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How Well can Delhi Predict Air Quality?

Insights for India's Decision Support Systems

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Executive summary

Air pollution is one of the greatest threats to public health. While short-term exposure can aggravate conditions such as asthma and impair lung function, long-term exposure can lead to chronic obstructive pulmonary disease (COPD), diabetes, and cancers, among other health issues (EEA 2024).

About 70 per cent of India's population breathes air with the PM2.5 levels above the *National Ambient Air Quality Standards* (NAAQS) of 40 μg/m^3 (S. Guttikunda and Ka 2022). To control air pollution in major cities, India launched the *National Clean Air Programme* (NCAP) in 2019, with a focus on 131 non-attainment cities (NACs) that do not meet the NAAQS. The increased attention to air pollution mitigation led to increased monitoring and, consequently, the generation of a large volume of air quality data. In India, air quality data is available from monitoring stations, source apportionment/emission inventory (SA/EI) studies, air quality forecasting models, satellite-based measurements, and other sources at various spatial and temporal scales.

Manual analysis of such voluminous data is impractical; hence, there is a need for digital tools to perform data analytics and provide actionable information. An air quality decision support system (AQDSS) serves this purpose. An AQDSS aggregates air quality data from different sources, performs the necessary analytics, and provides actionable insights to support air quality decision-making.

In the wake of Delhi's worst smog episode in 17 years and a deadly dust storm in 2018, the Ministry of Earth Sciences (MoES) launched the Air Quality Early Warning System (AQEWS) in 2018 to provide air quality forecasts three days in advance for Delhi and select Indian cities. In 2021, the MoES launched a decision support system (DSS) for Delhi as an extension of the AQEWS. The DSS provides information on sectoral and regional contributions to Delhi's PM2.5 levels during winter, including emissions from transportation, industry, and neighbouring districts. While the AQEWS provides forecasts of PM2.5 levels, the DSS complements it by providing information on the contribution of various sources. The Commission for Air Quality Management in National Capital Region and Adjoining Areas (CAQM) implements the *Graded Response Action Plan* (GRAP) in the Delhi NCR region based on the forecasts provided by the AQEWS and DSS.

Under the NCAP, the Ministry of Environment, Forest and Climate Change (MoEFCC) intends to commission AQEWS across all NACs. Apart from Delhi, seven other cities—Ahmedabad, Jaipur, Pune, Mumbai, Kolkata, Bengaluru, and Hyderabad—currently have similar operational AQEWSs. Given that Delhi's AQEWS and DSS serve as models for other cities, assessing their effectiveness is essential. Therefore, through this study, we intend to analyse the performance of Delhi's AQEWS and DSS in order to improve their effectiveness.

Methodology

We assess the performance of Delhi's AQEWS and DSS both qualitatively and quantitatively. We review the literature from around the world to identify the characteristics of an ideal AQDSS, and then we compare its features with those of Delhi's AQEWS and DSS.

We also evaluate the AQEWS's ability to accurately predict the air quality index (AQI) during winter 2023–24 and 2024–25. We compare the AQI forecast from the AQEWS with the observed AQI from the Central Pollution Control Board (CPCB). We then assess the ability of two forecasting models part of the AQEWS – namely, the Weather Research and Forecasting model coupled with Chemistry at 400-metre resolution (WRF-Chem (400 m)) and the India Meteorological Department's System for Integrated Modelling of Atmospheric Composition (IMD SILAM) – to predict the hourly PM2.5 and PM10 accurately. To understand the system's performance during different phases of winter, we analyse forecasts across four phases:

- stubble burning phase (16 October–30 November)
- post-stubble burning phase (1 December–15 December)
- peak winter phase (16 December–15 January)
- post-peak winter phase (16 January–28 February).

We also analyse the system's performance during summer 2024.

Key insights

- **Delhi’s AQEWS and DSS satisfy most of the requirements for an ideal AQDSS. Our qualitative analysis shows that** Delhi’s system includes several features that an ideal AQDSS should possess, such as aggregating data from diverse sources, performing necessary data analytics, and disseminating it to the stakeholders in an easily understandable format. However, it lacks outcome monitoring and does not provide actionable short-term pathways for air pollution reduction. Moreover, it does not provide information on the potential impact of medium and long-term policy measures on Delhi’s air quality.

- **Forecasts from Delhi’s AQEWS could predict ‘very poor and above’ (AQI > 300) pollution episodes more than ~80 per cent of the time in winter 2023-24 and 2024-25.** If Delhi’s AQEWS forecasts the AQI to be ‘very poor and above’ (AQI > 300), the actual AQI is likely to be in the ‘very poor’ (AQI between 300 and 400) or ‘severe and above’ (AQI > 400) categories around 80 per cent of the time (Figure ES1).

- **The ability of the forecasts to predict ‘severe and above’ (AQI > 400) pollution episodes improved in 2024–25.** While the AQEWS could only predict 1 out of 15 air pollution episodes with an AQI > 400 in 2023–24, it forecasted 5 out of 14 such episodes in 2024–25, displaying a marked improvement.

- **While the AQI forecasting ability of the AQEWS has improved, the best-performing model’s ability to predict PM2.5 and PM10 concentrations remains unchanged.** The WRFChem (400 m) model outperforms IMD SILAM in forecasting PM2.5 and PM10 concentrations; however, its performance remained unchanged in 2024–25 compared to 2023–24.

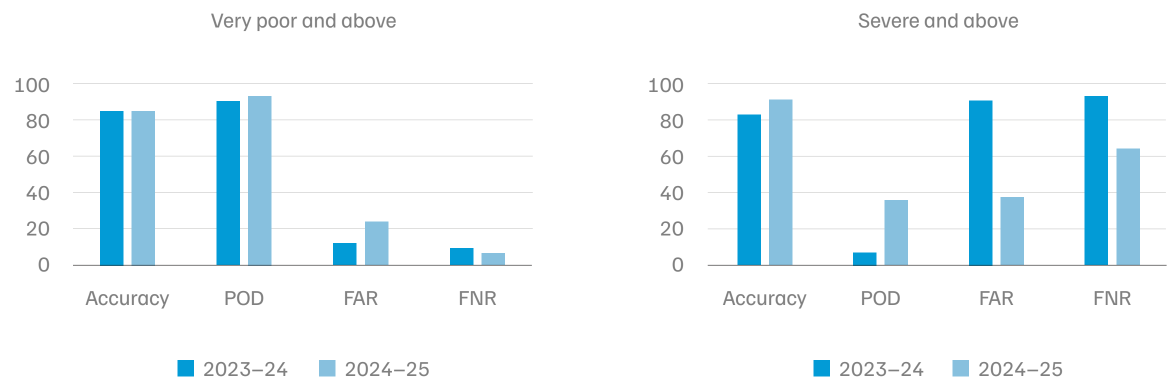
- **The CAQM imposed the GRAP based on the observed AQI rather than forecasts in winter 2023–24 and 2024–25.** Although the GRAP schedule directs implementation of the restrictions under the GRAP based on forecasts, we observe that the CAQM imposed GRAP Stages III and IV based on the observed AQI.

- **The performance of AQEWS in predicting PM2.5 and PM10 differed across different phases of winter.** However, it underpredicted both PM2.5 and PM10 in summer 2024.

Scope for improvement

Improving Delhi’s DSS would require incorporating actionable air pollution reduction scenarios, displaying the impact of GRAP restrictions, including sectoral

Figure ES1. The performance of the AQEWS in predicting the ‘severe and above’ category improved in 2024–25



Source: Authors’ analysis

Note: POD = probability of detection. The ideal value for accuracy and POD for a model is 100%.
FAR = false alarm ratio. FAR is the rate at which a model falsely predicts pollution episodes. FNR = false negative rate.
FNR is the rate at which a model fails to predict pollution episodes. The ideal value for FAR and FNR for a model is 0%.
The AQI data was not available for 13 days and 2 days from the AQEWS portal and CPCB, respectively, in 2024-25.

contributions from NCR districts, and regularly updating emission inventories (EI). Additionally, a year-round operational DSS with open-access data and inclusion of specific chemical components of PM for advanced users will further aid independent research to improve Delhi’s AQEWS and DSS.

Recommendations

- **The MoEFCC and CAQM should together revamp the emission inventories across India with an immediate focus on Delhi NCR.** The MoEFCC should develop a new national-level EI with a provision for regular updates, taking inspiration from the way US and Chinese EIs are updated. There should be a framework in place to update the EI every two to three years. The immediate focus should be on upgrading the EI for the Delhi NCR region to improve Delhi’s forecasts.

- **The Indian Institute of Tropical Meteorology (IITM) and the India Meteorological Department (IMD) should revamp the DSS to include simulations of policy scenarios and GRAP restrictions and display the sectoral contributions from the NCR districts.** The DSS should incorporate actionable scenarios, such as the impact of restricting the movement of all BS-IV vehicles in Delhi and surrounding areas. It should also enable stakeholders to visualise the impact of GRAP and showcase the impact of implementing short-, medium-, and long-term CAQM policy measures wherever possible.

- **The Union government should allocate additional funding to revamp the AQEWS and DSS for Delhi and run the DSS year-round.** Air quality modelling using a chemical transport model (CTM) is expensive; however, only a CTM can provide the detailed contributions of various sources and enable experiments to assess air quality improvements by reducing contributions from one or more sources. This additional funding will also help IITM and IMD run the DSS year-round.

- **The IITM and IMD should use machine learning (ML) models to correct errors in the forecasts.** Even after revamping the EI, the model output may still have errors. Using ML models for bias correction can improve prediction accuracy (Xu et al. 2021).

- **IITM and IMD should make the data from the AQEWS and DSS publicly available.** Public access will allow researchers to independently assess weather and air quality forecasts, which will facilitate independent research and collaborative improvements to the system.

1. Introduction

Air pollution is a significant global health burden, impacting 99 per cent of the global population (WHO 2024). It is the second leading risk factor for deaths worldwide, with a significant burden of disease in South Asia and Africa (HEI 2024). Global studies show that India is among the most polluted countries in the world, alongside many other developing countries (Gurjar 2021). According to the World Bank, the economic burden of illnesses linked to air pollution accounts for approximately 1.4 per cent of India's gross domestic product (GDP) (World Bank 2024). Although air pollution levels in rural and urban environments can be similar (Basu 2023), the burden in cities is significantly higher due to their greater population density (Yuan et al. 2014). To address this, India launched the *National Clean Air Programme* (NCAP) in January 2019, aiming to reduce PM10 concentrations in cities by 20–30 per cent by 2024–25 (PIB 2024), relative to 2017 levels. This target was later revised to a 40 per cent reduction in PM10 levels by 2025–26 compared to 2019–20 levels (MoEFCC 2022).

India currently has 131 non-attainment cities (NACs) and million plus cities/urban agglomerations that do not meet the *National Ambient Air Quality Standards* (NAAQS), which indicate air quality levels considered safe for public health (PIB 2023).

The NCAP provided the impetus for cities to scale up air quality mitigation measures. According to the fourth National Apex Committee (September 2024), 95 out of the 131 cities showed at least a 1 per cent improvement in PM10 levels in 2023–24 compared to 2018–19 levels with 21 cities recording an improvement greater than 40 per cent (MoEFCC 2024). However, only 18 cities met the annual PM10 NAAQS value of 60 $\mu g/m^3$. Successfully managing air quality requires cities to overcome administrative, governance, financial, and technical challenges, among others. Some of the key challenges are as follows:

- **Location- and season-specific pollution sources:** Sources of air pollution vary by location (Nagpure 2021) and season (Sukkhum et al. 2022). Cities should have the means to identify and quantify these sources to develop effective mitigation plans. For instance, a city with an industrial area within its boundaries should have a year-round plan to monitor and tackle industrial pollution, along with a specific action plan to curb pollution from biomass burning for heating in winter.
- **Diverse data sources:** Air quality data generated comes in various formats. For example, many Indian cities operate continuous ambient air quality monitoring stations (CAAQMS), which provide data on major pollutants at 15-minute time intervals (CPCB 2015b). In addition, cities conduct manual monitoring at specific locations twice a week (CPCB, n.d.). Some cities also commission studies to identify dominant sources of air pollution, adopt air quality forecasting models, or conduct customised surveys to identify hyperlocal sources of air pollution. Analysing this diverse data and generating actionable insights remains a significant challenge.
- **Limited institutional capacity:** Cities do not have adequate capacity to address all possible sources simultaneously (Vachana et al. 2023). As a result, they may have to prioritise actions that yield the most significant air quality benefits.
- **Insufficient monitoring coverage:** Cities lack a sufficient number of CAAQMS to cover their entire jurisdictions (Roychowdhury et al. 2023). The estimated cost of installing a single CAAQMS is around INR 1.2 crore, making it difficult for cities to meet the number of stations prescribed by the Central Pollution Control Board (CPCB).

The volume and varied nature of air quality data make manual analysis impossible. Therefore, cities require digital tools to analyse data and generate timely, actionable insights to support air quality decision-making. A decision support system (DSS) is one solution – a computer-based tool that supports decision-making through the automated analysis of data. While a DSS does not make decisions independently, it provides users with necessary information to inform their decision-making (Loucks

The vast and varied nature of air quality data requires cities to use digital tools, such as decision support systems, to design effective pollution mitigation strategies.

1995). Decision support tools improve transparency in the decision-making process and help quantitatively address the uncertainties involved (Sullivan 2002). Originally developed to support business decisions, the concept of DSS was extended to environmental systems due to the complex nature of environmental management. Thus, the term environmental decision support system (EDSS) emerged. An EDSS adopted in air quality management is an air quality decision support system (AQDSS).

India has been a pioneer in adopting state-of-the-art models and tools for air quality management. The System of Air Quality and Weather Forecasting and Research (SAFAR), under the Ministry of Earth Sciences (MoES), established an air quality forecasting system for Delhi during the 2010 Commonwealth Games (MoES 2009). The Indian Institute of Tropical Meteorology (IITM) and the India Meteorological Department (IMD) developed and operationalised an Air Quality Early Warning System (AQEWS) in 2018. The system provides three- to ten-day air quality forecasts for Delhi and six other cities – Mumbai, Pune, Ahmedabad, Kolkata, Hyderabad, and Bengaluru. In 2021, IITM and IMD developed a DSS for the Delhi NCR region.

