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Recent improvements in $PM_{2.5}$ air quality in India benefited from meteorological variation

Yuanyu Xie[1*], Mi Zhou[1], Kieran M. R. Hunt[2,3], Denise L. Mauzerall[1,4*]

[1]Center for Policy Research on Energy and Environment, School of Public and International Affairs, Princeton University, Princeton, NJ 08544, USA

[2]Department of Meteorology, University of Reading, Reading, UK

[3]National Centre for Atmospheric Sciences, University of Reading, Reading, UK

[4]Department of Civil and Environmental Engineering, Princeton University, Princeton, NJ 08540, USA

***Corresponding authors:** Yuanyu Xie (Email: yuanyux@princeton.edu)

Denise L. Mauzerall (Email: mauzerall@princeton.edu)

Abstract

Improving air quality amid rapid industrialization and population growth is a huge challenge for India. To tackle this challenge, the Indian government implemented the National Clean Air Programme (NCAP) to reduce particulate matter ($PM_{2.5}$ and PM_{10}) pollution in hundreds of non-attainment cities that failed to meet the national ambient air quality standards. Here, we evaluate the efficacy of the NCAP, using data from the national air quality monitoring network combined with regional model simulations. Our results show an 8.8% per year decrease in annual $PM_{2.5}$ pollution in the six non-attainment cities with continuous air pollution monitoring since 2017. Four out of the six cities had over 20% $PM_{2.5}$ reduction in 2022 relative to 2017 and thus met the NCAP target. However, we identify that ~30% of the annual $PM_{2.5}$ air quality improvements, and approximately half during winter when pollution is high, can be attributed to favorable meteorological conditions which are unlikely to persist as the climate warms. Meanwhile, annual $PM_{2.5}$ levels in 44 out of 57 non-attainment cities with continuous monitors still failed to meet air quality standards in 2022. This work highlights the need for substantial additional mitigation measures beyond current NCAP policies to improve air quality in India.

Introduction

Millions of people in India are breathing the most polluted air in the world. Rapid economic growth as the country strives to become a $5 trillion economy by 2025 has led to enormous increases in emissions of air pollutants[1, 2]. In 2023, 9 out of 10 of the most polluted cities in the world were in India[3]. Severe surface air pollution was estimated to be responsible for 1.67 million premature mortalities in India in 2019[4], approximately 8 (13) years of life expectancy lost for 248 million residents of northern India (Delhi)[5] with a resulting economic cost of $36.8 billion[4].

In January 2019, the Ministry of Environment, Forest and Climate Change (MoEFCC) in India launched the National Clean Air Programme (NCAP) as a national level strategy to reduce particulate matter (PM) air pollution. The NCAP goal is to reduce $PM_{2.5}$ and PM_{10} pollution by 20–30% by 2024 (updated in 2022 to reduce by 40% by 2026) relative to 2017 in 102 non-attainment cities identified by the Central Pollution Control Board (CPCB) in 2019[6]. Total number of non-attainment cities increased to 131 in 2023[7]. NCAP has provided over 10,400 Crores (~1.2 billion USD) financial support to the non-attainment cities for expansion of surface continuous pollution monitoring capacity, development and implementation of city action plans, and public awareness campaigns[8, 9]. There is an urgent need to assess the resulting changes in surface $PM_{2.5}$ air quality nationwide to inform future air pollution control strategies.

Air pollution control policies target reductions of emissions at the source. However, observed concentrations of air pollutants are modulated by meteorological variability through changing ventilation and resulting pollution dilution, and the formation of secondary particulates[10, 11, 12]. Previous studies suggest meteorological variability drives large daily to inter-annual variations in surface $PM_{2.5}$ concentrations across India[13, 14, 15, 16]. Changing pollution concentrations in turn affect local meteorology and regional climate through perturbation to radiation and cloud formation[17, 18, 19], which subsequently feedback to surface pollution levels. These meteorology influence complicates the interpretation of policy effectiveness on pollution concentration trends and health outcomes[20, 21, 22, 23]. For instance, past research has estimated that meteorological variability contributed 10–27% of the $PM_{2.5}$ reduction over China during the Clean Air Action Campaign[23, 24]. Understanding the relative importance of emissions versus meteorological variability on surface air pollution concentrations thus has implications for effective air quality policy design.

In this study, we compile and apply strict quality controls to recently available continuous hourly PM data from ~500 stations across India in the Continuous Ambient Air Quality Monitoring network (CAAQM) and five stations in the United States Department of State AirNow (US AirNow) networks for 2017–2022 (see Methods). While the National Air Quality Monitoring Program (NAMP) manual PM monitoring data is used by the Indian government to identify non-attainment cities when continuous monitors are not widely available, we only analyze manual data in the Supplementary Information due to large uncertainties related to manual monitoring and data reporting[6]. We perform a comprehensive evaluation of the observed changes in annual, seasonal, and daily PM air quality from CAAQM/US AirNow in non-attainment cities and nationwide. To understand the drivers of the PM air pollution trends, we disentangle the role of anthropogenic emissions versus meteorological variations using surface and satellite observations as well as regional online-coupled meteorology-chemistry model simulations (see Methods). Our analysis highlights the need for better air pollution monitoring data and more stringent emission controls to improve surface air quality and public health over India.

Results

Observed improvements in surface particulate matter air quality

To evaluate pollution trends and the effectiveness of NCAP policies, we first examine the availability of quality-controlled continuous PM monitoring data from the CAAQM and US AirNow networks in 131 non-attainment cities and nationwide. We then analyze, for each non-attainment city with continuous PM monitoring, the observed changes in annual, seasonal and daily mean PM concentrations since the NCAP baseline year 2017 for comparison with the policy target. To be consistent with seasonal analyses, we calculate annual means as averages from March in the current year through February of the subsequent year.

