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Effects of urbanization, scale, and geography on air pollution in India

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Indian cities have recently emerged as some of the locations with the worst air pollution on Earth. However, the sources of these increases and potential mitigation paths are complex, involving an interplay between urbanization, economic growth, energy systems and environmental management. Here, we analyse an extensive set of satellite and ground-level air quality monitoring data sets to create a detailed examination of geographical and temporal patterns of NO_2 pollution across all districts and most large cities in India. For the period 2005–19, we find that urbanization has an inverse relationship with NO_2 increase, but at the same time, the most urbanized districts also have the highest NO_2 burden. Districts at intermediate levels of urbanization $(30-40\%)$ show both high levels of NO_2 and the largest increases in NO_2 pollution. Our analysis also reveals that the region of the Indo-Gangetic Plain (IGP) is of particular concern both in terms of high absolute levels of NO_2 and relative NO_2 increase over the period from 2005 to 2019. Studying PM_{10} levels across 106 cities, we find that they exceed national air quality standards in over 80% of cases, with the problem also being particularly acute in IGP's urban areas. Scaling analysis reveals that NO_2 concentrations increase super-linearly with population in cities in the IGP, in contrast to the sublinear scaling observed for other cities. This implies that larger cities in the IGP are characterized by both higher NO_2 concentrations and increased per capita exposure. Moreover, recent mitigation efforts in the largest cities could signal the flow of technologies and strategies down the urban hierarchy and impact the rising levels of air pollution across the nation and over time. For now, the impetus of development and poverty alleviation implies that environmental challenges are likely to worsen, unless immediate and sustained pollution mitigation can address the severe air quality problem in India, especially across the Indo-Gangetic Plain.

Air pollution has been a critical area of concern for public health for decades[1]. In most nations, economic development and urbanization entail growing energy generation, traffic, and industrial activity, which tend to generate high levels of air pollution[2–4]. Historically, high levels of air pollution tend to be addressed and mitigated as they become intolerable, especially in each nation's largest cities. This general trajectory of the rise and fall of air pollution with development is well illustrated by famous episodes such as the great smog of London in 1952[5], which was largely SO_2 from coal and water vapor, or, more recently, the particulate matter pollution in Beijing in the runup to the 2008 Olympic Games[6,7]. In these and other cases, critical levels of air pollution in large cities, often driven locally by different mixes of pollutant contributions, unleash systematic policy responses capable of substantially mitigating the problem locally. This then leads to an uneven spatial pattern of air pollution increases and decreases across a national territory.

The relationship between urbanization and air pollution has been theorized using various frameworks, such as the environmental Kuznets curve (EKC) and the urban environmental transition theory. The EKC theory predicts an inverse U-shaped curve between urbanization and pollution, with pollution rising initially with urbanization, reaching a turning

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point, and then declining[8]. The EKC posits a two-step process for this pattern: first, as a region begins to urbanize and experience economic growth, there is rising exploitation of natural resources and consequent industrialization, which results in increasing pollution; this is followed by the second step, where the economic basis of the city changes from a predominantly industrial to a service-based economy coupled with the use of clean technologies to reduce industrial pollution, resulting in a decreasing trend in air pollution even as high levels of energy consumption and socioeconomic activity persist and expand. However, empirical analysis shows that there is no single relationship between urbanization and air pollution: Any relationship depends upon the type of pollutants, and turning points (if extant) vary substantially[9]. The urban environmental transition theory posits that cities go through a series of environmental challenges with development: at low levels of development, the challenges relate to basic infrastructure and services such as water and sanitation. As industrialization expands, the challenges transition to manufacturing and vehicular pollution. In post-industrial cities, the agenda shifts to "green" issues such as greenhouse gas emissions and ozone-depleting substances[10]. Studies reveal that the time scales have been very different in Western cities, which experienced these transitions sequentially over two centuries, while Asian cities, which have experienced both rapid economic development and faster environmental transitions over the last 70 years[11,12]. One key component of anthropogenic air pollution is nitrogen dioxide (NO_2), a relatively short-lived pollutant, resulting primarily from combustion in power plants and internal combustion engines of vehicular traffic[13–16]. It contributes to the formation of fine particulate matter ($PM_{2.5}$) and ozone (O_3), and is associated with acute as well as chronic respiratory and pulmonary illnesses[17–23].

Another major constituent of air pollution is particulate matter (PM_{10}). This refers to particles with aerodynamic diameters less than or equal to $10\mu m$ [24,25]. These particulates arise from multiple sources, including pollen, spores, products of combustion, tire and brake wear, road surface abrasion, as well as breakup of soil and crust[26]. High levels of PM_{10} air pollution are associated with increases in both cardiovascular and respiratory mortality and morbidity[26–28].