Under the NCAP framework, all 131 NCAP cities aim to establish their own AQEWS (MoEFCC 2023). However, as of now, only eight cities in India have an operational AQEWS. This study analyses Delhi's AQEWS and DSS to assess their potential for replication across other NCAP cities. Based on our analysis, we reflect on the characteristics of an effective AQDSS and provide recommendations for designing effective and sustainable systems for air quality management in Indian cities.

1.1 What makes an air quality decision support system effective?

Despite the proliferation of DSSs in environmental management, their adoption remains limited (Zasada et al. 2017; Arnott et al. 2020). Walling and Vaneeckhaute (2020) categorised the key challenges associated with the success of an EDSS into three areas:

- **Stakeholder-oriented:** The identification of relevant stakeholders and the degree and process of their participation in the system's design and development are crucial (Ferretti and Montibeller 2016). Even a well-designed system can fail if it does not account for how users actually engage with it in the decision-making processes (Pearman and Cravens 2022).

- **Model-oriented:** The selection of models, uncertainties inherent in those models, design limitations, etc., often limit the adoption of EDSS.

- **System-oriented:** Challenges in this category include user interface design and the users' understanding of the limitations of the outputs generated by the system (Walling and Vaneeckhaute 2020).

There are no universally defined factors attributed to the effectiveness of an EDSS. However, various studies examining the success and failure of different decision support tools have outlined some of the criteria associated with effective EDSSs. Since the system's development aimed to support decision-making, the most critical factor for its success is its actual use by decision-makers. The number of users and their use of the system in decision-making for the intended purpose imply its success (Walling and Vaneeckhaute 2020). Wong-Parodi et al. 2020 reviewed the literature on DSS and synthesised the success criteria of an EDSS, as given in Table 1. We analyse what makes an AQDSS effective by drawing on this broader literature on EDSS success factors and challenges and Table 1 gives the criteria in detail.

Since an AQDSS is an EDSS, an ideal AQDSS should also possess the characteristics listed in Table 1.

Table 1. Characteristics of an effective environmental decision support system

Characteristics	Description
The system must have a 'clearly defined goal'.	• The system must have a well-defined objective (Wong-Parodi et al. 2020) and clearly identify the environmental problem it should address.
The system must 'identify alternatives'.	• The system must identify and list the possible paths of action that are both technically and economically feasible (Sullivan 2002).
The system must 'obtain relevant information'.	• The system must provide pertinent queries and results (Walling and Vaneeckhaute 2020). • The information supplied must be easily understandable to different stakeholders (Sullivan 2002), not just experts.
The system must 'articulate values'.	• A DSS must convert data into meaningful and actionable information. The system must be able to produce understandable results and support the analyst in producing results that address end-user questions (McIntosh et al. 2011).
The system must 'evaluate alternatives'.	• The system must not only identify the alternatives but also provide the impact of these choices based on the information obtained by the system (Wong-Parodi et al. 2020).
The system must 'monitor the outcomes'.	• The system must review and monitor the outcomes and evaluate them (Wong-Parodi et al. 2020). • The outcome obtained on the ground also determines the success of a DSS developed to support decision-making in policy (McIntosh et al. 2011).

Source: Authors' compilation

AQDSSs around the world

Cities, states, and countries around the world use forecast-based AQDSSs to issue warnings and alerts or impose emergency measures to control emissions. Table 2 gives some global examples of AQDSSs.

Table 2. A review of air quality decision support systems around the world

Air Quality and Meteorology Information System (AQMIS) and Pollution Mapping Tool – California, USA	The California Air Resources Board's (CARB) AQMIS provides real-time and historical air quality and meteorological data, ranging from local to state levels. Its pollution mapping tool consolidates various emission inventories into a single database, enabling the mapping of emissions from different sources across California. The platform includes built-in analytics functionality to present emission information at the state, regional, local community, and facility levels. It enables users to compare emission trends and access data in both chart and tabular formats. All data is publicly downloadable (Ruiz and Edwards 2017). Moreover, San Diego County issues agricultural burn permits based on air quality forecasts generated by the system (San Diego County Air Pollution Control District, n.d.).
irCELine – Belgium	Belgium uses multiple models for both weather and air quality forecasting. The country's three regions – Brussels, Walloon, and Flemish – invoke the 'pre-alarm' and 'alarm' phases when predicted air pollutant concentrations exceed predefined thresholds. Each region activates its own regional action plan, which contains emergency measures. For instance, the Brussels region initiates 'intervention 1' under either of the following conditions: if the 24-hour rolling average of PM2.5 exceeds 50 μg/m^3, the daily average of PM10 exceeds 70 μg/m^3, or the daily maximum hourly nitrogen dioxide (NO2) concentration crosses 150 μg/m^3. Public transport is free for the day in Brussels. Moreover, the city reduces the speed limit from 120 kmph to 90 kmph during this time (Brussels Environment, n.d.). The plans of the Walloon and Flemish regions contain similar restrictions. The irCELine platform publishes all data on its web portal, including forecasts, which are available for download (irCELine, n.d.).
Airparif – France	In France, Airparif issues alerts when observed or forecast concentrations exceed defined thresholds. There are two thresholds: 'information and recommendation' and 'alert'. The concentration of low-altitude ozone (O3), nitrogen dioxide (NO2), and PM10 defines these thresholds. For example, Airparif activates the 'information and recommendation' procedure when the observed 24-hour average concentration of PM10 exceeds 50 μg/m^3. The 'alert' procedure gets triggered if the 'information and recommendation' threshold persists for two or more consecutive days (Airparif, n.d.).
Healthier Environment through Abatement of Vehicle Emission and Noise (HEAVEN)	A research project under the European Union (EU), HEAVEN, is a strong example of improved decision-making using an AQDSS. The system assessed the results of the environmental impacts of different traffic scenarios. In Berlin, modelling a truck ban scenario projected a potential 11 per cent improvement in PM10 concentrations; the implementation achieved an 8 per cent reduction. Similarly, a scenario to limit vehicle speeds to 30 kmph showed a potential improvement of 4 per cent in PM10 levels, while the implemented intervention resulted in a 3 per cent reduction (Tullius 2003).
AirQUIS	AirQUIS is a geographic information system (GIS)–based DSS developed by the Norwegian Institute of Air Research (NILU). It comprises four modules – measurement, EI, models, and GIS. The system contains models that estimate exposure from various sources, including traffic, industry, and others. It evaluates the impact of multiple scenarios using population exposure, cost-benefit, or cost-efficiency analyses (Slørdal et al., n.d.). Based on these assessments, the system ranks the scenarios to help authorities prioritise and plan appropriate control measures.
AirWARE	AirWARE, a project supported by different international projects and reserach works including EU sponsored projects, has historical and real-time monitoring data, an EI, emission scenarios, and modelling modules. The system offers the user to assess the impact of the high pollution levels and gives the best reduction strategy considering cost and effectiveness (Fedra 2002).

Source: Authors' compilation

Based on our review of AQDSSs across the world and the criteria that make an EDSS effective, we identify the components that an AQDSS should generally possess.

Components of an air quality decision support system (AQDSS)

Air quality data

- The AQDSS should be capable of fetching real-time air quality data from monitoring stations. It should also have the provision to fetch data from calibrated and validated low-cost sensors deployed at pollution hotspots, construction sites, and other key locations.

Air quality forecasts

- The system should incorporate data from air quality forecasting models. These models may be chemical transport models (CTM), machine learning (ML) models, or a combination of both.

- Reliable forecasts enable authorities to issue timely alerts, especially to protect vulnerable populations, and to plan air pollution mitigation measures in advance.

Data analysis and visualisation

- The AQDSS should be equipped to either automatically analyse incoming data or present pre-analysed data in the form of visualisations from monitoring stations and forecasts to provide some actionable insights.

Recommendations

- A fully automated AQDSS can recommend a set of interventions based on the data. For instance, if an emergency response plan is integrated within the AQDSS, it could suggest suitable emergency response interventions depending on the severity of air pollution. In addition to short-term measures, an AQDSS can also recommend medium- and long-term measures, such as tackling air pollution from a particular sector or region, depending on its design.

Scenarios

- An ideal AQDSS should allow users to evaluate alternatives. For instance, users may want to gauge the impact of shutting down industries on a city's periphery compared to the effect of traffic restrictions within the city on its air pollution. The AQDSS should enable users to conduct such simple experiments to aid in identifying optimal solutions.

Response

- Ideally, stakeholders will implement the most effective response option identified by the AQDSS from among the alternatives it recommends.

Outcome monitoring

- An ideal AQDSS must support monitoring the outcome of the decisions made using its insights. For instance, it should enable users to assess the effectiveness of traffic restrictions by quantifying changes in pollution concentration after implementation, compared to the levels that would have prevailed without the intervention.

1.2 Air quality early warning and decision support system for Delhi

Delhi experienced its worst smog incident in 17 years in November 2016, with PM2.5 levels reaching 14 times the 24-hour NAAQS standard of 60 μg/m^3 (EPCA 2017). In response, the Environment Pollution (Prevention and Control) Authority (EPCA) submitted a proposal to the Supreme Court (SC) for a smog alert system, drawing on international examples from China, the US, and France. The SC subsequently directed the CPCB and EPCA to develop an emergency response system for smog episodes. This led to the MoEFCC notifying the *Graded Response Action Plan* (GRAP) in January 2017. First implemented in the winter of 2017, GRAP outlined emergency interventions required under different AQI categories. Its purpose was to be a response plan to rising pollution rather than a substitute for long-term actions (EPCA 2017).

In 2018, the MoES launched an AQEWS for Delhi NCR to provide three-day air quality and weather forecasts (PIB 2018). Followed by this, in 2021, the ministry launched a DSS as an extension to the AQEWS to support decision-making for air quality management in Delhi and surrounding areas (IITM 2021). It provides source contributions to Delhi's PM2.5 levels from 29 sectors, with a lead time of three days. The DSS complements the AQEWS: the AQEWS predicts pollutant concentrations, while the DSS attributes these concentrations to different sources. The CAQM, which replaced EPCA in 2020, formally linked GRAP implementation to the forecasts provided by the AQEWS and DSS in 2022 (Vibhaw 2022), marking a shift from reactive to proactive air quality management in Delhi. Currently, the information provided by the AQEWS and DSS guides the air quality management in the city during the winter season.

Air Quality Early Warning System

The AQEWS provides air quality forecasts and information on current air quality and weather conditions among others. Its major components are the following.

Air quality and weather data

- The AQEWS provides real-time air quality data over Delhi and its surrounding regions, including the observed PM2.5 and PM10 values at both city and station levels.
- It also offers real-time weather information, including temperature, relative humidity, and wind speed at both city and station levels.

Air quality and weather forecasts

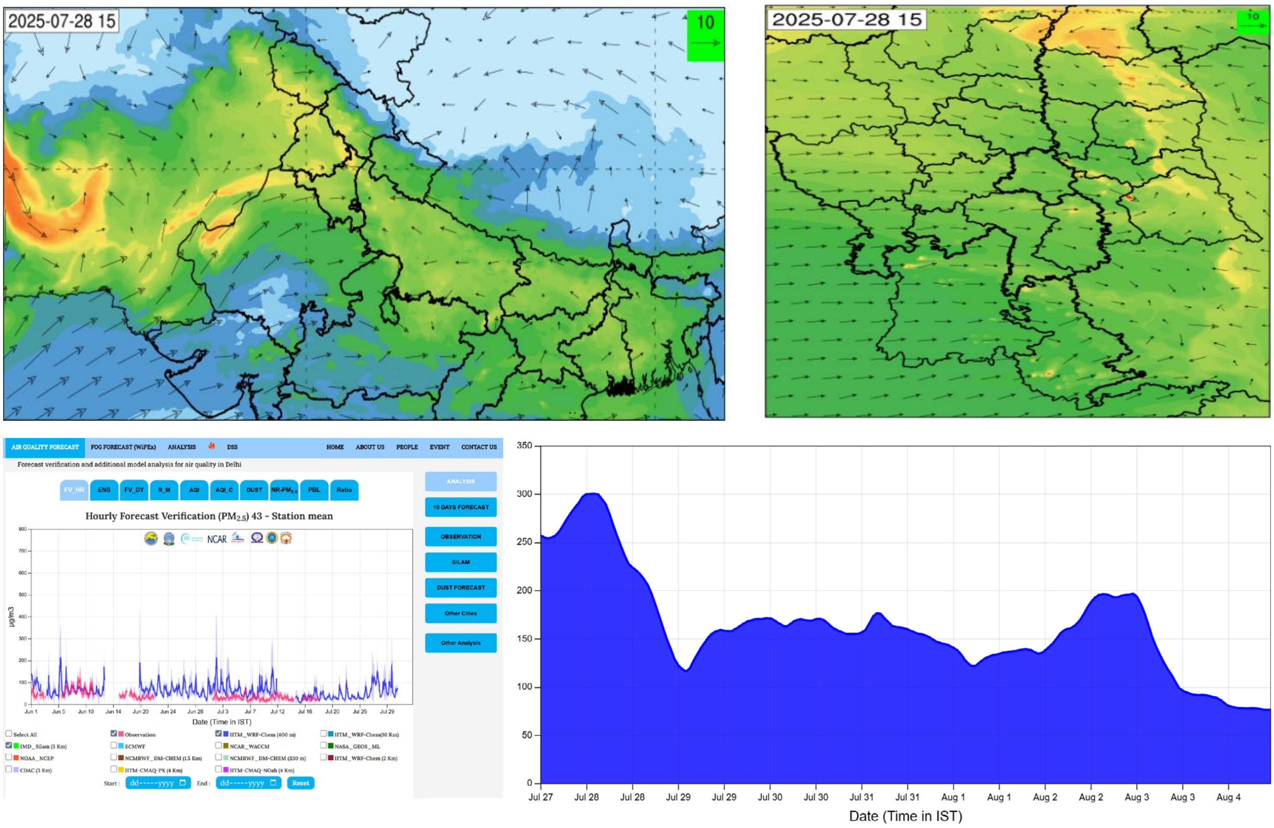
- The AQEWS uses CTMs to generate air quality predictions with a 72-hour lead time. Two operational models provide air quality forecasts for Delhi: the IITM WRF-Chem (Indian Institute of Tropical Meteorology's Weather Research and Forecasting coupled with Chemistry) and the IMD SILAM (India Meteorological Department's System for Integrated Modelling of Atmospheric Composition). The WRF-Chem model provides forecasts for PM2.5, PM10, carbon monoxide (CO), and dust. The second model, IMD-SILAM, provides forecasts for sulphur dioxide (SO_2), NO_2, and O_3, in addition to PM2.5, PM10, and CO. The IMD issues air quality and weather forecast bulletins based on this model.
- The system also provides three-day forecasts of key weather variables, such as temperature, wind speed, precipitation, and relative humidity, among others, for Delhi.
- It assimilates data from monitoring stations, satellite-derived aerosol optical depth (AOD), and fire counts from Visible Infrared Imaging Radiometer Suite (VIIRS) to improve forecast performance through data assimilation.
- It also incorporates a feedback mechanism that accounts for the implementation of the GRAP, ensuring that forecasts remain dynamic and responsive to on-ground policy interventions that lead to emission reductions (Ghude et al. 2024).