Figure 1 shows the locations of the 131 non-attainment cities and all cities with continuous $PM_{2.5}$ pollution monitoring from the CAAQM and US AirNow networks (Extended Data Fig. 1). There are a total of 150 cities, including 62 non-attainment cities, that had at least one year of continuous $PM_{2.5}$ data during 2017–2022. However, only seven cities (six non-attainment) had six consecutive years of $PM_{2.5}$ observations that we require to assess pollution trends. Data coverage is better for individual seasons than for annual averages (Extended Data Fig. 2). The most extensive data exists for winter where 36 cities (28 non-attainment) had six consecutive years of winter $PM_{2.5}$ monitoring data since 2017. Thus, winter pollution trends may be more representative of actual national pollution trends than annual averages. Data availability for PM_{10} is poorer than for $PM_{2.5}$, with 134 cities (48 non-attainment) having at least one year of data and only one city (Delhi) having six consecutive years of data (Extended Data Fig. 3). Despite a notable 10-fold increase in CAAQM stations from 2017 to 2022 (Fig. 1b), in part fueled by NCAP support, lack of consecutive PM pollution monitoring since 2017 hinders the ability of the government to evaluate pollution trends and to determine for most non-attainment cities whether they are meeting the NCAP targets.

We find, across Indian cities with continuous air pollution measurements, improvements in surface $PM_{2.5}$ air quality during 2017–2022 (Fig. 2). Annual $PM_{2.5}$ have decreased at a rate of 8.0 μg/m^3 (–8.8%, $p < 0.01$) per year since 2017 in the six non-attainment cities with continuous $PM_{2.5}$ monitoring (Fig. 2b). Average $PM_{2.5}$ in those cities was 91.0±36.7 μg/m^3 in the NCAP baseline year 2017, more than twice the national annual standard of 40 μg/m^3 and ~18 times the current World Health Organization (WHO) standard of 5 μg/m^3. In 2017 none of the six cities had annual $PM_{2.5}$ in compliance with the national annual standard. Annual mean $PM_{2.5}$ decreased to 51.8±24.5 μg/m^3 in 2022, with two cities (Chennai and Varanasi) having $PM_{2.5}$ pollution levels meeting the national annual standard. Reductions of $PM_{2.5}$ concentrations in 2022 relative to 2017 exceeded 20% in four out of six non-attainment cities - surpassing the NCAP targets two years early. Consistent but smaller $PM_{2.5}$ decreases were also observed in 33 cities (25 non-attainment) with continuous monitoring since 2018 (Fig. 2b and Extended Data Fig. 4), as well as in 32 cities (21 non-attainment) with manual monitors during 2017–2021 (Supplementary Figure 1).

Larger improvements in $PM_{2.5}$ air quality occurred in fall through winter, the two most polluted seasons in India (Fig. 2c, Extended Data Fig. 4 & 5). In 13 (28) non-attainment cities with consecutive fall (winter) pollution monitoring, seasonal mean $PM_{2.5}$ decreased at a rate of 7.7% per year (p<0.01) for fall and 5.5% per year (p=0.03) for winter since 2017. Surface $PM_{2.5}$ concentrations in 2022 compared to 2017 was 43% and 25% lower in fall and winter, respectively. Daily pollution levels in fall-winter have also shifted substantially towards lower values over the most polluted Indo Gangetic Plain (Fig. 2c). We find a 35% increase in the frequency of days which met the 60 μg/m^3 national 24-hour standard during 2020–2022 compared to 2017–2019. Meanwhile, the occurrence of days with very poor (>120 μg/m^3) or severe (>250 μg/m^3) $PM_{2.5}$ air pollution, according to National Air Quality Index, decreased by one-third. While $PM_{2.5}$ reductions in spring-summer are smaller, significantly lower $PM_{2.5}$ levels by 30–40% were observed during the national COVID-19 lockdown (Mar–May in 2020) and partial lockdown (April–June in 2021, Supplementary Figure 2) consistent with previous studies[25, 26].

No significant trends in PM_{10} pollution were observed in Delhi, the only city with six years of continuous PM_{10} monitoring since 2017, or in the 13 cities with consecutive PM_{10} observations since 2018 (Extended Data Fig. 3). Consistent with $PM_{2.5}$, surface PM_{10} pollution were 30–40% lower during the COVID-19 lockdown (Supplementary Figure 3), indicating the importance of anthropogenic contribution (e.g., road dust, construction) to surface PM_{10} pollution in India[27]. However, no significant PM_{10} reductions in 2020 were reported by the NAMP manual monitoring data as compared to the 2019 and 2021 averages (Supplementary Figure 4). This may in part be linked to gaps in data collection due to difficulties in making manual measurements during the COVID-19 lockdown periods in 2020. Moreover, PM_{10} trends observed by the NAMP monitoring network were inconsistent with those from CAAQM continuous monitoring networks in the 12 cities where annual PM_{10} measurements from both networks are available. Such data discrepancies raise concerns regarding the robustness of the manual data used to identify non-attainment cities and to assess pollution trends.

Changes in anthropogenic emissions were small

We first examine whether the observed air quality improvements since 2017 can be explained by changes in anthropogenic emissions of primary $PM_{2.5}$ and key precursors nationwide as these species have been targeted in various pollution control policies[6, 28, 29]. We focus our analysis on $PM_{2.5}$ pollution with better data coverage and consistency. We use emission data from three global emission inventories as national inventories do not provide data after 2017 (see Methods). Observational constraints from satellite-retrieved column concentrations and surface measurements are included for comparison as uncertainties exist in the emission estimates from global and regional databases of activity levels, emission factors and spatial distributions used to estimate emissions across India[30, 31, 32, 33].