India presently faces a significant burden of air pollution, which imposes high health and economic costs on the nation and its people[29]. India's cities are impacted by very high levels of air pollution from multiple sources, such as NO_2 and PM [30], and exposure risk to particulate matter in many Indian cities falls in the "high risk" and "risk" categories of WHO's Air Quality Guidelines[31]. These pollutants are significant contributors to morbidity and premature mortality[32].

In this context, it becomes an important question to explore the extent to which recent efforts to mitigate the problem are starting to succeed. In addition, it is important to ask where air pollution continues to worsen and learn from other historic examples how to create solutions that can address these environmental and health challenges more quickly and equitably. Understanding the impact of urbanization, scale, and geography, on air pollution in India is the main objective of this paper.

In line with global experience, vehicular emissions and burning of fossil fuels in industries and power plants are known to be the two major sources of NO_2 pollution in Indian cities[33–37]. Open burning of municipal solid waste in Indian cities also emits particulate matter and NO_x pollutants. At present, it is estimated that over 30% of municipal waste generated in India is burnt[38,39]. It is also becoming apparent that air pollution in India is not just an urban problem, as highlighted by the severity of fine particulate matter ($PM_{2.5}$) levels in many rural areas[40].

The national government has attempted to control vehicular emissions in cities by changing fuel regulations to reduce NO_2 and particulate matter, expanding public transportation, including metro rail networks, adoption of cleaner alternate fuels, removing older vehicles from cities, and incentivizing the manufacture of electric cars[34,41,42]. In general, the transition to improved fuel regulations predominantly begins with the largest cities—the metropolises atop India's urban hierarchy—and then flows down to other cities over time[42]. This is in line with findings on the provision of basic infrastructure and services in the larger cities, and their subsequent emergence in the small and medium cities[43].

Measures to contain urban industrial emissions have included improved emissions standards for coal-based power plants, transitioning industrial units to piped natural gas, and requiring highly polluting industries to install continuous emissions monitoring devices[42]. In addition, the National Clean Air Mission (NCAP) was introduced by the central government with a target to combat air pollution in 132 cities across the nation through strategies such as improved monitoring, waste management, and transport infrastructure[44].

Even as all these policies and regulations are now in place, the problem of air pollution remains persistent. This is attributable to multiple practical challenges, such as institutional proliferation, overlapping government agency mandates, economic constraints in adopting requisite technologies, lack of political will to implement policies, and administrative weaknesses in monitoring and inspection, among other issues[34].

Most studies of NO_2 and particulate matter pollution in India so far have focused on trends in specific cities. On average, these studies found that large cities experiencing fast economic growth over the last 25 years show corresponding increases in air pollution[34,37,41,42,45–50]. Very few studies have attempted to provide both comparative analyses covering all of India and high spatial resolution (at district level, for instance), to explore nationwide trends in NO_2 pollution and to identify and analyse pollution hotspots[33,51,52]. These three studies cumulatively cover the period from 2003 to 19 and demonstrate that, in addition to large urban metropolitan areas across the country, the entire stretch of land from Punjab all the way across to West Bengal has been a region with very high and increasing levels of NO_2 concentration. This is attributed to the dense concentration of thermal power plants, heavy industry, mining, as well as freight and transportation networks[33].

In this study, using both satellite and ground-level monitoring data, we present an updated, detailed examination of geographical and temporal patterns of NO_2 and particulate matter (PM_{10}) pollution across all districts and a number of large cities in India, in order to develop a deeper understanding of the impacts of urbanization, scale, and geography. Specifically, we address the following questions:

- What are the temporal and spatial patterns of NO_2 pollution in India's districts (incorporating both rural and urban areas) for the period 2005–19?
- How does the level of urbanization influence NO_2 pollution in India?
- What are the temporal and spatial patterns of NO_2 and PM_{10} concentration in Indian cities (2010–19)?
- How do the levels of NO_2/PM_{10} scale with city size (population)—is there an urban hierarchy, in terms of cities ordered by population size, evident in the burden of these pollutants?

We consider the period 2005–19 because we have access to satellite-based pollutant data for this period, and it captures a period of high economic growth for India.

By developing a detailed analysis in space, time, and by city size of the emergent patterns of air pollution, we seek to benchmark the Indian situation for future studies and place its results within the context of the current urban science as well as global trends.