Data analysis and visualisations

- The AQEWS presents both forecasts and observations in a single visualisation, allowing users to verify the performance of the forecasts. It also converts modelled forecast pollution concentrations into AQI values, making the information easier for the public to interpret. These insights are disseminated through the air quality and weather forecast bulletins.
- The system offers a range of visual formats, including plots, animations, maps, and line charts. Figure 1 shows an example of the forecast visualisation available on the portal. The analysis is publicly accessible via the AQEWS website (https://ews.tropmet.res.in/).

> Delhi's Air Quality Early Warning System provides air quality forecasts three days in advance.

Figure 1. The Air Quality Early Warning System for Delhi portal displays information through line charts, maps, GIFs, etc.



Indian Institute of Tropical Meteorology. Air Quality Early Warning System for Delhi. Ministry of Earth Sciences, Government of India. https://ews.tropmet.res.in/

The DSS linked to the AQEWS provides sectoral and regional contributions to Delhi's PM 2.5 concentrations. Specifically, it estimates contributions from:

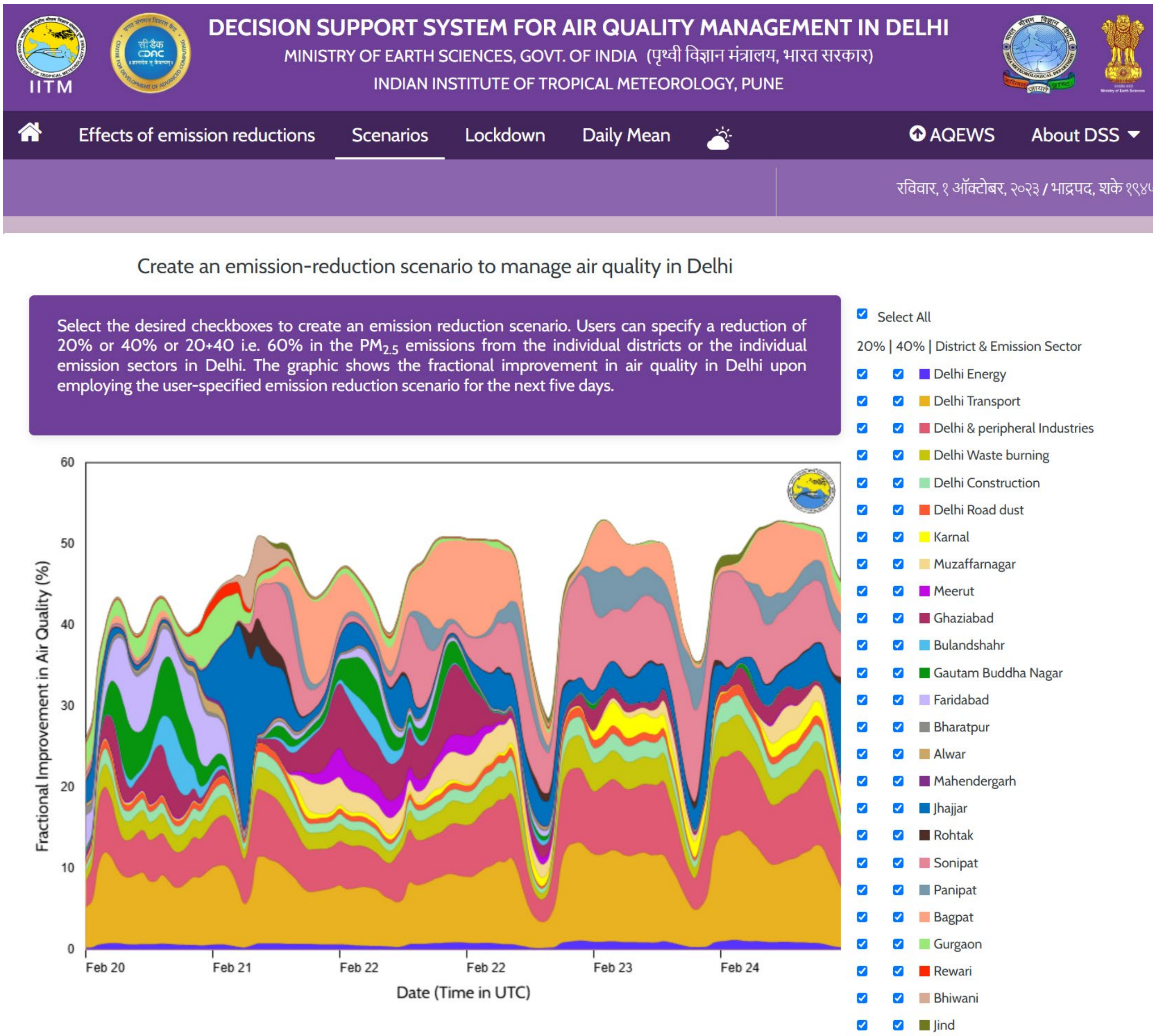
- Seven major sectors within Delhi and its periphery: energy, transport, industry, construction, residential, road dust, and waste burning.
- Stubble burning in upwind states.
- 20 districts surrounding Delhi.

Scenario analysis

While the publicly available version of the DSS did not include an operational scenario module during the winter of 2024–25, it was operational in the previous year. In 2023–24, it offered users two scenarios to analyse the impact of source-level interventions on Delhi's PM2.5 levels.

- Emission reduction scenarios: Users could explore the effect of reducing emissions by 20 per cent or 40 per cent from individual sources or combinations of sources. For instance, the DSS could display the potential improvement in Delhi's PM2.5 levels following a 20 per cent reduction in emissions from the transport sector.
- Source shutdown scenarios: The system also enabled users to simulate the impact of completely shutting down specific sources. For example, it could model the change in PM2.5 concentrations following the shutdown of Delhi's energy sector. Figure 2 shows a screenshot of the scenario player that was available on the DSS in the winter of 2023–24.

Figure 2. The scenario player on the Decision Support System (DSS) in the winter of 2023–24 showed potential improvement to Delhi's PM2.5 with source-level interventions



Indian Institute of Tropical Meteorology. Air Quality Early Warning System for Delhi. Ministry of Earth Sciences, Government of India. https://ews.tropmet.res.in/

Response

As discussed earlier, the CAQM considers the data from the AQEWS and DSS before imposing the GRAP. The GRAP schedule consists of four stages, with increasing severity of restrictions based on air pollution levels. Figure 3 shows the AQI categories and the corresponding stages of GRAP.

Figure 3. AQI categories and corresponding GRAP stages

Stage	Category	AQI
Stage I	Poor	201–300
Stage II	Very Poor	301–400
Stage III	Severe	401–450
Stage IV	Severe Plus	451 and above

Source: Commission for Air Quality Management in National Capital Region and Adjoining Areas. Graded Response Action Plan (GRAP) for the National Capital Region (NCR). New Delhi: CAQM, 2024.

Under Stage I, the GRAP requires construction sites to strengthen the implementation of dust mitigation measures. It mandates the authorities to regularly clear solid waste and construction and demolition waste, along with periodic mechanised sweeping and water sprinkling on roads.

Stage II calls for the intensified implementation of Stage I measures and targeted action across air pollution hotspots in the Delhi NCR region. Additional measures are introduced at this stage to promote and augment public transport.

Stage III prohibits construction activities and imposes restrictions on entry of vehicles using unclean fuels into Delhi.

Stage IV prohibits the entry of polluting vehicles into Delhi and allows government employees to work from home.

Image: iStock

The Commission for Air Quality Management in National Capital Region and Adjoining Areas enforces the Graded Response Action Plan (GRAP) in Delhi, guided by forecasts from the air quality early warning and decision support system.

2. Approach and methodology

We evaluate Delhi's AQEWS and DSS using both qualitative and quantitative parameters. For the qualitative assessment, we compare the features of the AQEWS and DSS with those of an ideal AQDSS listed in Table 1. For the quantitative evaluation, we compare the ability of the forecasts from AQEWS to accurately predict both the AQI category and pollutant concentrations. To this end, we scrape the 'Day 1' forecast data from the AQEWS web portal for the 2023–24 and 2024–25 periods.

The forecasted AQI on AQEWS is from the WRF-Chem model, which operates at a spatial resolution of 400 metres (WRF-Chem 400 m). The AQI displayed corresponds to the higher of the two AQI values computed from forecasted PM2.5 and PM10 concentrations. To assess the model's ability to forecast AQI categories accurately, we rely on the metrics listed in Table 3. Annexure 1 provides the confusion matrix and the formulae used to compute these metrics. We restrict our evaluation to two categories – 'very poor and above' (AQI > 300) and 'severe and above' (AQI > 400). 'Severe and above' is a subset of 'very poor and above'. GRAP contains stringent measures under Stages II, III and IV, and the CAQM imposes these stages when the AQI crosses 300. Therefore, we restrict the evaluation to the above two categories. Moreover, according to the CPCB, an AQI above 300 has an adverse impact on the general population (Annexure 2). Since CPCB's AQI is the average AQI between 4 PM of a given day and 4 PM of the previous day, we similarly compute the average forecast AQI for comparison.

Table 3. Metrics used to assess the ability of the forecasts to predict the AQI

Metrics	Description	Ideal value
Accuracy	The ability of the model to correctly classify true and false events.	100
False alarm ratio (FAR)	The rate at which the model predicts false events as true events.	0
Probability of detection (POD)	The ability of the model to detect true events.	100
False negative rate (FNR)	The rate at which the model predicts a true event as a false event.	0

Source: Authors' compilation

To assess the ability of the AQEWS to accurately forecast pollutant concentrations, we compare the PM2.5 and PM10 forecasts from the WRF-Chem (400 m) and IMD-SILAM models with the actual concentrations observed in Delhi. To analyse the performance, we compute the metrics listed in Table 4. We obtain the actual PM2.5 and PM10 values from the AQEWS through web scraping. Both models provide spatially averaged hourly forecasts for PM2.5 and PM10 concentrations over Delhi. Although the AQEWS hosts 13 models for PM2.5 and 8 models for PM10 on its web portal, we limit our discussion to

WRF-Chem (400 m) and IMD-SILAM. This is because the IMD issues air quality and weather forecast bulletins based on the IMD-SILAM model output, and the DSS runs on the WRF-Chem (400 m) model. Moreover, most other models on AQEWS do not offer continuously available data.

We analyse forecast performance for winter 2023–24 and 2024–25 (October–February). Also, we analyse the performance for summer 2024–25 (May and June). Additionally, to assess if the forecast performance varies during different periods within winter, we break the winter period into four phases. These phases are 'stubble burning phase' (16 October–30 November), 'post-stubble burning phase' (1 December–15 December), 'peak winter phase (16 December–15 January) and 'post-peak winter phase' (16 January–28 February).

Table 4. List of metrics used to analyse the performance of the AQEWS to predict the pollutant concentration

Metrics	Description
Root mean squared error (RMSE)	It is the square root of the mean-squared difference between the predicted and observed values.
Mean absolute error (MAE)	It is the average of the absolute difference between the predicted and observed values.
Mean absolute percentage error (MAPE)	It is the average of the absolute percentage difference between the predicted and observed values.
Mean bias error (MBE)	It is the average difference between the predicted and observed values.
Pearson correlation coefficient (R value)	The Pearson correlation coefficient indicates the degree to which the predicted and observed values are correlated.

Source: Authors' compilation

3. Evaluating the performance of Delhi's air quality early warning system and decision support system

In June 2024, the Rajasthan State Pollution Control Board (RSPCB) launched an AQEWS and DSS covering Jaipur city and its surrounding districts (The Times of India 2024). Similarly, Gujarat plans to extend an AQEWS to all industrial towns and NACs (Dave and John 2025).

India is also part of the World Meteorological Organization's Global Atmosphere Watch (GAW) Programme, specifically the Global Air Quality Forecasting and Information System (GAFIS), which aims to provide air quality forecasting information in a globally harmonised and standardised way tailored to society's need (WMO, n.d.). Delhi's system thus serves as a model for countries that are yet to adopt forecasting systems. This highlights the need to evaluate the performance of Delhi's operational AQEWS and DSS, both qualitatively and quantitatively. While IITM/IMD has conducted a quantitative evaluation of the system, it was limited to the post-monsoon winter months between October and January, using data from 2019 to 2024.

3.1 Qualitative analysis of Delhi's decision support system

Table 5 presents a comparison of the features of Delhi's AQEWS and DSS with those of an ideal AQDSS.

Table 5. Delhi's Air Quality Early Warning System and decision support system satisfy most requirements of an ideal air quality decision support system

Characteristic	Remarks
The system must have a 'clearly defined goal'.	• The AQEWS has a clear goal – to provide air quality forecasts so that authorities can put emergency response measures in place.
The system must 'identify alternatives'.	• The DSS version of 2024–25 provides the absolute contributions of 29 different sectors and districts to Delhi's PM2.5. • The DSS version of 2023–24 provided users with two emission reduction scenarios at the sector and district level –20 or/and 40 per cent and a complete shutdown.