We find slight decreases in emissions of primary particles but little change or increases in emissions of key $PM_{2.5}$ precursors since the NCAP baseline year 2017 (Fig. 3, Extended Data Fig. 6). Emissions of black carbon (BC) and organic carbon (OC) have decreased since around 2010 (Fig. 3a-b), consistent with the observed decreasing trends of surface BC concentrations across India since 2011 [34] and in Delhi since 2012 [35]. The emission reductions were primarily from the residential sector. This was in part driven by the wide success of *Pradhan Mantri Ujjwala Yojana* launched in 2016, which aims to replace solid fuel cooking with liquified petroleum gas (LPG) through subsidizing 96 million LPG connections to socioeconomically poor rural households across India. The percentage of Indian household that use LPG as primary cooking fuel has increased from 28.5% in 2011 to 71% in 2020[36]. Surface carbon monoxide (CO), a gas pollutant co-emitted during biomass burning, was also observed to decrease in 4 cities with five years of continuous monitoring starting in 2018 (Fig. 3b). Rapid penetration of clean cooking fuel over the past several years may thus be one of the important drivers of the observed $PM_{2.5}$ air quality improvements since 2017[37]. In addition, emission reductions of BC have resulted from decreases in the use of diesel in the transport sector and replacement with compressed natural gas[35], and are expected to decrease further with the introduction of electric buses.

In comparison, no significant decreasing trends are seen in key $PM_{2.5}$ precursors (SO_2, NO_x and NH_3) from emissions inventories during 2017–2019, or from surface or satellite observations during 2017–2022 (Fig.3 a-c, Supplementary Figure 4). In fact, we find a 7% increase in total column SO_2 nationwide in 2022 compared to 2017, especially over regions where major coal power plants are located (Extended Data Fig. 7). Observed surface SO_2 concentrations were also 14% higher in 2022 than in 2018 averaged from 18 cities with five consecutive years of monitoring data. These observed SO_2 increases were likely associated with the soaring coal consumption in India following a small decrease in 2019–2020[38]. Moreover, currently over 70% of coal power plants are still out of compliance with the updated 2015 emission standard for thermal power plants[39]. As the world's largest SO_2 emitter and with increasing energy demand, India will need stronger enforcement of the emission standards and an increase in generation from clean energy sources to reduce its SO_2 emissions.

Insignificant changes in NO_x and slight increases in NH_3 concentrations were observed during 2018–2022 compared to 2017 (Fig. 3b-c). Total column NO_2 from TROPOMI shows a 6% increase in 2022 relative to 2018 despite slight decreases in 2019–2020. The increases were most significant in the Indo Gangetic Plain and in major cities across the country (Extended Data Fig. 7), likely associated with increased emissions from transportation due to growing numbers of vehicles. These may offset emission reductions resulting from the implementation of Bharat Stage IV emission standards since 2010 (equivalent to Euro IV) and the Bharat Stage VI emission standards since 2020 (based on Euro VI)[40]. In 2018 the Indian government also launched the E-Mobility Program to encourage adoption of electric vehicles. Over 6% of vehicle sales in 2023 were EVs and increasing EV adoption may significantly contribute to future air quality improvements. Atmospheric NH_3 in India has increased by 5–10% during 2018–2022 compared to 2017 observed from both satellite and surface measurements (Fig. 3c). The largest increase was over the Indo Gangetic Plain, a global hotspot of NH_3 emissions due to intense agriculture activity, unregulated use of chemical fertilizer, and numerous cattles[41, 42]. Currently few polices of which we are aware target NH_3 reductions and therefore emissions may continue to increase due to growing demand for food. Consistent with previous studies, during the COVID-19 lockdown in March–May 2020 we find significantly lower levels of NO_x (–17%) and SO_2 (–20%) in major cities as well as in regions with numerous thermal power plants across India (Supplementary Figure 5).

Meteorology contributes to air pollution reductions

Since changes in anthropogenic emissions were small, we next investigate the extent to which the observed decrease in $PM_{2.5}$ pollution over India can be explained by meteorological variability. To isolate the meteorological contributions, we conduct six years of WRF-Chem model simulations during 2017–2022 using varying meteorology but with anthropogenic emissions fixed at the NCAP baseline year of 2017 (see Methods). The meteorological contributions are estimated as the difference between the simulated $PM_{2.5}$ changes during 2018–

2022 versus 2017 relative to that observed. Detailed model evaluations are provided in the Supplementary Information (Text S2, Supplementary Figures 6–14). Briefly, model simulations reproduce the observed surface $PM_{2.5}$ concentrations across Indian cities and the simulated $PM_{2.5}$ chemical compositions at the Delhi Aerosol Supersite in baseline year 2017[43]. The model also captures the monthly variations of meteorological variables and $PM_{2.5}$ concentrations during 2017–2022, supporting the credibility of the model simulated interannual variations in surface $PM_{2.5}$ concentrations driven by meteorological variations.