Results

Our analysis of NO_2 concentrations at the district and city levels, and PM_{10} at the city level, relies on both satellite and ground-level monitoring stations' data. Details of these data sources and methods are provided in the Methods section. Districts in India are administrative subdivisions of states and, as such, allow for their spatial disaggregation, at a level where other statistics are given, for example, by the Census of India. There are 742 districts in our analysis in 2019, comprised of both rural and urban areas. Cities are urban centers that are typically contained within districts, except in the case of the largest urban centers, such as Delhi and Mumbai, which extend across multiple districts.

Temporal and spatial analysis of NO_2 pollution in India's districts

Temporal analysis of air pollution between 2005 and 2019 reveals that average NO_2 column densities at the district level have increased from 29.4 to 33.5 μmol/m^2. This increase is largely due to the rise in the proportion of cities with NO_2 levels $> 40\mu$mol/m^2, from 14% to 24%. Overall, the NO_2 burden increased in 86% of all districts over 2005–19, in line with the findings of ref.[51], who also estimated that NO_2 pollution exhibited an increasing trend for most of India in this period. This increase in NO_2 is also confirmed by ref.[50]., specifically for Indian megacities over the longer period 1996–2015.

In order to characterize the detailed geographic footprint of this increase in NO_2, we study India's 742 districts in 2019. We find that there is a contiguous spatial band of districts with high NO_2 levels extending from Punjab in the north-west to West Bengal in the east, covering the entirety of the Indo-Gangetic Plain (IGP) (Fig. 1a). It is also apparent that NO_2 levels in the IGP belt have appreciably increased since 2005 (Fig. 1b). In 2019, NO_2 levels in the IGP districts are, on average, 45.6μmol/m^2, compared to 28.9μmol/m^2 in other Indian districts (Fig. 1d). The prevalence of high NO_2 levels in the IGP region is also in agreement with prior satellite-based studies of NO_2 pollution in India[33,51,52].

To get a more precise sense of the geographical gradient in NO_2 pollution, we separate the IGP districts (from the states of West Bengal, Bihar, Jharkhand, Uttar Pradesh, Uttarakhand, Delhi, and Punjab) and other (non-IGP) districts into two distinct categories, and construct the distribution of districts by NO_2 concentration (Fig. 1b). We find that the NO_2 distributions of these two regions indicate substantial disparities, with 56% of IGP districts showing NO_2 levels greater than 40μmol/m^2 against only 12% of non-IGP districts; correspondingly, only 3% of IGP districts have NO_2 levels in the range $20 - 30\mu$mol/m^2, compared to 47% of non-IGP districts. The extent of these disparities is brought into sharper relief when we consider population numbers: 23–25% of India's population lives in the IGP districts with NO_2 levels greater than $40\mu mol/m^2$, compared to 8–10% of India's population from the corresponding non-IGP districts. Most of the heavily urbanized non-IGP districts (visible in Fig. 1a, b), such as Bengaluru, Chennai, Ahmedabad, Pune, and Jaipur, have NO_2 levels in the range of $30 - 40\mu$mol/m^2. The outliers, (as seen in Fig. 1d), in the non-IGP districts with very high NO_2 levels are districts that are adjacent to the IGP from the states of Haryana, Chhattisgarh, Madhya Pradesh, and Odisha. Among the IGP districts, the outliers with very high NO_2 levels are districts in and around New Delhi. On the other end, there are a few outliers in the IGP