Characteristic	Remarks
The system must 'obtain relevant information'.	• The AQEWS aggregates and displays a wide range of data like satellite-derived fire counts, monitoring station data, weather information, modelled air pollutant concentrations, etc.
The system must 'articulate values'.	• AQEWS analyses the forecasts and disseminates the forecasts to the public through daily air quality and weather forecast bulletins.
The system must 'evaluate alternatives'.	• The scenario player that was operational in 2023–24 on the DSS provided a comparison of the impact of different combinations of source and district-level interventions on Delhi's PM 2.5 levels. However, it was absent in the 2024–25's publicly available version of the DSS.
The system must 'monitor the outcomes'.	• AQEWS incorporates the potential impact of on-ground interventions into the models to predict the next day's air quality (Ghude et al. 2024). • However, it lacks a component to monitor the actual impact of the implementation of GRAP. For instance, it could display the potential PM2.5 levels under 100 per cent GRAP compliance, PM2.5 levels without GRAP, and the actual PM2.5 levels following the implementation of GRAP to the users for a small period. A recent study led by IITM Pune demonstrates the feasibility of such visualisations (Ghude et al. 2024).

Source: Authors' analysis

We observe that the AQEWS and DSS align well with most characteristics of an ideal AQDSS. They have a clearly defined goal – to support air pollution mitigation through forecasts. The systems integrate and analyse large volumes of air quality and weather information and disseminate it to the public in accessible formats. In 2023–24, the DSS enabled users to examine the impact of source-level reductions. However, it did not outline actionable pathways to achieve those reductions. Similarly, while AQEWS incorporated GRAP interventions into its forecasts, the system does not monitor the outcomes.

> The Air Quality Early Warning System and decision support system for delhi satisfy most of the characteristics of an ideal air quality decision support system.

3.2 Quantitative analysis of the forecasts from Delhi's Air Quality Early Warning System

AQI prediction performance during winter

Winter 2023–24 recorded 92 days classified as 'very poor and above', including 15 'severe and above' days. Annexure 3 presents the number of days in each category, along with the corresponding AQI predictions. The WRF-Chem (400 m) forecasts accurately predicted the AQI under both categories more than 80 per cent of the time in winter 2023–2024. Its POD exceeded 90 per cent for the 'very poor and above' category but dropped to around 7 per cent for 'severe and above'. Moreover, the FAR for 'severe and above' was greater than 90 per cent. Table 6 summarises the model's performance in forecasting AQI categories during winter 2023–24.

Table 6. Performance of Delhi's Air Quality Early Warning System in winter 2023–2024

S. No.	Category	Accuracy	False alarm ratio	Probability of detection	False negative rate
1	Very poor and above (AQI > 300)	84.89	12.63	90.21	0.09
2	Severe and above (AQI > 400)	82.73	90.9	6.67	0.93

Source: Authors' analysis

According to the IITM/IMD analysis of the system's performance during the post-monsoon months between 2019 and 2024, the accuracy of the system in predicting 'very poor and above' and 'severe and above' categories was approximately 80 per cent. The FAR for 'very poor and above' was around 18 per cent, while that for 'severe and above' was about 42 per cent. The POD of 'very poor and above' was 94 per cent, and 33 per cent for 'severe and above' (Ghude et al. 2024).

Our analysis shows that in winter 2024–25, the AQEWS's ability to forecast 'severe and above' episodes improved. The accuracy under this category rose to 91 per cent from 83 per cent in 2023–24. The FAR dropped to 37 per cent from 91 per cent, and the POD increased to 36 per cent from around 7 per cent. The FNR also improved to 0.64 from 0.93. While the system correctly predicted only 1 out of 15 'severe and above' days in 2023–24, it accurately predicted 5 out of 14 such episodes in 2024–25.

However, the metrics for 'very poor and above' remained the same in 2024–25 compared to 2023–24. Accuracy remained same at about 85 per cent, the FAR increased to 24 per cent, and the POD increased to 93 per cent. Similarly, the FNR marginally improved to 0.07. This suggests that while the system's performance in predicting air pollution episodes with AQI between above 300 remained the same, its ability to forecast AQI levels above 400 improved substantially. Table 7 summarises the WRF-Chem (400 m) model's performance in forecasting AQI during winter 2024–25. Figure 4 presents a comparison of the system's performance across the 2023–24 and 2024–25 periods.

Table 7. Performance of Delhi's Air Quality Early Warning System in winter 2024–25

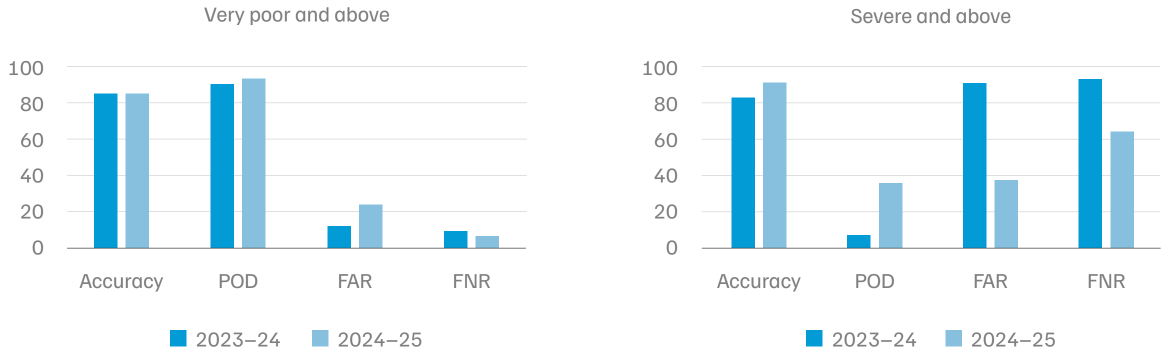
S. No.	Category	Accuracy	False alarm ratio	Probability of detection	False negative rate
1	Very poor and above (AQI > 300)	84.67	23.94	93.1	0.07
2	Severe and above (AQI > 400)	91.24	37.5	35.71	0.64

Source: Authors' analysis

Note: The AQI data was not available for 13 days and 2 days from the AQEWS portal and CPCB, respectively, in 2024-25.

We conclude that when the AQEWS forecasts the AQI to be 'very poor and above', the observed AQI is likely to fall within the 'very poor', 'severe', or 'severe plus' categories with high probability.

Figure 4. The accuracy of predicting the 'severe and above' category improved in 2024–25 but remained the same for 'very poor and above'



Source: Authors' analysis

Note: POD = probability of detection; FAR = false alarm ratio; FNR = false negative rate.

The AQI data was not available for 13 days and 2 days from the AQEWS portal and CPCB, respectively, in 2024-25.

Pollutant concentration prediction performance during winter

According to the IITM/IMD analysis of the model's performance in predicting PM2.5 during the post-monsoon months between 2019 and 2024, the RMSE for PM2.5 was approximately 70 μg/m^3 (Ghude et al. 2024). While Ghude et al. (2024) computed additional metrics such as the index of agreement (IOA), mean fractional bias (MFB), normalised mean bias (NMB), normalised mean square error (NMSE), we calculate the MAPE, MAE, MBE, and R value.

In 2023–24, the MAPE of PM 2.5 and PM10 forecasts from the WRF-Chem model (400 m) was 35 per cent and 37 per cent, respectively. For the IMD SILAM model, the MAPE was around 49 per cent for PM2.5 and 38 per cent for PM10. The MBE of PM2.5 and PM10 forecasts from WRF-Chem (400 m) were around −18 μg/m^3 and −34 μg/m^3, respectively. For the IMD SILAM model, the MBE was 0.67 μg/m^3 for PM2.5 and −29 μg/m^3 for PM10. Tables 8 and 9 present the metrics for the WRF-Chem (400 m) and IMD SILAM models, respectively, for the period 2023–24. While the two models displayed comparable performance for PM 10, their performance for PM2.5 differed significantly. Other metrics listed in Table 8 reflect the same. Notably, the Pearson correlation (R value) between the forecasts and observations was stronger for the WRF-Chem (400 m) model (0.59 and 0.54 for PM2.5 and PM10, respectively) compared to the IMD SILAM model (0.37 and 0.42 for PM2.5 and PM10, respectively).

Table 8. Performance of WRF-Chem (400 m) during winter 2023–24

S. No.	Pollutant	RMSE (μg/m^3)	MAE (μg/m^3)	MAPE (%)	MBE (μg/m^3)	R value
1	PM2.5	78.87	58.64	35	−18.22	0.59
2	PM10	132.73	103.02	37	−34.16	0.54

Source: Authors' analysis

The total number of hourly readings for PM2.5 and PM10 during this period[2] was 3,120. The average observed PM2.5 concentration, corresponding to available WRF-Chem (400 m) data, was 181 μg/m^3, while the average predicted PM2.5 concentration from the model was 163 μg/m^3. For PM10, the average

2. The period considered is between 16 October 2023 and 29 February 2024 (total 3,288 hours).

Table 9. Performance of IMD SILAM during winter 2023–24

S. No.	Pollutant	RMSE (μg/m³)	MAE (μg/m³)	MAPE (%)	MBE (μg/m³)	R value
1	PM2.5	111.62	82.9	49	0.67	0.37
2	PM10	150.9	113.5	38	−29.9	0.42

Source: Authors' analysis

observed PM10 concentration was 304 μg/m³, and the corresponding average predicted PM10 concentration was 270 μg/m³.

The total number of hourly readings for PM2.5 and PM10 during this period was 2,916. The average observed PM2.5 concentration, corresponding to available IMD SILAM data, was 179 μg/m³, while the average predicted PM2.5 concentration from IMD SILAM was 180 μg/m³. For PM10, the average observed PM10 concentration was 303 μg/m³, corresponding to available IMD SILAM data, and the average predicted concentration from IMD SILAM was 273 μg/m³.

In winter 2024–25, the performance of the WRF-Chem (400 m) model in predicting PM2.5 and PM10 remained largely unchanged. The MBE for PM2.5 deteriorated by 7 μg/m³, and by 25 μg/m³ in the case of PM10. The RMSE value for PM2.5 worsened to 93 μg/m³, whereas it worsened to 136 μg/m³ in the case of PM10. While the correlation between PM2.5 forecasts and actual values remained unchanged, the correlation between PM10 forecasts and actual values improved from 0.54 to 0.6. Conversely, PM2.5 forecasts from the IMD SILAM model improved on all metrics in 2024–25 except for MBE, while PM10 forecasts deteriorated on all metrics except for R values (correlation).

We therefore conclude that the WRF-Chem (400 m) model outperforms the IMD SILAM model in forecasting both PM2.5 and PM10. However, the negative MBE values from WRF-Chem (400 m) indicate consistent underprediction during both winters. Tables 10 and 11 summarise the performance of both models in 2024–25. Seven other Indian cities now have an operational AQEWS, and we present the analysis for these cities in Annexure 4.

Table 10. Performance of WRF-Chem (400 m) during winter 2024–25

S. No.	Pollutant	RMSE (μg/m³)	MAE (μg/m³)	MAPE (%)	MBE (μg/m³)	R value
1	PM2.5	92.53	58.75	35	−25.21	0.61
2	PM10	136.09	103.47	38	−60.8	0.60

Source: Authors' analysis

The total number of readings for PM2.5 and PM10 during this period[3] was 2,598 (hourly data). The average observed PM2.5 concentration was about 175 μg/m³, and the average predicted PM2.5 concentration from WRF-Chem (400 m) was 149 μg/m³. In the case of PM10, the average observed PM10 concentration was 292 μg/m³, and the average predicted PM10 concentration from WRF-Chem (400 m) was 231 μg/m³.

3. The time period considered is between 1 October 2024 and 28 February 2025 (total 3,512 hours).

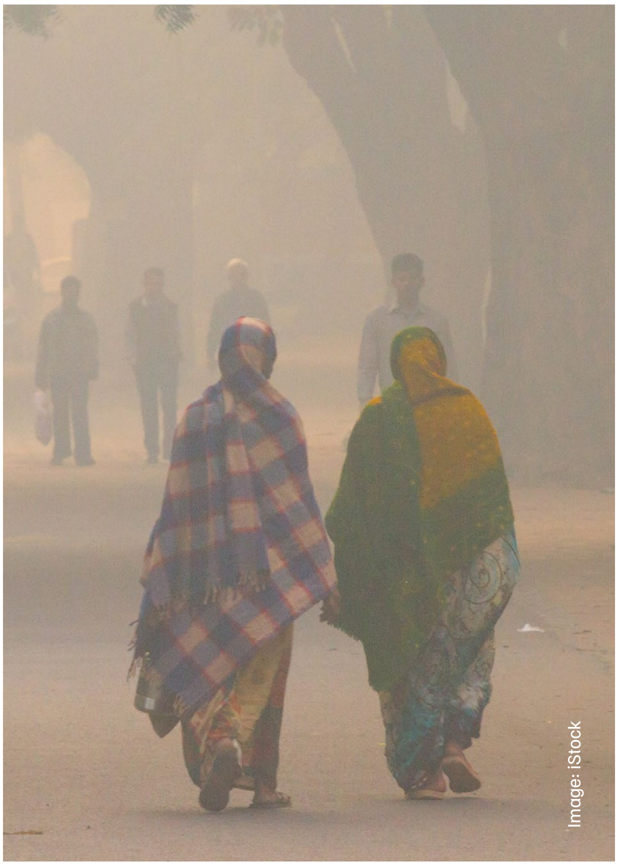
Table 11. Performance of IMD SILAM during winter 2024–25

S. No.	Pollutant	RMSE ($\mu g/m^3$)	MAE ($\mu g/m^3$)	MAPE (%)	MBE ($\mu g/m^3$)	R value
1	PM2.5	107.95	71.68	45	–22.88	0.47
2	PM10	180.06	135.23	50	56.62	0.45

Source: Authors' analysis

The total number of hourly readings for PM2.5 and PM10 during this period was 2,173 and 2,170, respectively. The average observed PM2.5 concentration was 177 $\mu g/m^3$, corresponding to available IMD SILAM data, while the average predicted PM2.5 concentration from IMD SILAM was 154 $\mu g/m^3$. For PM10, the average observed concentration was 306 $\mu g/m^3$, and the average predicted PM10 concentration from IMD SILAM was 363 $\mu g/m^3$.

A recent study led by IITM notes that uncertainties associated with emissions from large-scale stubble burning during the post-monsoon months contribute to a deterioration in forecast accuracy. Moreover, these uncertainties compound those arising from the simulation of weather variables, such as wind speed, temperature, and planetary boundary layer height (PBLH). The study found that the system performs exceptionally well on the first and second days, and moderately well on the third day (Ghude et al. 2024).