With anthropogenic emissions fixed at the 2017 baseline level, model simulations show a 3–15% decrease in annual mean $PM_{2.5}$ during 2018–2022 compared to 2017 in the six non-attainment cities (Fig. 4a). The meteorology-driven decreases accounted for approximately 30% of the observed annual $PM_{2.5}$ decrease in those six cities. Notably, model simulations indicate over half of the observed annual $PM_{2.5}$ pollution decrease in Hyderabad (100%) and Chennai (50%), and one third in Delhi (36%) were attributable to meteorological variations (Fig. 4b). In other words, the NCAP $PM_{2.5}$ reduction target would not have been met in 2022 in these non-attainment cities without favorable meteorological contributions. The role of meteorology was smaller in Agra (16%), Kanpur (12%), and negligible in Varanasi (1%), indicating the more critical role of anthropogenic emission controls in those cities. For instance, Varanasi was ranked top three in the clean air survey in 2022 for actions to reduce air pollution[44]. Across India, meteorology alone was estimated to have contributed an average of 4.0±2.8 $\mu g/m^3$ decrease (–6% relative to 2017) in annual mean $PM_{2.5}$ during 2018–2022 in 110 out of the 131 non-attainment cities.

Meteorology-driven $PM_{2.5}$ decreases were most significant in winter, accounting for approximately half of the observed $PM_{2.5}$ decreases in 28 non-attainment cities with consecutive winter pollution monitoring (Fig. 4c-d). In particular, over 90% of the winter air quality improvements were estimated to be driven by favorable meteorological conditions in three cities (Faridabad, Gobindgarh, Patna) in northern India and in four cities (Chennai, Dewas, Hyderabad, Visakhapatnam) in southern India. This highlights the critical role of meteorological variations in driving the observed seasonal pollution trends. Meteorological variations also contributed to ~40% of the observed $PM_{2.5}$ decrease in fall in 13 non-attainment cities. In contrast, we find a negligible role of meteorology in summer pollution trends and slight increases in spring pollution driven by meteorological variations.

The most significant improvements in $PM_{2.5}$ air quality (>50% decrease) occurred on days with precipitation and better ventilations in winter 2021, when largest decrease in regional pollution were recorded, relative to the 2017 baseline (Fig. 5). These meteorological variables also show stronger correlations with daily $PM_{2.5}$ among others (Extended Data Fig. 8). During winter 2021, northern India recorded 62% more precipitation relative to the 2000–2022 mean and 45% fewer days with inversions (i.e., better vertical ventilation, Extended Data Fig. 9). This is largely associated with a southward shift of the subtropical jet and increased baroclinic instability that favors more frequent and intense western disturbances (Supplementary Figure 15), a mid-tropospheric low-pressure system that enhances vertical mixing and contributes to the majority of winter precipitation over Northern India[45]. In contrast, winter 2017 featured prolonged inversions, below-normal precipitation (–51%), and 10% fewer high-wind episodes because of the weaker western disturbances, leading to a more stable condition in the lower atmosphere that favored the buildup of surface pollution.

These meteorological variations may be linked to variability in sea surface temperature and the location of subtropical jet streams resulting from modes of climate variability such as the North

Atlantic Oscillation, El Niño and the Antarctic Oscillation[15, 46]. Previous studies have not been able to agree on the trend of western disturbances frequency over the last century[47, 48]. However, they are projected to decline in future climate scenarios, due to widening and weakening of the subtropical jet streams, resulting in reduced surface wind speed[14, 49, 50]. Projected decreases in winter western disturbances are likely to increase stagnation and decrease atmospheric dispersion, suggesting meteorologically driven $PM_{2.5}$ decreases over past winters may not persist in the future and more stringent emission controls are necessary for reducing surface air pollution in India.

We further perform two sets of sensitivity simulations for winter 2017 and 2021 to better understand the effects of possible emission changes (Methods). With a 25% increase or decrease in anthropogenic emissions over India relative to the 2017 baseline level, the resulting $PM_{2.5}$ changes due to emission increases (decreases) alone is 24% (–21%) averaged in the 28 cities with continuous pollution monitoring (Extended Data Fig. 10). Model simulation with both meteorology varying and emission reductions better reproduce the observed $PM_{2.5}$ decrease compared to simulations with emission fixed at the baseline level (Fig. 4c, Extended Data Fig. 10). This indicates the observed air quality improvements are likely driven by both emissions controls and favorable meteorological conditions. Moreover, simulations with emission reductions show an additional ~0.2 K decrease in the simulated surface temperature inversion, which favors pollution dispersion and thus provide additional benefits to surface air quality improvements.

Discussion

We provide a comprehensive evaluation of the recent PM air quality trends over India under NCAP – the first national air pollution control program with a specific pollution reduction target. Our study reveals significant improvements in annual and seasonal surface $PM_{2.5}$ air quality consistent with the NCAP target across India and in non-attainment cities with continuous air quality monitoring since 2017. If surface air pollution levels nationwide decreased sufficiently to meet the NCAP target everywhere, studies have estimated that India's national life expectancy would increase by 1.7 years, and by 3.1 years for residents living in the heavily polluted cities like Delhi[5].

However, in addition to efforts on emission controls, the recent achievement of the pollution reduction targets (about 30% of annual and half of the winter air quality improvements) benefited from favorable meteorological conditions that enhance pollution dispersion and wet removal. Unfortunately, these more favorable meteorological conditions appear unlikely to persist under future climate change and thus additional pollution control measures will be needed to simply maintain current air quality levels in India. Meanwhile, satellite and surface observations reveal increasing concentrations of $PM_{2.5}$ precursors over the past several years despite more stringent emission standards for vehicles and thermal power plants. Such increases may offset pollution reductions gained from controlling primary emissions, e.g., household solid fuel use, and result in further degradation of surface air quality and adverse health impacts.