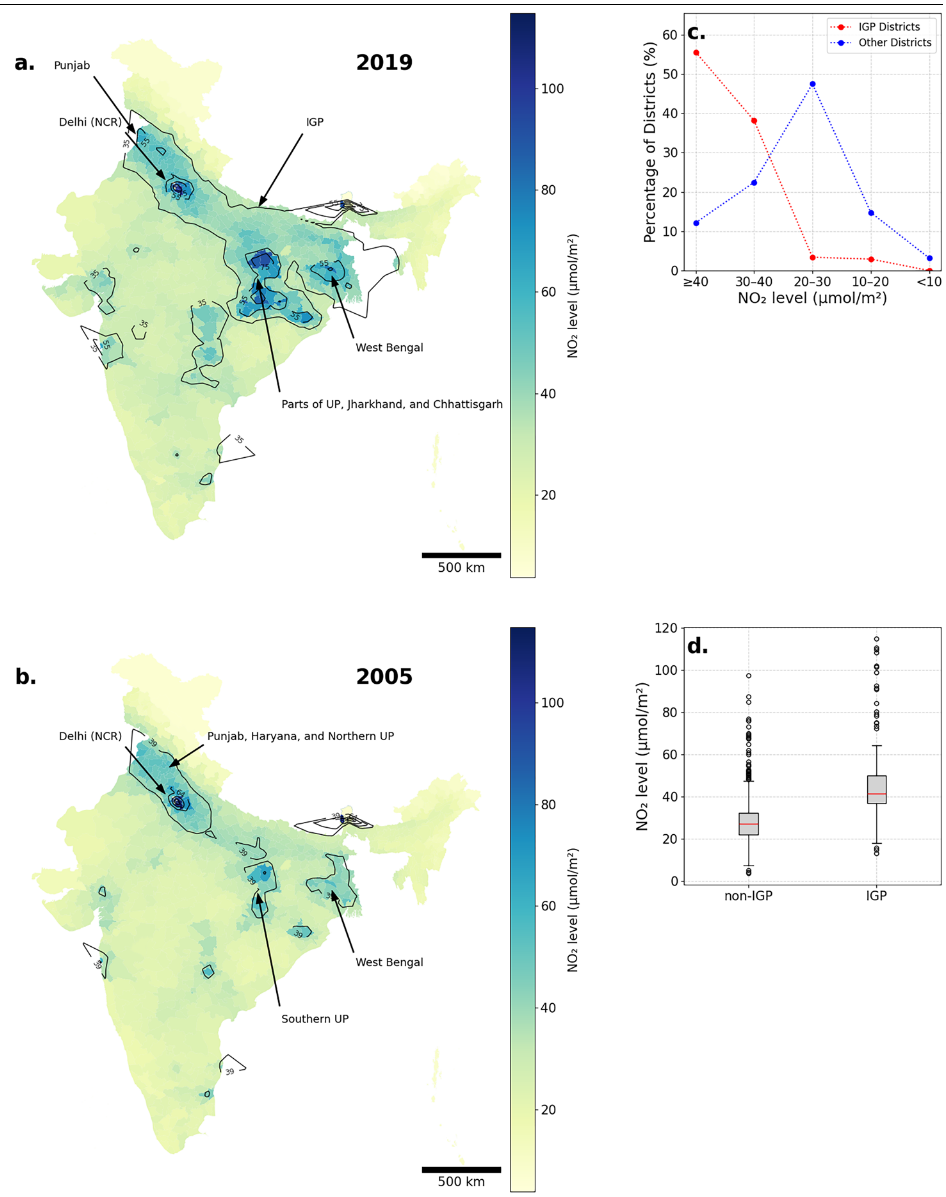


Fig. 1 | District-level NO_2 burden in India. a NO_2 levels for Indian districts in 2019. The highest levels are in the Indo-Gangetic Plain (IGP) belt that extends from Punjab in the west to West Bengal in the east. **b** NO_2 levels for Indian districts in 2005. While there is a cloud of high NO_2 burden districts along the IGP, it is not as pronounced as in 2019. **c** Distribution of districts by NO_2 levels (2019) in two sets –IGP districts (red) and non-IGP districts (blue). **d** Boxplot of NO_2 levels in IGP and non-IGP districts (2019). Here, the gray box refers to the interquartile range (Q1–Q3) with central red lines indicating the median value, whiskers refer to values in the range of 1.5×IQR from Q1 and Q3, and the circles denote observations outside this range (outliers). The highest NO_2 levels are disproportionately found in IGP districts.