Reliable air quality forecasts enable the authorities to take preemptive measures and alert citizens to reduce exposure during air pollution episodes.

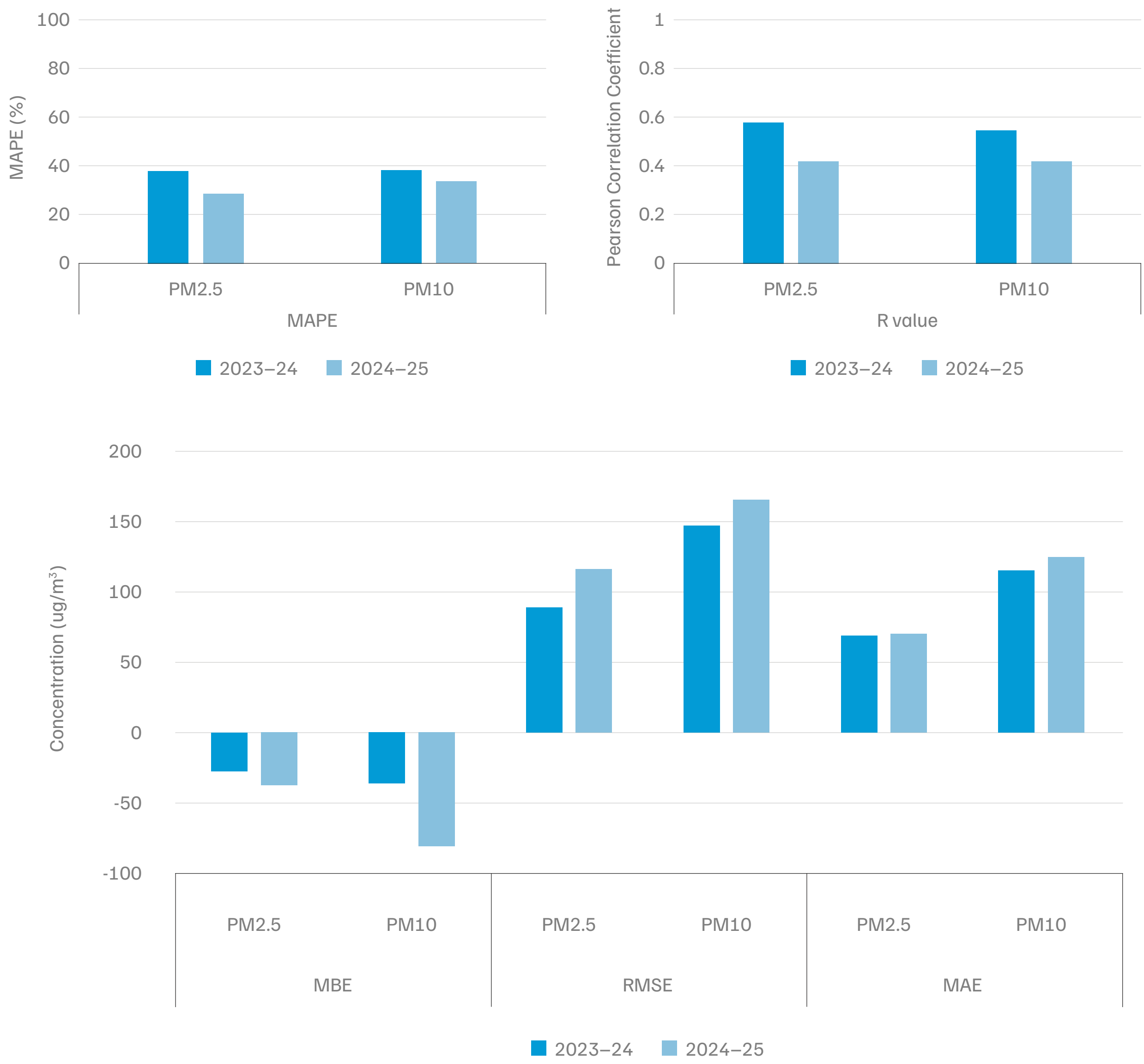
Phase-wise performance in winter

We assessed the AQEWS's performance across four phases of winter – 'stubble burning phase', 'post-stubble burning phase', 'peak winter phase', 'post-peak winter phase'. Tables 12 and 13 present the phase-wise analysis results for PM2.5 and PM10, respectively.

Stubble burning phase

In 2023–24, the MAPE for predicting PM2.5 and PM10 was around 37 per cent during the stubble burning phase. It improved to 28 per cent for PM2.5 and 33 per cent for PM10 in 2024–25. However, despite this improvement in MAPE, all other metrics during this phase deteriorated in 2024–25 compared to 2023–24. The MBE for PM2.5 declined to –36 $\mu g/m^3$ in 2024–25 from –26 $\mu g/m^3$ in 2023–24. Similarly, for PM10, the MBE worsened to –80 $\mu g/m^3$ in 2024–25 from –35 $\mu g/m^3$ in 2023–24. The RMSE values for PM2.5 and PM10 also worsened by 27 $\mu g/m^3$ and 18 $\mu g/m^3$, respectively, in 2024–25. The MAE for PM2.5 and PM10 deteriorated by 2 $\mu g/m^3$ and 9 $\mu g/m^3$, respectively, in 2024–25. Additionally, the R value for both PM2.5 and PM10 worsened from 0.5 in 2023–24 to 0.42 in 2024–25.

Figure 5. The mean absolute percentage error during the stubble burning phase improved for both PM2.5 and PM10 in 2024–25, whereas the other metrics deteriorated

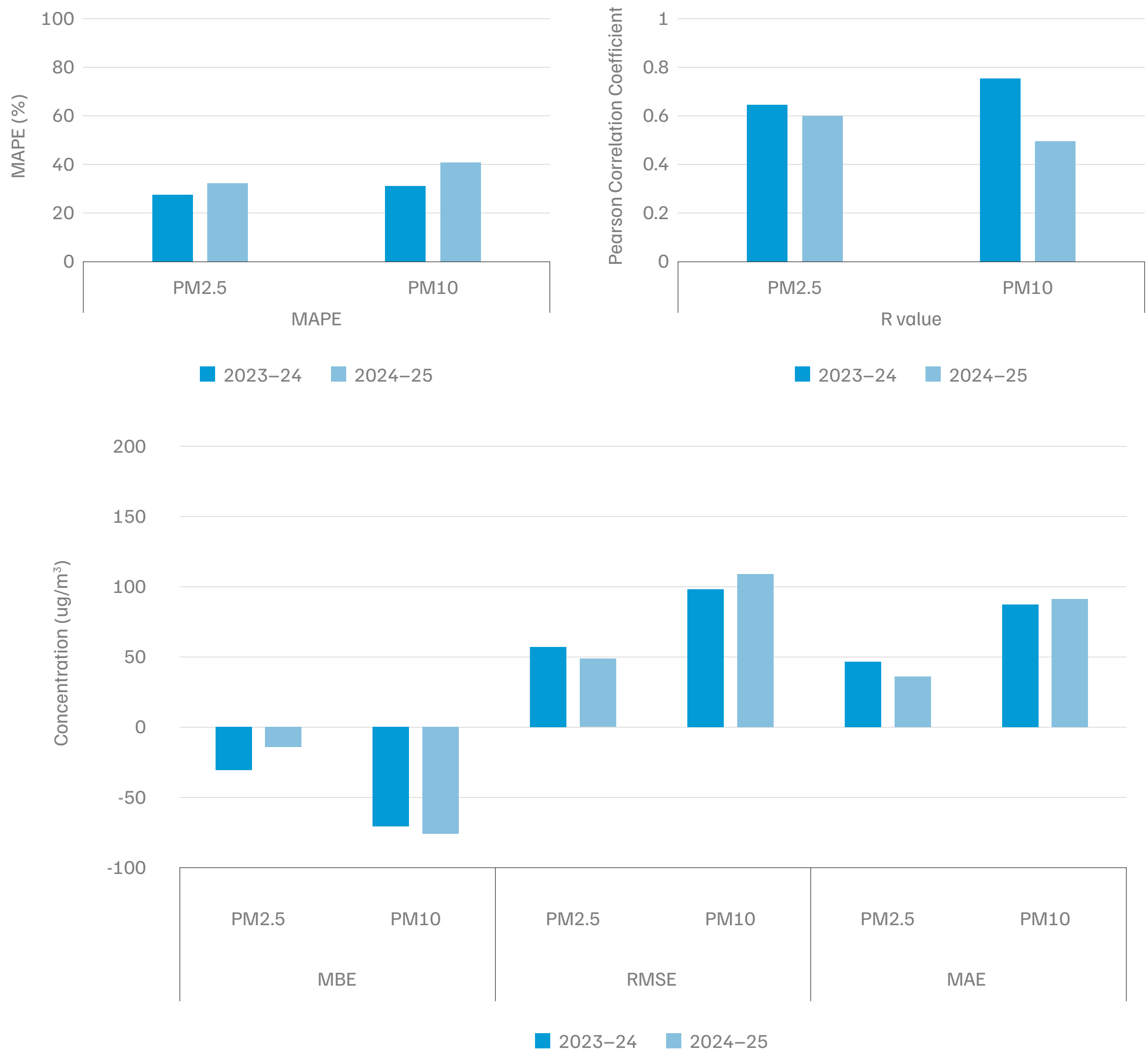


Source: Authors' analysis

Post-stubble burning phase

In 2023–24, the MAPE during the post-stubble burning phase for PM2.5 and PM10 were 27 per cent and 31 per cent, respectively. However, in 2024–25, it deteriorated to 32 and 41 per cent for PM2.5 and PM10, respectively. The performance of MBE, RMSE and MAE during this phase improved for PM2.5 in 2024–25 but deteriorated for PM10. The MBE for PM2.5 improved to –14 $\mu g/m^3$ from –30 $\mu g/m^3$, and the RMSE value improved to 48 $\mu g/m^3$ from 57 $\mu g/m^3$. Similarly, the MAE for PM2.5 improved to 36 $\mu g/m^3$ in 2024–25 from 47 $\mu g/m^3$ of the previous year. The RMSE value of PM10 worsened by 10 $\mu g/m^3$ in 2024–25, whereas the MBE and MAE worsened by around 5 $\mu g/m^3$. While the R value of PM2.5 remained largely unchanged in 2024–25, it worsened to 0.49 from 0.75 in the case of PM10.

Figure 6. The performance of the WRF-Chem (400 m) model to predict PM10 deteriorated in 2024–25



Source: Authors' analysis

Table 12. Phase-wise performance of air quality early warning system in predicting PM2.5 in 2023–24 and 2024–25

Phase	Year	RMSE (μg/m³)	MAE (μg/m³)	MAPE (%)	MBE (μg/m³)	R value
Stubble burning phase	**2023–24**	88.24	67.37	37	−26.13	0.58
	2024–25	115.32	69.49	28	−36.25	0.42
Post-stubble burning phase	**2023–24**	56.84	47.38	27	−30.09	0.64
	2024–25	48.08	36.08	32	−13.97	0.61

Phase	Year	RMSE (µg/m³)	MAE (µg/m³)	MAPE (%)	MBE (µg/m³)	R value
Peak winter phase	**2023–24**	90.3	69.82	33	−19.54	0.42
	2024–25	72.83	57.72	35	−22.97	0.75
Post-peak winter phase	**2023–24**	66.78	46.75	36	−5.8	0.58
	2024–25	112.98	90.86	73	−27.15	0.03

Source: Authors' analysis
Note: Orange and green colours indicate deterioration and improvement in 2024–25 compared to 2023–24, respectively.

Table 13. Phase-wise performance of air quality early warning system in predicting PM10 in 2023–24 and 2024–25

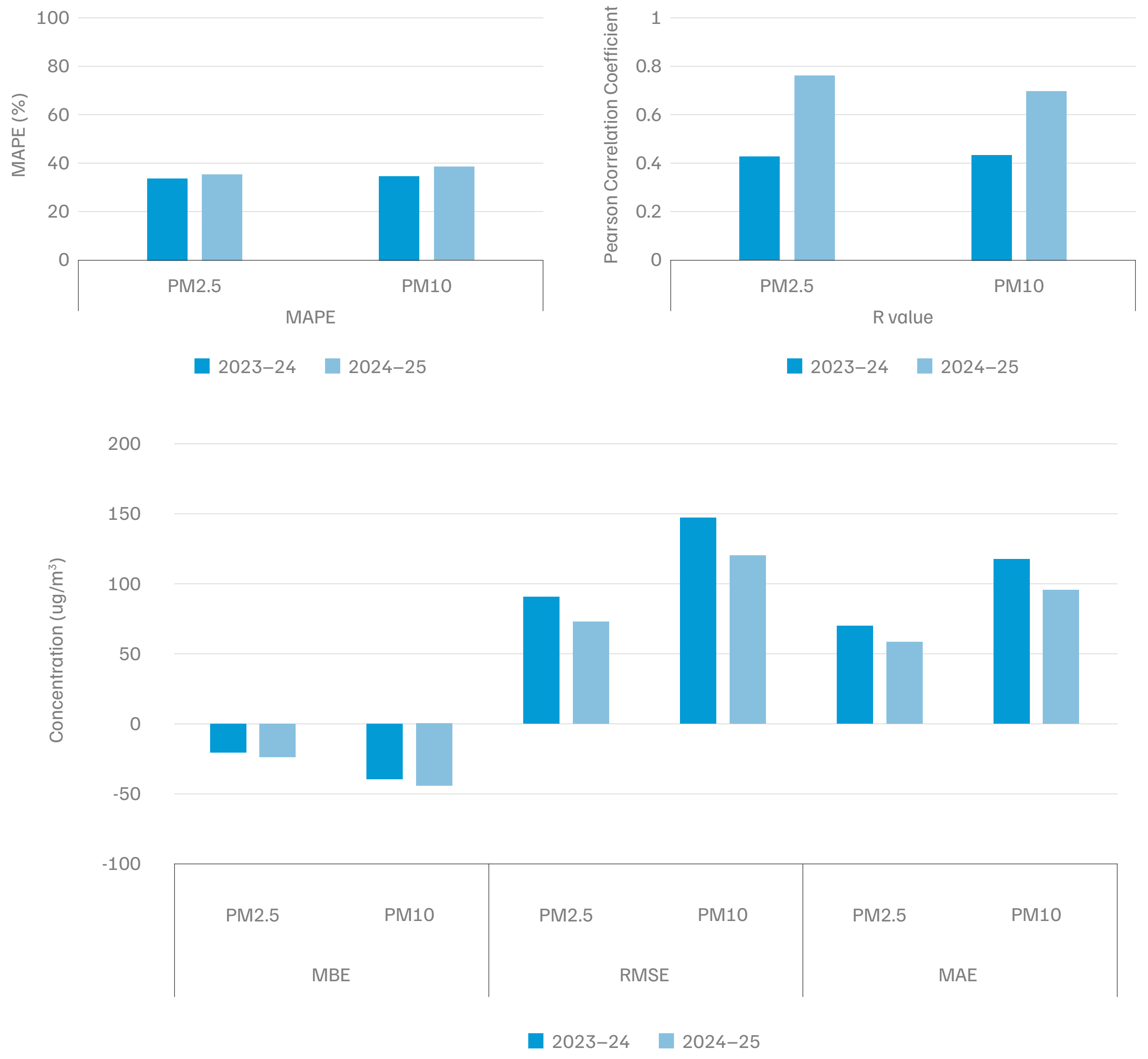
Phase	Year	RMSE (µg/m³)	MAE (µg/m³)	MAPE (%)	MBE (µg/m³)	R value
Stubble burning phase	**2023–24**	145.98	114.46	38	−34.63	0.55
	2024–25	163.96	123.74	33	−79.85	0.42
Post-stubble burning phase	**2023–24**	98.48	86.04	31	−70.29	0.75
	2024–25	108.41	90.98	41	−75.24	0.49
Peak winter phase	**2023–24**	147.08	117.91	34	−39.96	0.43
	2024–25	119.91	95	38	−42.66	0.69
Post-peak winter phase	**2023–24**	118.84	88.01	39	−17.68	0.46
	2024–25	130.03	99.83	57	−3.67	0.22

Source: Authors' analysis
Note: Orange and green colours indicate deterioration and improvement in 2024–25 compared to 2023–24, respectively.