The Indian government has made great efforts over recent years to expand in situ continuous monitoring capacity in urban centers to identify air quality non-attainment and to warn the public of dangerous pollution levels in support of the NCAP target. Nonetheless, continuous and quality data are still lacking in most non-attainment cities. One limitation of our study thus lies in the availability and quality of surface air quality data as our trend assessments are primarily based on $PM_{2.5}$ monitoring in 6 out of the 131 non-attainment cities (28 in winter) with quality controlled CAAQM/US AirNow data starting from 2017. While surface $PM_{2.5}$ data is also available from the more extensive NAMP manual monitoring network, we identify large discrepancies in annual pollution trends measured in cities where both CAAQM (continuous) and NAMP (manual) data are available. Such discrepancies raise concerns of the robustness of manual monitored pollution data for identifying non-attainment cities as well as for assessing pollution trends. Reporting of daily data from NAMP, rather than just annual averages, would be valuable in evaluating the robustness of NAMP data.

In addition, there is little continuous pollution monitoring in rural areas where both outdoor and indoor air pollution are severe[51], or in the eastern states where numerous coal power plants are located[52] and satellite observations show elevated SO_2 and NO_2 concentrations. As a result, no ground-level information is available for our study to characterize attainment of air quality standards or trends in emissions in those regions. Apparent compliance with surface air quality standards is likely misleading for large areas of India. Increased siting of pollution monitoring over emission hotspots and improvements in data collection as well as quality control that results in manual and continuous measurements without large temporal gaps or errors, systematic information on monitoring station's locations and surroundings, and easier access to observations (e.g., ability to download data simultaneously from multiple stations for different chemical species) are necessary to enhance the utility of these measurements in order to determine trends and compliance with the standards[53].

Another critical issue arises from the lack of an up-to-date national emission inventory that accurately represents emissions changes resulting from pollution control policies under NCAP. Model sensitivity simulations for winter 2021 with anthropogenic emissions reduced by a quarter relative to the 2017 baseline emissions better reproduce the observed $PM_{2.5}$ decrease compared to simulations with emissions fixed at 2017 baseline level. Such emission reduction is greater than the trends extrapolated from the existing emission datasets. In addition, biases in the model simulated $PM_{2.5}$ components (e.g., ~40% overestimation in nitrate) may be partly due to emission uncertainties. For instance, national NO_x emissions vary by 40% and sectoral contributions (e.g., residential) vary by as much as 4 times among available emission inventories from India. Improving the accuracy of the national emission inventory over time is essential for policy makers to determine whether NCAP goals are being met at national and sub-national scales.

The NCAP is an important step towards addressing severe and deteriorating ambient air quality in India. However, surface $PM_{2.5}$ levels remain very unhealthy even after meeting the NCAP pollution reduction targets. In 2022, annual $PM_{2.5}$ pollution in 44 out of 57 non-attainment cities with continuous monitors still exceeded the 40 $\mu g/m^3$ national standard. India, together with other developing countries in the global south, faces dual challenges in the coming decades as fast-growing population and energy consumption risks a dramatic increase in the emission of air pollutants and greenhouse gases. Increasing pollution emissions and feedback from a warming climate (e.g., heatwave, wildfires and stagnation) will, without strong policy intervention, place a huge health burden on a growing and aging population in developing counties and globally. Substantial additional mitigation beyond current air pollution control policies, especially those that simultaneously mitigate greenhouse gas and air pollutant emissions such as decarbonatization of the energy system, electrification, reductions in agricultural waste burning, are essential for fast-developing economies to bring air pollution to healthy levels and to play a positive role in slowing the rate of global climate change.

Methods

Surface PM observations. Surface hourly observations of $PM_{2.5}$ and PM_{10} during 2017–2022 are obtained from ~500 stations in the Continuous Ambient Air Quality Monitoring network (CAAQM) operated by the Central Pollution Control Board (CPCB) and State Pollution Control Board (SPCB)[54], and from 5 stations in the U.S. Department of State AirNow continuous monitoring network. These continuous monitors are mostly located in urban environments (e.g., bus stations, industry, or residential centers) and may be subject to the influence of local pollution sources. The measurements are made using the beta ray attenuation method and data collection as well as validation follows the U.S. Environmental Protection Agency standards[55]. To ensure the robustness of the data, we perform rigorous quality control procedures on the hourly data following the methods of a recent study[56] with a few modifications. Specifically, we replace repetitive hourly values occurring more than five times in a row with a single value and screen the data for abnormal spikes and remove unexplained outliers[57]. We also remove measurement sites that report constant data values with standard deviation less than 5% of that long-term mean value[58]. To further ensure representative monthly and seasonal statistics for trend analysis, we apply a 1/3 data coverage criteria: daily data is considered valid if at least two measurements are available for each of the four six-hour period in one day; monthly data is included if at least three daily averages are available for each 10-day period. For seasonal data we require at least two monthly averages are available for each season. We also obtain hourly observations of SO_2, NO_x, NH_3 and CO from CAAQM and apply the same quality control and temporal averaging criteria as described for the PM data.

The CPCB characterized 102 non-attainment cities in 2019 based on the National Air Quality Monitoring Programme (NAMP) manual pollution monitoring stations reporting of annual average concentrations. These cities had surface air pollution exceeding National Ambient Air Quality Standards (NAAQS, annual standards for $PM_{2.5}$: 40 $\mu g/m^3$, PM_{10}: 60 $\mu g/m^3$, SO_2: 50 $\mu g/m^3$ or 20 $\mu g/m^3$ for ecologically sensitive area, NO_2: 40 $\mu g/m^3$ or 30 $\mu g/m^3$ for ecologically sensitive area) consecutively for five years during 2011–2015. In addition, cities listed as one of the top ten polluted in the World Health Organization Fourth Ambient Air Quality Database report for 2014–2018[6] are also considered non-attainment. Among the 102 non-attainment cities identified in 2019 by CPCB, 94 cities had annual PM_{10} measurements during 2011–2015 exceeding the NAAQS, 16 cities had annual $PM_{2.5}$ measured at NAMP manual stations or CAAQM continuous stations exceeding the national standards since 2015, and 10 cities were listed in the WHO report[6]. Total number of non-attainment cities increased to 131 in 2023 according to a list compiled by CPCB[7]. To assess the NCAP policy effectiveness, we average PM measurements made within the same city and distinguish between attainment and non-attainment cities. Daily surface $PM_{2.5}$ data from the CAAQM and US AirNow networks are averaged when located in the same city as good data consistency has been found (Extended Data Fig. 1).

