust-filled road in Kota, Rajasthan

Recommendations

Data completeness and coverage are prerequisites for credible trend detection.

Since the inception of the NCAP, there has been a significant increase in the number of monitoring stations, leading to the availability of a large volume of air quality data. In fact, trend analysis shows that complete and consistent data is essential to establish stable and reliable patterns. Therefore, it is important for cities to ensure that monitoring stations record data as completely as possible.

> Under the NCAP, a performance criterion to reflect data completeness and coverage can be included; an example would be a minimum percentage of data availability throughout seasons, ensuring that the air quality monitors generate representative data.

Rolling averages work better.

Year-on-year absolute changes in pollutant levels can be misleading. While analytical approaches such as deseasoning and weather normalization can help correct biases, these approaches are complex and time-consuming and may not always be fit-for-purpose when conducting regulatory analyses.

> Using a rolling average (e.g., 3-year rolling averages) can provide clear trend in pollutant concentrations. It smoothens short-term fluctuations, reduces anomalies, and provides more accurate long-term trends.

One city, different patterns.

Results show that different monitoring stations within the same city can display significantly different trends, reflecting the diverse nature of hyperlocal pollution sources. Nevertheless, potential influence from other factors such as differences in instrument calibration cannot be entirely ruled out. Citywide average air quality data can fail to capture the real impact of interventions carried out by urban local bodies at the local level.

> Each city should have at least one monitor dedicated to compliance monitoring or trend assessment, preferably the background monitor. Additional monitors can be strategically classified based on specific site characteristics, including known hotspots, residential areas, and commercial or industrial zones, to better understand local air quality dynamics and to understand the efficiency of city-level and sectoral level interventions.

City skyline under heavy smog

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07 Abbreviations

AQI	Air Quality Index
CAAQMS	Continuous Ambient Air Quality Monitoring System
CAQM	Commission for Air Quality Management
CEMS	Continuous Emission Monitoring Systems
CPCB	Central Pollution Control Board
CREA	Centre for Research on Energy and Clean Air
CSE	Centre for Science and Environment
CSTEP	Centre for Study of Science, Technology and Policy
GDP	gross domestic product
GLS	generalized least squares
LOESS	locally estimated scatterplot smoothing
MoEFCC	Ministry of Environment, Forest and Climate Change
MoF	Ministry of Finance
NAAQS	National Ambient Air Quality Standard
NAMP	National Air Quality Monitoring Programme
NCAP	National Clean Air Programme
PCC	Pollution Control Committee
PM_{10}	particulate matter ≤10 μm in aerodynamic diameter
$PM_{2.5}$	particulate matter ≤2.5 μm in aerodynamic diameter
PMUY	Pradhan Mantri Ujjwala Yojana
QA	quality assurance
QC	quality control
RF	random forest
SPCB	State Pollution Control Board
SPM	suspended particulate matter
SVS	Swachh Vayu Survekshan
US EPA	United States Environmental Protection Agency
UT	union territory
WHO	World Health Organization

08 References

Carslaw DC, Ropkins K. 2012. Openair: an R package for air quality data analysis. Environ Model Softw 27–28:52–61, *https://doi.org/10.1016/j.envsoft.2011.09.008*.

Center for Study of Science, Technology and Policy (CSTEP). 2022. Identification of Polluting Sources for Bengaluru — Source Apportionment Study. Available: *https://prana.cpcb.gov.in/ncapDashboard/downloadEmissionFiles/Bangalore.pdf*.

Central Pollution Control Board (CPCB). 1994. National Ambient Air Quality Standards. New Delhi, India: CPCB.

Central Pollution Control Board (CPCB). 1998. Ambient Air Quality Standards for Ammonia. Available: *https://cpcb.nic.in/displaypdf.php?id=aG9tZS9haXItcG9sbHV0aW9uL1NPLTkzNUUucGRm*.

Central Pollution Control Board (CPCB). 2009. National Ambient Air Quality Standards. Available: *https://cpcb.nic.in/uploads/National_Ambient_Air_Quality_Standards.pdf*.

Central Pollution Control Board (CPCB). 2014. National Air Quality Index. Available: *http://app.cpcbccr.com/ccr_docs/FINAL-REPORT_AQI_.pdf*.

Central Pollution Control Board (CPCB). 2025, October 15. Minutes of the 19th meeting of the Implementation Committee under the National Clean Air Programme (NCAP). Available: *https://prana.cpcb.gov.in/ncapDashboard/download_public_portal_file/19th_IC_MoM_15-10-2025_1762516117431776.pdf*.

Centre for Research on Energy and Clean Air (CREA). 2023. Tracing the Hazy Air 2023 Progress Report on National Clean Air Programme (NCAP). Available: *https://energyandcleanair.org/wp/wp-content/uploads/2023/01/Tracing-the-Hazy-Air-2023_-Progress-Report-on-National-Clean-Air-Programme-NCAP_10th-January-2023.pdf*.

Centre for Research on Energy and Clean Air (CREA). 2024. Tracing the Hazy Air 2024: Progress Report on National Clean Air Programme (NCAP). Available: *https://energyandcleanair.org/wp/wp-content/uploads/2024/01/Tracing-the-Hazy-Air-2024-Progress-Report-on-National-Clean-Air-Programme-NCAP.pdf*.