Peak winter phase

The MAPE for PM2.5 and PM10 during the peak winter phase in 2023–24 was 33 per cent. In 2024–25, it deteriorated to 35 per cent and 38 per cent for PM2.5 and PM10, respectively. The MBE for both PM2.5 and PM10 during this phase remained unchanged during both winters. It was around −20 µg/m³ for PM2.5 and −40 µg/m³ for PM10. The RMSE and MAE values improved for both PM2.5 and PM10 in 2024–25 compared to 2023–24. The RMSE values for PM2.5 improved to 73 µg/m³ in 2024–25 from 90 µg/m³ in 2023–24. In the case of PM10, it improved to 120 µg/m³ in 2024–25 from 147 µg/m³ in 2023–24. Similarly, the MAE for PM2.5 and PM10 improved by 12 µg/m³ and 23 µg/m³, respectively, in 2024–25. Moreover, the R value of PM2.5 improved to 0.75 in 2024–25 from 0.42 in 2023–24. Similarly, it improved to 0.69 in 2024–25 from 0.43 in 2023–24.

Figure 7. The Pearson correlation coefficient (R value) for both PM2.5 and PM10 improved in 2024–25

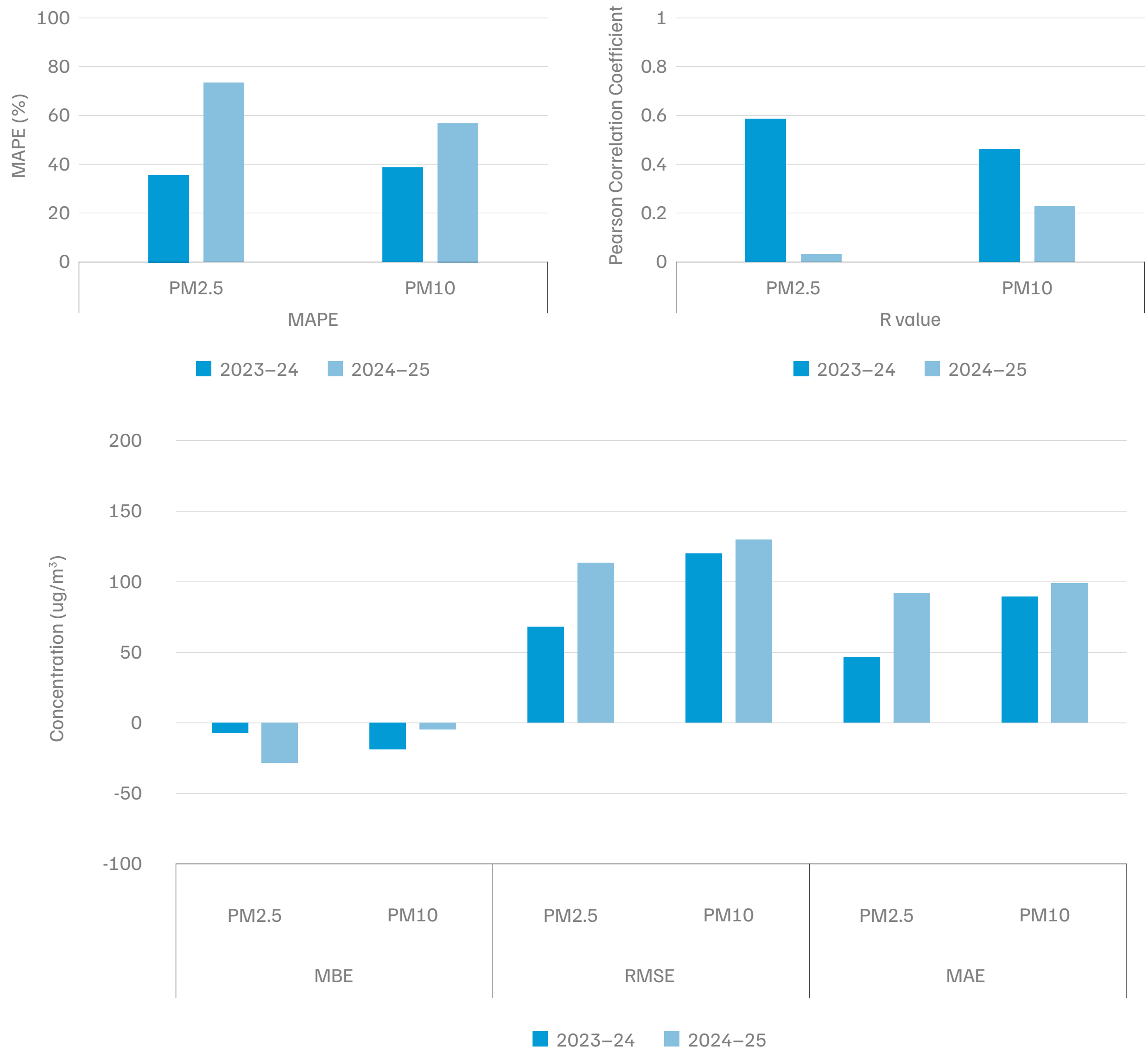


Source: Authors' analysis

Post-peak winter phase

The MAPE for PM2.5 and PM10 during the post-peak winter phase was 36 per cent and 39 per cent, respectively. It deteriorated to 73 per cent and 57 per cent for PM2.5 and PM10, respectively, in 2024–25. The MBE for PM2.5 and PM10 in 2023–24 was –6 μg/m^3 and –18 μg/m^3 respectively. While the MBE for PM2.5 deteriorated to –27 μg/m^3 in 2024–25, it improved to –4 μg/m^3 for PM10. The RMSE values for PM2.5 and PM10 in 2023–24 were 67 μg/m^3 and 119 μg/m^3, respectively. However, it worsened by 46 μg/m^3 for PM2.5 and by 11 μg/m^3 for PM10 in 2024–25. Similarly, the MAE values also deteriorated for both PM2.5 and PM10. For PM2.5, it worsened by two times to 91 μg/m^3 in 2024–25 from 47 μg/m^3 in 2023–24. Similarly, it worsened to 100 μg/m^3 from 88 μg/m^3 in the case of PM10. Similarly, the R value of PM2.5 worsened to 0.03 in 2024–25 from 0.58 in 2023–24, whereas it worsened to 0.22 from 0.46 in the case of PM10.

Figure 8. The performance of the air quality early warning system in predicting both PM2.5 and PM10 during post-peak winter phase deteriorated in 2024–25 compared to 2023–24



Source: Authors' analysis

Pollutant concentration prediction performance during summer

We analysed the performance of the AQEWS in forecasting pollutant concentration in summer (May–June). Table 14 summarises the results of our analysis.

The PM2.5 and PM10 observations during this period[4] were available for 1,400 hours.[5] The average observed PM2.5 concentration was 76 µg/m^3, corresponding to available WRF-Chem (400 m) data, while the average predicted concentration was 72 µg/m^3. In the case of PM10, the average observed concentration was 222 µg/m^3, and the average predicted concentration was 167 µg/m^3.

4. The time period considered is between 1 May 2024 and 30 June 2024.
5. Total hours: 1,464.

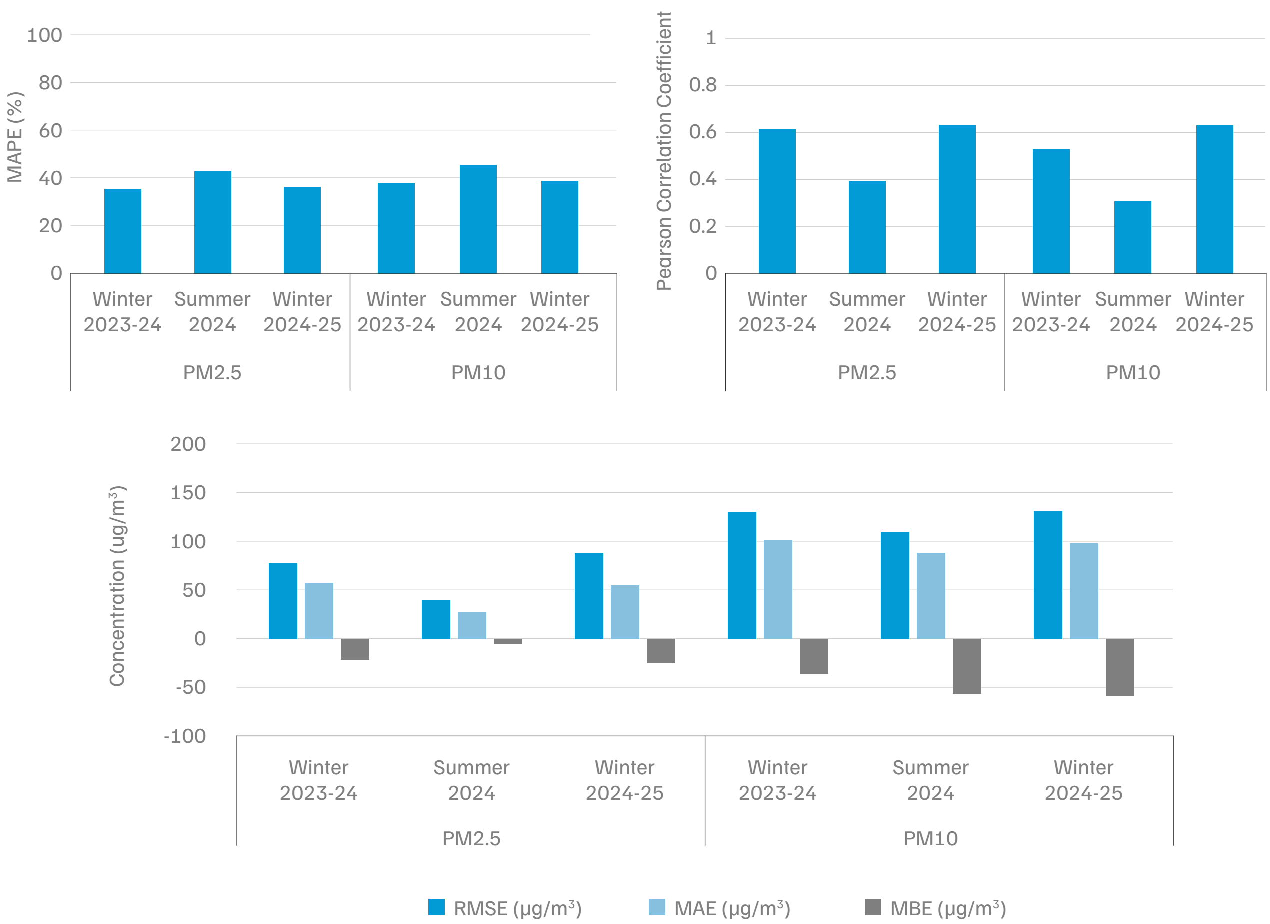
Table 14. The WRF-Chem (400 m) model recorded a mean absolute percentage error of about 40% in summer 2024

S. No.	Pollutant	RMSE ($\mu g/m^3$)	MAE ($\mu g/m^3$)	MAPE (%)	MBE ($\mu g/m^3$)	R value
1	PM2.5	39.16	28.69	42	−3.71	0.39
2	PM10	111.49	90.33	45	−55.16	0.3

Source: Authors' analysis

The MAPE for PM2.5 during summer 2024 was 42 per cent, about a 6 per cent increase from that of winter 2023–24 and 2024–25. Similarly, the MAPE for PM10 during summer was 45 per cent, about 7 per cent higher than winter 2023–24 and 2024–25. Moreover, the R value worsened to 0.39 and 0.3 for PM2.5 and PM10 during summer 2024, whereas it was above 0.5 for both during winter 2023–24 and 2024–25. Despite the decline in MAPE and R values in summer 2024, the RMSE and MAE values for PM2.5 and PM10 improved in summer 2024 compared to winter 2023–24 and 2024–25. The RMSE and MAE values for PM2.5 during summer improved to 39 $\mu g/m^3$ and 29 $\mu g/m^3$, respectively.