We provide additional analysis of the recent PM pollution trends using the annual data reported by NAMP in the Supplementary Information Text S1. The surface PM pollution trends based on NAMP data are compared with those based on CAAQM/US AirNow in cities where both manual and continuous pollution monitoring stations are available. It should be noted that the NAMP manual monitoring data is described by the NCAP report as 'indicative' rather than 'absolute' due to uncertainties in sampling intervals, chemical analyses and data reporting[6]. In addition, reporting of the manual data does not include detailed information for the temporal sampling frequency we need for quality control procedures.

Anthropogenic emissions and satellite observations. We examine changes in anthropogenic emissions of primary particles (black carbon, organic carbon, and other anthropogenic coarse and fine particles) and major gaseous precursors (SO_2, NO_x and NH_3) over India since 2010 from the Community Emissions Data System (CEDSv2021_04_21, update to 2019) global emission inventory[59]. Emissions over India are estimated based on the Regional Emissions Inventory in Asia (REAS 2.1) and calibrated to Greenhouse gas–Air pollution Interactions and Synergies (GAINS) emission factors[60]. To reflect uncertainties in the global emission inventories, we also compare emissions from the Emissions Database for Global Atmospheric Research (EDGARv6.1, updated 2018)[61] and Evaluating the Climate and Air Quality Impacts of Short-Lived Pollutants (ECLIPSE v6b, updated to 2018)[60]. National emission inventories, for instance Speciated Multipollutant Generator (SMoG-India)[62] or The Energy and Resources Institute[63], may provide more accurate information on fuel consumption levels, emission factors, as well as emissions from urban dust not available in global emission inventories[30, 64]. However, neither SMoG nor TERI provide emission estimates after 2016 and are therefore not included in our trend analysis.

To validate trends indicated in the emission inventories as well as to provide additional information beyond 2019 when emission data are not available, we include top-down constraints from satellite-retrieved total column concentrations of SO_2, NO_2 and NH_3 over India during 2010–2022. Total SO_2 columns are obtained from the Level-3 Aura/OMI Global gridded OMSO2e product[65] available during 2004–2022 at a horizontal resolution of 0.25°×0.25°. Tropospheric NO_2 columns are obtained from Level-3 Aura/OMI global gridded Nitrogen Dioxide Product (OMNO2d)[66] available during 2004–2022 at 0.25°×0.25° where cloud fraction is less than 30%, and from the TROPOspheric Monitoring Instrument (TROPOMI)[67] during 2018–2022 at 0.125°×0.125°. Satellite NH_3 columns are obtained from the Level-3 IASI onboard Metop-B satellite[68, 69, 70, 71] during 2013–2022 at 1°×1° horizontal resolution.

Meteorology data. Daily time series of meteorological data during 2000–2022 are obtained from the fifth generation European Centre for Medium-Range Weather Forecasts (ECMWF) reanalysis of global climate and weather (ERA5, 0.25°×0.25°)[72]. Tracking of western disturbances are based on the ERA5 500 hPa relative vorticity[45]. We perform linear regression analysis between surface $PM_{2.5}$ and meteorological variables shown in previous studies to be correlated with $PM_{2.5}$[13, 14]. The meteorological variables we analyze includes surface (2m) temperature, total precipitation, relative humidity, boundary layer height, surface pressure, wind speed at surface (10m), 850 hPa and 500 hPa, and lower atmospheric instability represented by temperature inversion between 850 hPa and surface (Extended Data Fig. 8). Considering daytime boundary layer height during winter may be below 1000 m based on lidar observations over New Delhi[73], we also compare temperature inversion between 925 hPa and the surface. Our results indicate an overall stronger correlation between surface $PM_{2.5}$ and temperature inversion between 925 hPa and the surface. For linear regression analysis, we further regrid all data to 2°×2.5° to increase statistical robustness[74, 75]. Both $PM_{2.5}$ and meteorological variables are deseasonalized and detrended for linear regression analysis to avoid correlations from common seasonality or long-term trends associated with anthropogenic emission changes[24].

WRF-Chem model experiments. We conduct simulations with the Weather Research and Forecasting model coupled with Chemistry[76] (WRF-Chem, version 3.6.1) at 27 km^2 horizontal resolution to characterize the role of meteorology in the observed annual and seasonal surface $PM_{2.5}$ air quality improvements in India. The WRF-Chem model used in this study was configured following a previous study[77] but with domain focus on India. Specifically, the meteorological initial and lateral boundary conditions are from ERA5 at 0.25°×0.25° resolution. Chemical initial and boundary conditions are from the Community Atmosphere Model with Chemistry (CAM-Chem)[78]. The biogenic non-methane VOC emissions are calculated online by the Model of Emissions of Gases and Aerosols from Nature (MEGAN)[79] coupled with WRF-Chem. Anthropogenic emissions for the NCAP baseline year 2017 are from the CEDS global emission inventory. Emissions of primary $PM_{2.5}$ other than black carbon and organic carbon are not provided by CEDS and are thus from the ECPLISE global emission inventory over the WRF-Chem domain.