Centre for Science and Environment (CSE). 2025. Driving Clean Air Action Under NCAP. Available: *https://www.cseindia.org/driving-clean-air-action-under-ncap-12713*.

Chetna DSK, Longiany G, Panwar V, Kumar V, Malik S, Rao AS, et al. 2023. Trends and variability of PM2.5 at different time scales over Delhi: long-term analysis 2007–2021. Aero Air Quality Res 23: 220191, *https://doi.org/10.4209/aaqr.220191*.

Chetna DSK, Walker SE, Rawat V, Singh N. 2024. Decoding temporal patterns and trends of PM10 pollution over Delhi: a multi-year analysis (2015–2022). Environ Monit Assess 196:500, *https://link.springer.com/article/10.1007/s10661-024-12638-7*.

Climate Trends; Respirer Living Sciences. 2024. Five years of the National Clean Air Programme. Available: *https://www.respirer.in/wp-content/uploads/2024/01/Five-years-of-the-National-Clean-Air-Programme.pdf*.

Confederation of Indian Industry (CII); Clean Air Fund; Dalberg. 2021. Air Pollution in India and Its Impact on Business. *https://www.cleanairfund.org/resource/air-pollution-in-india-and-the-impact-on-business/*.

Dammalapti SK, Guttikunda S. 2024. How to Spot Anomalies in Data Trends: Evaluating AQI Data from Indian Cities (No. SIM-air working paper series #49-2024). UrbanEmissions.Info. Available: *https://urbanemissions.info/wp-content/uploads/docs/SIM-49-2024.pdf*.

Department of Environment, Government of NCT of Delhi. 2024. Management Interventions to Mitigate Air Pollution in Delhi. Available: *https://www.dpcc.delhigovt.nic.in//uploads/pdf/Final-Air-Pollution-Book-Augustpdf-47e6bea306683f3db355aefe52549ffa.pdf*.

Ganguly T, Kurinji LS, Guttikunda S. 2020. How Robust are Urban India's Clean Air Plans? An Assessment of 102 Cities. Available: *https://www.urbanemissions.info/wp-content/uploads/docs/2020-06-CEEW-UEinfo-India-NCAP-Review.pdf?_ga=2.976625.1920810849.1704098195-2146246320.1702368568&_gl=1*60tgis*_ga*MjE0NjI0NjMyMC4xNzAyMzY4NTY4*_ga_64XLW7JTP7*MTcwNDA5ODE5NC4yLjEuMTcwNDA5OTUyMS4wLjAuMA*.

Ganguly T, Selvaraj KL, Guttikunda SK. 2020. National Clean Air Programme (NCAP) for Indian cities: review and outlook of clean air action plans. Atmos Environ X 8:100096, *https://doi.org/10.1016/j.aeaoa.2020.100096*.

Grange SK, Carslaw DC. 2019. Using meteorological normalisation to detect interventions in air quality time series. Sci Total Environ 653:578–588, *https://doi.org/10.1016/j.scitotenv.2018.10.344*.

Grange SK, Carslaw DC, Lewis AC, Boleti E, Hueglin C. 2018. Random forest meteorological normalisation models for Swiss PM10 trend analysis. Atmos Chem Phys 18:6223–6239, *https://acp.copernicus.org/articles/18/6223/2018/*.

Guttikunda SK, Dammalapati SK, Pradhan G. 2025. Assessing air quality during India's National Clean Air Programme (NCAP): 2019–2023. Atmos Environ 343:120974, *https://doi.org/10.1016/j.atmosenv.2024.120974*.

Guttikunda SK, Kopakka RV, Dasari P, Gertler AW. 2013. Receptor model-based source apportionment of particulate pollution in Hyderabad, India. Environ Monit Assess 185:5585–5593, *https://link.springer.com/article/10.1007/s10661-012-2969-2*.

Health Effects Institute (HEI). 2025. State of Global Air 2025: A Report on Air Pollution and Its Role in the World's Leading Causes of Death. Boston, MA: Health Effects Institute. Available: *https://www.stateofglobalair.org/resources/report/state-global-air-report-2025*.

Hersbach H, Bell B, Berrisford P, Hirahara S, Horányi A, Muñoz-Sabater J, et al. 2020. The ERA5 global reanalysis. QJR Meteorol Soc 146:1999–2049, *https://doi.org/10.1002/qj.3803*.

Mogno C, Palmer PI, Knote C, Yao F, Wallington TJ. 2021. Seasonal distribution and drivers of surface fine particulate matter and organic aerosol over the Indo-Gangetic Plain. Atmos Chem Phys 21:10881–10909, *https://doi.org/10.5194/acp-21-10881-2021*.

Tiwari S, Srivastava AK, Bisht DS, Parmita P, Srivastava MK, Attri SD. 2013. Diurnal and seasonal variations of black carbon and PM2.5 over New Delhi, India: influence of meteorology. Atmos Res 125–126:50–62, *https://doi.org/10.1016/j.atmosres.2013.01.011*.

US Environmental Protection Agency (US EPA). 2021. Best Practices for Review and Validation of Ambient Air Monitoring Data. Available: *https://www.epa.gov/system/files/documents/2021-10/data-validation-guidance-document-final-august-2021.pdf*.

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