Figure 9. The model underpredicted both PM2.5 and PM10 during summer and winter



Source: Authors' analysis

Similarly, the RMSE and MAE values for PM10 during summer improved to 111 µg/m^3 and 90 µg/m^3, respectively. Moreover, the MBE value for PM2.5 during summer was –4 µg/m^3, whereas it was about –18 µg/m^3 in winter 2023–24 and –24 µg/m^3 in winter 2024–25. However, the MBE value of PM10 during summer worsened to –55 µg/m^3 from that of –34 µg/m^3 during winter 2023–24. It worsened to –59 µg/m^3 during winter 2024–25. The negative MBE values indicate that the model consistently underpredicted both PM2.5 and PM10 values during winter and summer.

Implementation of GRAP in Delhi NCR

According to the GRAP schedules for 2022–23 and 2023–24, the criteria for implementing Stages II, III, and IV are thresholds based on dynamic forecasts from the IMD/IITM. These thresholds were set at an AQI of 300 ('very poor') for Stage II, 400 for Stage III, and 450 for Stage IV. In 2023–24, the CAQM invoked Stage III thrice and Stage IV once. These stages were not invoked pre-emptively but only after the AQI crossed the threshold for the respective stage. However, it relied on the AQI forecast to impose Stage II. In September 2024, the CAQM revised the GRAP schedule to precisely define the criteria for invoking each stage, including the likelihood of the predicted AQI levels to "sustain for longer periods (say three days or more)". In December 2024, the Supreme Court (SC) ordered for the invocation of Stages III and IV must be if the AQI crossed 350 and 400, respectively. Following this, the CAQM updated the imposition conditions to include the clause: "Even if the AQI forecasts do not indicate the AQI of Delhi to be breaching a particular threshold and under extreme meteorological conditions or due to any episodic event the AQI breaches the threshold, that particular stage of the GRAP shall be invoked with immediate effect in respect of actions/measures that can be invoked immediately." In 2024–25, the CAQM invoked Stage III six times, Stage IV twice, and Stage II once. However, the implementations of these stages relied on the observed AQI levels rather than forecasts. Moreover, the GRAP does not specify conditions for revoking a stage. In both 2023–24 and 2024–25, the CAQM revoked the GRAP stages once the observed AQI dropped below the lower threshold for the respective stage.

Annexure 5 details the AQI observed during the GRAP period in 2023–24 and 2024–25 and the implementation of different stages of GRAP in Delhi.

4. Scope for improving Delhi's air quality early warning and decision support system

Delhi's AQEWS and DSS satisfy most of the requirements of an ideal AQDSS. Moreover, forecasts from the AQEWS are fairly accurate. However, we observe some limitations. Addressing these could significantly enhance the system's effectiveness. While we list the limitations and suggestions for improvement for Delhi's systems, these apply to the systems in other Indian cities, as they are modelled similar to Delhi's systems.

4.1 Inclusion of actionable scenarios

The operational scenario module available in 2023–24 in Delhi's DSS included pollution reduction scenarios based on forecasted source apportionment outputs from the CTM. For example, users could visualise the reduction in the city's PM2.5 levels following a 20 per cent reduction in the transport sector's contribution. However, such scenarios are not actionable, as the pathway to achieving a 20 per cent reduction from the transport sector is unclear. A more actionable scenario could be restricting the plying of BSIV and below vehicles within the city. The air quality model could simulate this scenario by adjusting the EI to exclude emissions from vehicles below the BS-IV fuel standard. The resulting outputs would then clarify the contribution of these vehicles to air pollution and help the stakeholders justify the imposition or withdrawal of restrictions.

The current version of the DSS does not include short- and long-term policy scenarios. The CAQM's 2022 *Policy to Curb Air Pollution in the National Capital Region* outlines several short-, medium-, and long-term interventions. While simulating every intervention may not be feasible, it is possible to simulate major ones, such as the electrification of public and private transport or the conversion of industries from coal to gas. For instance, HEAVEN demonstrated the impact of introducing speed limits on air pollution in Beusselstrasse, Berlin. Such simulations can help policymakers prioritise interventions by evaluating their costs and benefits, and assist in formulating evidence-based short- and long-term policy measures.

4.2 Assessment of restrictions

Transport and construction are the most affected sectors under the GRAP. During winter, the transport sector contributes around 28 per cent, while dust sources (road dust, soil, and construction) contribute 17 per cent (TERI 2018). All stages of GRAP impose restrictions targeting both sectors. Stage III of GRAP bans non-essential construction activities in NCR. However, not all construction activities contribute to PM2.5 emissions. Interior works such as plumbing and electrical installations, for example, are relatively non-polluting. Moreover, the sector employs a large number of daily wage labourers. Studies estimate that a delay of just one month in construction can result in a three- to four-month delay in project delivery (REIAS INDIA 2024). Thus, while such restrictions are necessary during severe air quality episodes, they also have an adverse impact on livelihoods (Moneycontrol

2024; Business Standard 2024). The rationale for targeting these sectors lies in their substantial contribution to pollution. However, the efficacy of these restrictions remains unknown.

Ghude et al. (2024) evaluated the fractional improvement in Delhi's AQI under various scenarios to demonstrate how such assessments can guide policy design and the effects of such interventions. For instance, a 50 per cent reduction in stubble burning, combined with the utilisation of unburnt stubble in 11 coal-based power plants within 300 km of Delhi, was found to reduce Delhi's AQI by 15 per cent (Ghude et al. 2024). A similar assessment of GRAP restrictions could help quantify their effectiveness and optimise their design.

4.3 Addition of sectoral contributions from neighbouring districts

The current version of the DSS provides the total PM2.5 contribution to Delhi from 19 surrounding districts, such as Alwar, Ghaziabad, Gurgaon, and Karnal. However, it does not offer a sector-wise breakdown of these contributions. Stubble burning is the only external source for which the DSS provides explicit data. In the absence of information on which sectors contribute from which districts, and by how much, it becomes difficult to design targeted interventions. Therefore, revamping the DSS to include sectoral contributions from outside Delhi, in addition to those within the city, would significantly improve its utility for stakeholders in planning and implementing effective mitigation strategies.

4.4 Inclusion of specific chemical components of particulate matter

Currently, the DSS provides information only on the contributions of various sources to PM2.5 levels. However, it does not include data on the constituents of PM2.5, such as black carbon, nitrates, sulphates, etc. Information on the chemical constituents of PM2.5 would enhance our ability to identify the origins of pollutants, prioritise sources for intervention, and monitor the effectiveness of those interventions. Such data should be made available to advanced users through the DSS. A constituent-level assessment of the system's performance would further uncover the model's strengths and weaknesses.

Image: iStock

A robust emission inventory strengthens air quality forecasts. India should, like the US and China, update its national inventory every two to three years.

4.5 Updation of the emission inventory

An outdated EI is the primary reason behind the outlined limitations. The AQEWS and DSS rely on multiple EIs. For NCR districts, the systems utilise the EI developed by TERI for 2016; for Delhi, they employ the 2018 EI developed under the SAFAR project (Ghude et al. 2024). For regions outside the NCR, they use the Emissions Database for Global Atmospheric Research – Hemispheric Transport of Air Pollution (EDGAR-HTAP v2.2). In December 2024, the CAQM announced that it would no longer use the DSS for air quality management decisions due to the outdated EIs used to operate the system (Hindustan Times 2024).

An accurate air pollutant EI is important to design effective air pollution mitigation strategies (Shahbazi et al. 2016). Periodic updates can help the EI track changes in emissions over a region with time and raise public awareness regarding pollution sources (US EPA 2015). Regularly updating the EI at the national level is a common practice in developed countries. For instance, the UK updates its national EI every year, while the US does so every three years (Environmental Integrity Project, n.d.). Developing countries, such as China, update their EI through regular iterative processes led by Tsinghua University (MEIC, n.d.). Mexico City updates its EI every two years (CDMX, n.d.-b). The latest available national-level EI for India was compiled in 2016 (TERI 2021). Despite the NCAP setting a target to develop a comprehensive national EI by 2020 (MoEFCC 2019), India still lacks a national-level EI with provisions for regular updates. Moreover, as of September 2024, only 49 out of 131 cities had completed SA/EI studies (CPCB 2024).

In December 2023, the CAQM submitted an action plan to the NGT outlining targeted sector-wise interventions. One of the key action points was to update the SA/EI studies for Delhi by June 2024 (NGT 2024). However, Delhi has yet to have an updated EI. This highlights the immediate need to develop comprehensive national- and city-level EIs to improve forecasts from air quality models.

4.6 Accessibility of modelled data

The AQEWS and DSS do not allow users to download the modelled data. Users must scrape the data from the website to conduct any analysis. Weather data is available only as JPEG images, making extraction even more difficult than scraping data. As discussed earlier, several AQDSS platforms globally provide public access to downloadable data. For instance, Belgium's irCELine portal offers options to download all air quality data, including forecast data, in different formats (irCELine, n.d.). Similarly, Mexico City allows users to download 24-hour forecast data as animations and in NetCDF format (CDMX, n.d.-a). This enables multiple stakeholders, including the research community, to independently evaluate system performance. Such assessments contribute to periodic improvements in the system. Moreover, researchers can use raw data to develop ML-based bias-correction algorithms to improve forecast accuracy (Xu et al. 2021).

4.7 Year-round operation of the decision support system

While Delhi's AQEWS provides forecast data throughout the year, the DSS provides source contributions only during winter. However, air pollution is a year-round issue, and it is essential for stakeholders to understand the contributions of sources across seasons. Therefore, the DSS should be expanded to provide source contributions throughout the year.

Running policy and GRAP simulations, incorporating sectoral contributions from NCR districts, and operating the DSS throughout the year are expensive exercises. CTMs require substantial computing resources (S. K. Guttikunda and Dammalapati 2024), and implementing such simulations will necessitate additional funding.

5. Conclusion and recommendations

The AQEWS performs reasonably well in predicting high pollution episodes in Delhi. However, the above mentioned improvements will further strengthen the system to help decision makers design and implement effective mitigation measures. To achieve this, we recommend the following.

- **The MoEFCC and CAQM should revamp the EI across India, with an immediate focus on Delhi NCR**. The MoEFCC should develop a new national-level EI with a provision for regular updates. Both the National Emission Inventory (NEI) of the US and the Multi-resolution Emission Inventory for China (MEIC) are regularly updated and designed to be model-ready, which means they are compatible with widely used air quality models, such as WRF-Chem and the Community Multiscale Air Quality (CMAQ) model. The MoEFCC should aim to compile an EI on similar lines, enabling research groups across India and abroad to perform various air quality simulations to assess the impacts of current and future interventions. Regular updates, at least every two or three years, must be institutionalised. The immediate priority should be upgrading the EI for the Delhi NCR region under the CAQM's supervision to improve forecasts.

Image: iStock

Delhi's air quality early warning system predicts pollution episodes reasonably well. Its performance can be further improved with updated emission inventories, bias-corrected forecasts, and sectoral data from neighbouring districts.

- **The IITM and IMD should revamp the DSS to include simulations of policy scenarios and GRAP restrictions as well as display sectoral contributions from NCR districts.** The 2023–24 version of the DSS featured hypothetical scenarios that allowed users to visualise the impact of reducing one or more pollution sources by 20 or 40 per cent on Delhi's PM 2.5 levels. However, such hypothetical scenarios do not provide a clear, actionable path for stakeholders. It should therefore be revamped to include actionable scenarios, such as the impact of restricting the movement of all BS-IV vehicles in Delhi and surrounding areas, drawing inspiration from systems such as HEAVEN. Additionally, stakeholders should be able to visualise the impact of GRAP interventions, as well as short-, medium-, and long-term policy measures outlined by the CAQM wherever feasible.

> The IITM and IMD should revamp the DSS to include simulations of policy scenarios and GRAP restrictions while also displaying the sectoral contributions from NCR districts.

- **Provide additional funding to revamp the AQEWS and DSS and run the DSS throughout the year.** Air quality modelling using a CTM requires supercomputers and substantial operational costs. For instance, in the recent hearing in February 2025 on *Kankana Das vs Union of India and Others*, the Tamil Nadu Pollution Control Board (TNPCB) requested the CPCB to suggest an alternative to IITM's forecasting system, citing its prohibitive cost of around INR 100 crore (*Kankana Das Versus Union of India and others* 2025). However, only a CTM can accurately attribute emissions to specific sources and support experiments to assess air quality improvements by reducing contributions from targeted sources. The union government should therefore allocate additional funding to revamp Delhi's AQEWS and DSS and to operate the DSS year-round. It should also account for data storage systems to support the training of ML models and improve resource availability for future studies.

- **The IITM and IMD should integrate ML models to correct forecast errors.** Even with an updated EI, forecast errors are possible. ML-based bias-corrected models can significantly improve prediction accuracy (Xu et al. 2021). Although the GRAP is theoretically pre-emptive and linked to forecasts, the CAQM rarely implements measures based solely on forecasts. While AQEWS's ability to forecast 'severe and above' (AQI > 400) air pollution episodes has improved substantially, further improvements will help the CAQM impose GRAP measures pre-emptively, rather than waiting for AQI thresholds to be breached.

- **The IITM and IMD should make AQEWS and DSS data publicly available.** Although both the AQEWS and DSS host valuable data on their websites, this data is not publicly downloadable and must currently be scraped using web-scraping tools. Public access to this data would enable independent assessments of weather and AQ forecasts by the research community, which can, in turn, enhance the models in several ways. For instance, they could identify the possible causes of forecast errors or develop ML-based corrections. Moreover, information on the constituents of PM2.5 from various sources will enhance our understanding of it. CPCB's Central Control Room for Air Quality Management is a strong example of data transparency. It allows the public to access data from monitoring stations across the country and analyse it independently. Such assessments have helped track changes in air quality and suggest interventions for further progress. For instance, independent studies carried out by the Centre for Science and Environment (CSE) and the Centre for Research on Energy and Clean Air (CREA) analysed the progress under the NCAP and recommended prioritising PM2.5 over PM10, adopting an airshed approach, revising the list of NACs, and so on (N Manojkumar and Muruganandam 2025; Roychowdhury and Kumari 2024). The IITM and IMD must therefore follow CPCB's precedent and make data from the AQEWS and AQDSS publicly available to facilitate independent research and enable improvements to the system through collaborative efforts.