To isolate the impact of meteorological variability, we perform six years of model simulations (2017–2022) with meteorology varying but with anthropogenic emissions fixed at the NCAP 2017 baseline level. The differences between the observed and simulated $PM_{2.5}$ concentration during 2018–2022 relative to 2017 thus enable us to assess the impacts resulting from meteorological variability. The WRF-Chem model was reinitiated every 24 h to prevent the drifting effects of simulated meteorological fields. We acknowledge that this may lead to an underestimation of the emission–aerosol–meteorology interactions and may result in slightly larger $PM_{2.5}$ decrease with emission fixed at higher than actual levels[80]. The model simulated meteorological parameters are evaluated against surface observations obtained from the integrated surface data of NOAA National Centers for Environmental Information (https://www.ncei.noaa.gov/). The simulated surface $PM_{2.5}$ dry mass and major chemical components are evaluated against surface observations from the CAAQM and US AirNow continuous pollution monitoring networks, as well as from the Delhi aerosol super site[43] (see Supplementary Information Text S2, Fig. S6–S14).

We use two sets of sensitivity simulations to quantify the response of surface $PM_{2.5}$ concentrations to changing anthropogenic emissions alone as well as to both changing emissions and meteorology over India (Extended Data Fig. 10). For winters 2017 and 2021, we assume a 25% reduction in anthropogenic emissions over India relative to the 2017 baseline level. The 25% change we apply is consistent with the NCAP target of 20–30% reduction in $PM_{2.5}$ pollution as no up-to-date emission inventory is available. We include another scenario in which we assume a 25% increase in anthropogenic emissions resulting from increasing anthropogenic activities with little emission controls. The difference in the simulated $PM_{2.5}$ between the sensitivity simulations with emissions varying by +/-25% and the simulations with emissions fixed at the 2017 level allow us to assess the effect of emission changes alone for 2017 and 2021, respectively. The difference in the simulated $PM_{2.5}$ between the sensitivity simulation for 2021 with emissions varying by +/-25% and the simulation for 2017 with baseline emissions reflect the impacts of both changing emissions and meteorology.

Data availability

Surface $PM_{2.5}$ and other air pollution data from the CAAQM network are available at https://app.cpcbccr.com/ccr/#/caaqm-dashboard-all/caaqm-landing. Surface $PM_{2.5}$ data from the US AirNow network is available at https://www.airnow.gov/international/us-embassies-and-consulates/. Manual monitoring data for $PM_{2.5}$ and other air pollution data is available at https://cpcb.nic.in/manual-monitoring/. The CEDS emission database is available at https://github.com/JGCRI/CEDS/ . The EDGAR emission database is available at https://edgar.jrc.ec.europa.eu/dataset_ap61. The ECLIPSE emission database is available at https://iiasa.ac.at/models-tools-data/global-emission-fields-of-air-pollutants-and-ghgs. Satellite observations of SO_2 and NO_2 from OMI are available at https://giovanni.gsfc.nasa.gov/giovanni/ and from TROPOMI at https://www.temis.nl/airpollution/no2.php. Satellite observation of NH_3 is available at https://iasi.aeris-data.fr/nh3/ . Meteorology data from ERA5 is available at https://cds.climate.copernicus.eu/cdsapp#!/search?type=dataset and from NCEI at https://www.ncei.noaa.gov/. WRF-Chem outputs and processed air quality data generated in this study are publicly available on the Princeton archive at https://doi.org/10.34770/xtje-mj26.

Code availability

Source codes of the WRF-Chem model utilized in this study are available at https://www2.mmm.ucar.edu/wrf/users/download/get_sources.html#WRF-Chem. All custom codes are direct implementation of standard methods and techniques as described in detail in Methods.

Corresponding authors

Correspondence and requests for materials should be addressed to Yuanyu Xie (Email: yuanyux@princeton.edu) or Denise L. Mauzerall (Email: mauzerall@princeton.edu)

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Author contributions

Y.X. and D.L.M conceptualized the study. Y.X. retrieved and constructed the dataset and performed the analysis. M.Z. contributed to data processing, WRF-Chem model simulations, and model evaluations. K.H. analyzed the western disturbance. Y.X. and D.L.M. integrated the results and wrote the manuscript. All authors contributed to the interpretation of findings, provided revisions to the manuscript, and approved the final manuscript.

Competing interests

The authors declare no competing interest.

Fig.1 Continuous PM monitoring data availability in Indian cities. a, Location of the 131 non-attainment cities (red dots) and cities with continuous $PM_{2.5}$ monitoring available from the CAAQM/US AirNow networks for at least one year during 2017–2022 (black circles) on the topographic map (in meters) over India. **b.** Changes in the total number of NCAP non-attainment cities with continuous PM monitoring from the CAAQM/US AirNow networks (bars, left axis) and number of total surface PM monitoring stations from the CAAQM/US AirNow networks (lines, right axis) during 2017–2022; dashed horizontal grey lines indicate the percentage of the 131 non-attainment cities that had continuous PM monitoring data available.