Delhi's AQEWS and DSS satisfy most requirements of an ideal DSS. Moreover, the system performs reasonably well in predicting air pollution episodes in Delhi. However, a revamped system running year-round with an updated EI, along with bias-corrected forecasts, would strengthen the air quality mitigation measures in the NCR region. It will guide the decision makers to make informed decisions supported by evidence backed by scientific analysis and data. It will also serve as a stronger example for other cities that plan to adopt a similar system.

Acronyms

AQDSS	air quality decision support system
AQEWS	Air Quality Early Warning System
AQMIS	Air Quality and Meteorology Information System
AQI	air quality index
BS-IV	Bharat Stage-IV
CAAQMS	continuous ambient air quality monitoring station
CAQM	Commission for Air Quality Management in National Capital Region and Adjoining Areas
CARB	California Air Resources Board
CMAQ	Community Multiscale Air Quality
COPD	chronic obstructive pulmonary disease
CPCB	Central Pollution Control Board
CREA	Centre for Research on Energy and Clean Air
CSE	Centre for Science and Environment
CTM	chemical transport model
DSS	decision support system
EDSS	environmental decision support system
EI	emission inventory
EPCA	Environment Pollution (Prevention and Control) Authority
EU	European Union
FAR	false alarm ratio
FNR	false negative rate
GAFIS	Global Air Quality Forecasting and Information System
GAW	Global Atmospheric Watch
GIS	geographic information system
GRAP	*Graded Response Action Plan*

IITM	Indian Institute of Tropical Meteorology
IMD	India Meteorological Department
IMD SILAM	India Meteorological Department System for Integrated Modelling of Atmospheric Composition
MAE	mean absolute error
MAPE	mean absolute percentage error
MEIC	Multi-resolution Emission Inventory for China
MBE	mean bias error
ML	machine learning
MoEFCC	Ministry of Environment, Forest and Climate Change
MoES	Ministry of Earth Sciences
NAAQS	*National Ambient Air Quality Standards*
NAC	non-attainment city
NCAP	*National Clean Air Programme*
NCR	National Capital Region
NEI	National Emission Inventory
PBLH	planetary boundary layer height
POD	probability of detection
RMSE	root mean squared error
RSPCB	Rajasthan State Pollution Control Board
SA	source apportionment
SAFAR	System of Air Quality and Weather Forecasting and Research
SC	Supreme Court
TNPCB	Tamil Nadu Pollution Control Board
UK	United Kingdom
US	United States
VIIRS	Visible Infrared Imaging Radiometer Suite
WRF-Chem	Weather Research and Forecasting coupled with Chemistry

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Annexures

Annexure 1. Matrix used for computing performance metrics

		Observed	
		True	False
Predicted	True	True positive (TP)	False positive (FP)
	False	False negative (FN)	True negative (TN)

Where,

- True positives are the number of days on which the predicted and observed categories matched.
- False negatives are the number of days on which the predicted category failed to capture pollution episodes.
- False positives are the number of days on which the model falsely predicted pollution episodes.
- True negatives are the number of days on which the model rightly predicted good air quality days.

Table A1. Metrics used in the study

Metrics	Description	Equation
Accuracy	The ability of the model to correctly classify true and false events.	(TP + TN) / (TP + FP + FN + TN)
False alarm ratio (FAR)	The rate at which the model predicts false events as true events.	FP / (FP + TP)
Probability of detection (POD)	The ability of the model to detect true events.	TP / (TP + FN)
False negative rate (FNR)	The rate at which the model predicts a true event as a false event.	FN /(TP + FN)

Source: Authors' compilation

Annexure 2. AQI range and corresponding categories in India

AQI	Category	Colour code	Possible health impacts
0–50	Good		Minimal impact
51–100	Satisfactory		May cause minor breathing discomfort to sensitive people
101–200	Moderate		May cause breathing discomfort to the people with lung disease such as asthma and discomfort to people with heart disease, children and older adults
201–300	Poor		May cause breathing discomfort to people on prolonged exposure and discomfort to people with heart disease with short exposure
301–400	Very poor		May cause respiratory illness to the people on prolonged exposure. Effect may be more pronounced in people with lung and heart diseases
401–500	Severe		May cause respiratory effects even on healthy people and serious health impacts on people with lung/heart diseases. The health impacts may be experienced even during light physical activity

Source: CPCB (CPCB 2015a)

Annexure 3. Predicted and observed number of days in the 'very poor and above' and 'severe and above' categories in 2023–24 and 2024–25

Table A2. Predicted and observed number of days in the ' very poor and above' category in 2023–24

	Observed		
Forecast	**True**	**False**	**Total**
True	83	12	95
False	9	35	44
Total	92	47	139

Source: Authors' analysis

Table A3. Predicted and observed number of days in the 'severe and above' category in 2023–24

	Observed		
Forecast	**True**	**False**	**Total**
True	1	10	11
False	14	114	128
Total	15	124	139

Source: Authors' analysis

Table A4. Predicted and observed number of days in the 'very poor and above' category in 2024–25

	Observed		
Forecast	**True**	**False**	**Total**
True	54	17	71
False	4	62	66
Total	58	79	137

Source: Authors' analysis
Note: The AQI data was not available for 13 days and 2 days from the AQEWS portal and CPCB, respectively, in 2024-25.

Table A5. Predicted and observed number of days in the 'severe and above' category in 2024–25

	Observed		
Forecast	**True**	**False**	**Total**
True	5	3	8
False	9	120	129
Total	14	123	137

Source: Authors' analysis
Note: The AQI data was not available for 13 days and 2 days from the AQEWS portal and CPCB, respectively, in 2024-25.

Annexure 4: Performance of AQEWS of other Indian cities

Seven other Indian cities have an operational AQEWS based on the WRF-Chem model run at a resolution of two kilometres (WRF-Chem (2 km)). These cities are Pune, Bengaluru, Hyderabad, Ahmedabad, Kolkata, Jaipur, and Mumbai. The Rajasthan State Pollution Control Board (RSPCB) operationalised Jaipur's system only in the summer of 2024; hence, we exclude its data from our analysis. We also excluded the analysis of Kolkata due to the unavailability of data. Tables A6, A7, A8, and A9 present the performance metrics for these cities regarding PM2.5 and PM10 for the winters of 2023–24 and 2024–25, respectively.

Table A6. Performance of WRF-Chem (2 km) in predicting PM2.5 in winter 2023–24

Metrics	Pune	Bengaluru	Hyderabad	Mumbai	Ahmedabad
MAE (μg/m^3)	21.37	17.47	16.62	34	25.23
MAPE (%)	32	36	31	67	39
RMSE (μg/m^3)	30.26	40.30	38.88	43.46	35.77
MBE (μg/m^3)	−15.82	−8.02	7.61	31.76	14.05
R value	0.52	0.23	0.41	0.54	0.37

Source: Authors' analysis

The number of hours of PM2.5 and corresponding WRF-Chem (400 m) observations was available for 2,029 hours for Pune, 2,308 hours for Bengaluru, 2,157 hours for Hyderabad, 2,200 hours for Mumbai, and 186 hours for Ahmedabad, between 9 November 2024 and 29 February 2025 (total 2,696 hours).[6] The average observed and predicted PM2.5 concentrations are:

Pune: Observed: ~68 μg/m^3; Predicted: ~52 μg/m^3
Bengaluru: Observed: ~43 μg/m^3; Predicted: ~35 μg/m^3
Hyderabad: Observed: ~49 μg/m^3; Predicted: ~56 μg/m^3
Mumbai: Observed: ~52 μg/m^3; Predicted: ~84 μg/m^3
Ahmedabad: Observed: ~65 μg/m^3; Predicted: ~79 μg/m^3

Table A7. Performance of WRF-Chem (2 km) in predicting PM2.5 in winter 2024–25

Metrics	Pune	Bengaluru	Hyderabad	Mumbai	Ahmedabad
MAE (μg/m^3)	19.31	12.15	28.83	38.5	39.22
MAPE (%)	38	34	51	70	65
RMSE (μg/m^3)	24.71	15.64	53.92	43.98	51.68
MBE (μg/m^3)	7.59	2.52	23.73	37.25	35.05
R value	0.39	0.66	0.3	0.51	0.57

Source: Authors' analysis

6. Starting from 16:00 hours of 9 November 2024.

The number of hours of PM2.5 and corresponding WRF-Chem (400 m) observations were available for 1,970 hours for Pune, 1,462 hours for Bengaluru, 1,435 hours for Hyderabad, 1,461 hours for Mumbai, and 1,869 hours for Ahmedabad, between 4 November 2024 and 28 February 2025 (total 2,565 hours).[7] The average observed and predicted PM2.5 concentrations are:

Pune: Observed: ~53 μg/m^3; Predicted: ~61 μg/m^3
Bengaluru: Observed: ~38 μg/m^3; Predicted: ~40 μg/m^3
Hyderabad: Observed: ~56 μg/m^3; Predicted: ~80 μg/m^3
Mumbai: Observed: ~56 μg/m^3; Predicted: ~94 μg/m^3
Ahmedabad: Observed: ~64 μg/m^3; Predicted: ~99 μg/m^3

Table A8. Performance of WRF-Chem (400 m) in predicting PM 10 in winter 2023–24

Metrics	Pune	Bengaluru	Hyderabad	Mumbai	Ahmedabad
MAE (μg/m^3)	53.93	42.82	39	32.97	39.46
MAPE (%)	47	53	39	27	28
RMSE (μg/m^3)	65.07	49.57	67.73	43.12	61.44
MBE (μg/m^3)	−53.24	−42.56	−31.58	−16.8	−24.73
R value	0.55	0.51	0.36	0.51	0.41

Source: Authors' analysis

The number of hours of PM10 and corresponding WRF-Chem (400 m) observations were available for 2,029 hours for Pune, 2,307 hours for Bengaluru, 2,147 hours for Hyderabad, 2,200 hours for Mumbai, and 186 hours for Ahmedabad, between 9 November 2024 and 29 February 2025 (total 2,696 hours).[8] The average observed and predicted PM10 concentrations are:

Pune: Observed: ~114 μg/m^3; Predicted: ~61 μg/m^3
Bengaluru: Observed: ~80 μg/m^3; Predicted: ~37 μg/m^3
Hyderabad: Observed: ~94 μg/m^3; Predicted: ~62 μg/m^3
Mumbai: Observed: ~124 μg/m^3; Predicted: ~107 μg/m^3
Ahmedabad: Observed: ~129 μg/m^3; Predicted: ~104 μg/m^3

Table A9. Performance of WRF-Chem (400 m) in predicting PM 10 in winter 2024–25

Metrics	Pune	Bengaluru	Hyderabad	Mumbai	Ahmedabad
MAE (μg/m^3)	33.95	33.6	42.76	26.79	49.63
MAPE (%)	31	43	32	19	41
RMSE (μg/m^3)	42.55	41.47	77.33	34.06	75.75
MBE (μg/m^3)	−29.19	−32.42	−31.92	−18.65	34.21
R value	0.38	0.49	0.3	0.52	0.56

Source: Authors' analysis

7. Starting from 16:00 hours of 4 November 2024.
8. Starting from 16:00 hours of 9 November 2024.

The number of hours of PM10 and corresponding WRF-Chem (400 m) observations were available for 1,971 hours for Pune, 1,463 hours for Bengaluru, 1,412 hours for Hyderabad, 1,463 hours for Mumbai, and 1,925 hours for Ahmedabad, between 4 November 2024 and 28 February 2025 (total 2,565 hours).[9] The average observed and predicted PM10 concentrations are:

Pune: Observed: ~106 $\mu g/m^3$; Predicted: ~77 $\mu g/m^3$
Bengaluru: Observed: ~77 $\mu g/m^3$; Predicted: ~44 $\mu g/m^3$
Hyderabad: Observed: ~125 $\mu g/m^3$; Predicted: ~93 $\mu g/m^3$
Mumbai: Observed: ~140 $\mu g/m^3$; Predicted: ~122 $\mu g/m^3$
Ahmedad: Observed: ~123 $\mu g/m^3$; Predicted: ~158 $\mu g/m^3$

Annexure 5: Implementation of GRAP in 2023–24

Table A10 below provides the dates on which the CAQM imposed different stages of GRAP in 2023–24, between 6 October 2023 and 27 February 2024.

Table A10. Implementation of GRAP' in 2023–24

Date	Observed AQI	Remarks
06-10-23	212	Invocation of Stage I
21-10-23	248	Invocation of Stage II
02-11-23	392	Invocation of Stage III
05-11-23	454	Invocation of Stage IV
18-11-23	319	Revocation of Stage IV
28-11-23	312	Revocation of Stage III
22-12-23	409	Invocation of Stage III
01-01-24	346	Revocation of Stage III
14-01-24	447	Invocation of Stage III
18-01-24	318	Revocation of Stage III
19-02-24	231	Revocation of Stage II
27-02-24	159	Revocation of Stage I

Source: Authors' compilation

Implementation of GRAP in 2024–25

Table A11 displays the dates on which the CAQM imposed different stages of GRAP in 2024–25 between 14 October 2024 and 15 March 2025. In 2025, the CAQM extended the imposition of GRAP to the summer months. It imposed and revoked Stage 1 five times between 15 March 2025 and 15 June 2025.

9. Starting from 16:00 hours of 4 November 2024.

Table A11. Implementation of GRAP in 2024–25

Date	Observed AQI	Remarks
14-10-24	234	Invocation of Stage I
21-10-24	310	Invocation of Stage II
14-11-24	424	Stage III invoked – implemented starting from 15 November 2024
17-11-24	441	Stage IV invoked – implemented from 15 November 2024
05-12-24	165	Stages III and IV revoked
16-12-24	379	Stages III and IV invoked
24-12-24	369	Revocation of Stage IV
27-12-24	353	Revocation of Stage III
03-01-25	371	Invocation of Stage III
05-01-25	339	Revocation of Stage III
09-01-25	357	Invocation of Stage III
12-01-25	278	Revocation of Stage III
15-01-25	386	Invocation of Stages III and IV
16-01-25	302	Revocation of Stage IV
17-01-25	289	Revocation of Stage III
29-01-25	365	Invocation of Stage III
03-02-25	286	Revocation of Stage III
24-02-25	186	Revocation of Stage II
03-03-25	156	Revocation of Stage I
07-03-25	202	Invocation of Stage I
15-03-25	262	Revocation of Stage I

Source: Authors' compilation

The detailed GRAP schedule is available at https://caqm.nic.in

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