Fig.2 Observed surface $PM_{2.5}$ air quality improvements during 2017–2022. **a**, Annual mean $PM_{2.5}$ in Indian cities measured at continuous stations from the CAAQM and US AirNow networks in 2017–2022. Dots with black circles indicate the six non-attainment cities with six consecutive years of data. Number of total (non-attainment) cities that had $PM_{2.5}$ measurements are reported at the bottom left for each year. **b**, Time series of annual mean $PM_{2.5}$ concentrations in 2017–2022 averaged in non-attainment (black) and all (orange) cities with consecutive $PM_{2.5}$ data starting from 2017 (number of cities reported at the bottom), and for non-attainment cities with consecutive data starting from 2018–2021 (different shades of grey; number of cities reported at the bottom); the left axis represent the ratio relative to 2017, the NCAP baseline; data starting from 2018–2021 are scaled to match with the ratio relative to 2017; larger dots represent greater number of non-attainment cities included for averaging; error bars denotes ±one standard error of means across available cities (n=6 (7), 25, 29, 40, and 49 as reported at the bottom) . **c**, Probability distributions of daily $PM_{2.5}$ concentrations in fall and winter in non-attainment cities with six consecutive years of $PM_{2.5}$ measurements during 2017–2022 (n=2169, 2398, 2390, 2455, 2487, 2495, respectively), and the percentage of city-days (embedded bar plots) that fall within each pollution category (Good<=30 $\mu g/m^3$, Satisfactory: 30–60 $\mu g/m^3$, Moderately polluted: 60–90 $\mu g/m^3$, Poor: 90–120 $\mu g/m^3$, Very poor: 120–250 $\mu g/m^3$, Severe:>250 $\mu g/m^3$) defined by CPCB[81]. The dashed line in **c**) denotes the national 24-hourly standard for $PM_{2.5}$ in India.

Fig. 3 Changes in anthropogenic emissions and concentrations of primary $PM_{2.5}$ and key precursors since 2010. Timeseries of anthropogenic emissions of primary particles, including (**a)** black carbon (BC), **(b)** organic carbon (OC), (**c)** other primary fine particles ($PM_{2.5}$) and coarse particles (PM_{10}), and key $PM_{2.5}$ precursors, including (**d)** sulfur dioxide (SO_2), (**e)** nitrogen oxides (NO_x), (**f)** ammonia (NH_3) over India during 2010–2019 relative to 2017. **a, b, d-f** are from the CEDS (v2021-04-21) global emission inventory with updates to 2019, (**c**) is from the ECLIPSE (v6b) emission inventory with updates to 2018. Data from ECLIPSE during 2019–2020 are projections. Red lines in **d-f** are satellite-retrieved column total concentrations of SO_2 from OMI, NO_2 from OMI and TROPOMI (blue) and NH_3 from IASI, respectively. Black dots in **b, c, d-f** are annual average surface concentrations of carbon monoxide (CO), PM_{10}, SO_2, NO_x, NH_3 from cities with continuous CAAQM pollution monitoring for five years since 2018 (numbers of cities in parenthesis). Error bars in **b-f** represents ±one standard error of means across cities (n=4, 22, 18, 11, 10 as reported in parenthesis in each panel). Black triangles in **a,b** are observed surface concentrations of black carbon and organic carbon at the CSIR-National Physical Laboratory site in New Delhi[35].

Fig. 4 Meteorological contributions to recent $PM_{2.5}$ air quality improvements. (**a**) Annual (blue) and seasonal (green) mean $PM_{2.5}$ decrease during 2018–2022 in percent relative to 2017 averaged in non-attainment cities from observations (light blue/green) and from WRF-Chem model simulations (dark blue/green) driven by meteorological variations but with emissions fixed at 2017 level. Error bar represents

±one standard error of means across cities (n=6) for annual averages, and across cities (n=15, 11, 13, 28 as reported at the bottom) for seasonal averages. The light and dark green circles for MAM represent changes if 2020 (COVID-19 lockdown) is excluded. (**b**) Model simulated annual $PM_{2.5}$ decrease during 2018–2022 in percent relative to 2017 (colored background) and the percentage contributed by meteorological variations (dark green segments inside circles) in each of the six non-attainment cities. The size of the circles represents the magnitude of the observed $PM_{2.5}$ decrease. (**c-d**) same as (**a-b**) but for winter $PM_{2.5}$ changes in 28 non-attainment cities from observations (light blue) and model simulations driven by meteorological variations but with emissions fixed at 2017 level (dark blue), and number of non-attainment cities (orange) with <10%, 10–50%, 50–90% or >90% of the observed $PM_{2.5}$ decrease contributed by meteorological variations. The dark blue circle in **c** represents the simulated $PM_{2.5}$ decrease in 2021 with a 25% reduction in anthropogenic emission relative to the 2017 baseline level. Error bar in **c** represents ±one standard error of means across cities (n=28).

Fig. 5 Comparison of daily $PM_{2.5}$ and meteorological variables between winter 2017 and 2021. (**a**), Daily $PM_{2.5}$ concentrations from CAAQM/US AirNow observations (solid lines) and WRF-Chem model simulation with emission fixed at the 2017 baseline level (dashed lines) averaged from 17 cities where CAAQM/US AirNow sites are available in north India (north of 23°N) in the winter of 2017 (December 2017–February 2018, orange) and 2021 (December 2021–February 2022, blue), (**b-d**) same as **a** but for daily timeseries of collocated meteorological variables including inversion (temperature difference between 925hPa and at the surface), precipitation, and surface (10m) wind speed from ERA5 reanalysis . **e-h** same as **a-d** but for the differences between the two winters (winter 2021 minus 2017) from WRF-Chem simulations with emission fixed at the 2017 level (map) and observations (circles) for $PM_{2.5}$ from CAAQM/US AirNow monitoring sites and collocated meteorology from ERA5 reanalysis. Shading in **a-d** represent ±one standard error of means across available sites (n=17). The winter averages, and correlation coefficient *r* and *p* value for linear regression between $PM_{2.5}$ and each meteorological variable are reported for each year in **a-d**.

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