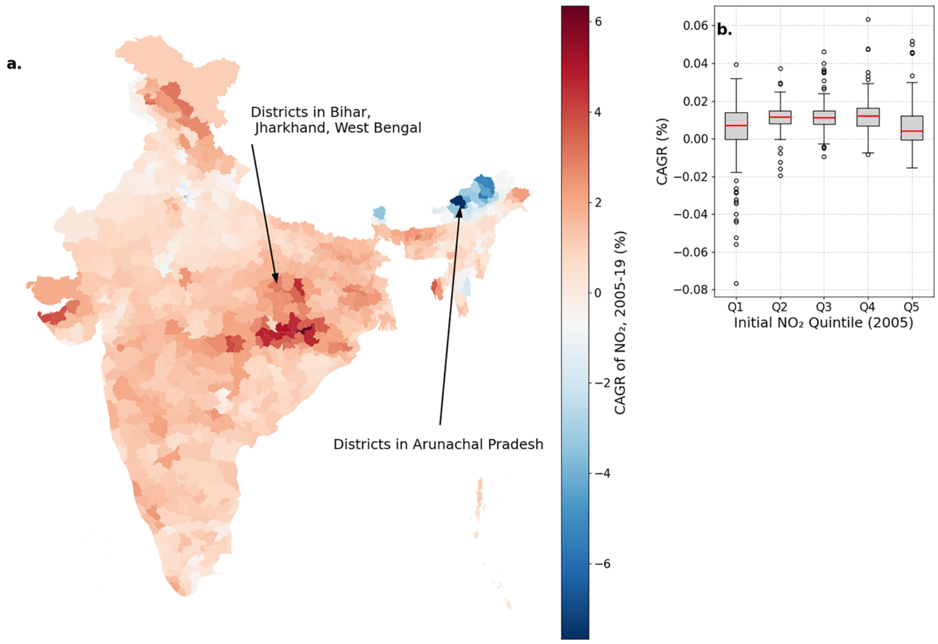


Fig. 2 | Annual change rates in NO_2 levels. **a** Colormap of NO_2 CAGR (2005–19). The eastern Gangetic plain, comprising Bihar, Jharkhand, and West Bengal, is a region of high rates of increase in NO_2. **b** Boxplot showing the distribution of the NO_2 CAGR (2005–19) v. initial NO_2 level by quintile (2005). CAGR increases in initially less polluted districts and then declines at high levels of initial NO_2.

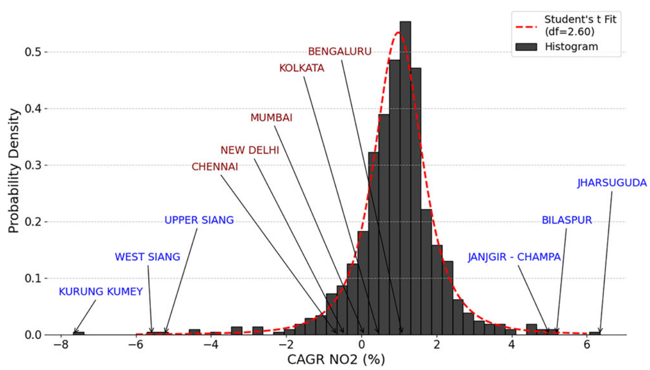


Fig. 3 | Probability density function of annual rates of change in NO_2 for districts (2005–19). About 75% of all districts lie between 0% and 2% CAGR, with an average CAGR of 0.93%. 14% of districts show CAGR <0%. The districts in blue represent the outliers at both ends of the distribution—the lowest and highest growth regions. The districts in red represent some of the largest urban (metropolitan) regions.

group that have very low levels of NO_2, which are primarily districts in hilly regions of Uttarakhand along the lower Himalayas, such as those with lower levels of urbanization. The most favorable conditions are found in the northeastern parts of the country in Arunachal Pradesh, which also exhibits low levels of urbanization.

We now examine the rate of increase in NO_2 levels over time to assess temporal changes. We find that the average annual increase (CAGR) at the district level is 0.93% (details of computation in the Methods section). We also find that the geographical signature of the IGP, which is highly pronounced in NO_2 levels, is less evident in the corresponding rates of change. For instance, 84% of IGP and 87% of non-IGP districts show CAGR > 0%, and 50% of both IGP and non-IGP districts show CAGR > 1%/year. However, there are some states that appear to be of particular concern, where a significant proportion of districts show a higher than average rate of increase in NO_2 levels. More than 75% of the districts are in Bihar, Jharkhand, West Bengal, Maharashtra, Karnataka, and Chhattisgarh and show CAGR > 1%/year.

We also find a pattern in the relationship between NO_2 levels in 2005 and the growth in NO_2 over time (2005–19). The annualized growth rate (CAGR) of NO_2 levels in Indian districts over 2005–19 shows an increasing trend with initial NO_2 levels (2005) until a certain point, beyond which there is a decline in NO_2 growth. Figure 2b shows that the CAGR in NO_2 for the bottom quintile of districts (ordered by NO_2 levels in 2005) is 0.38%, this increases to 1.21% for the third quintile (corresponding to NO_2 levels (2005) of $23 - 28\mu mol/m^2$), and peaks at 1.25% for the fourth quintile (NO_2 levels (2005) of $28 - 36\mu mol/m^2$). Beyond this, the CAGR of NO_2 declines to 0.69% for the highest quintile ($> 36\mu mol/m^2$).

Delving deeper into the fourth quintile of districts, which show the highest growth in NO_2 levels, we find that one-third of the districts (32.4%) lie in the states of Bihar, Jharkhand, and West Bengal; on average, these districts have a CAGR of 1.53%, as captured in the darker shade of this region in the CAGR heatmap (Fig. 2a).

Finally, we present the complete distribution of rates of increase in NO_2 for districts across India (Fig. 3). We see that 86% of districts in the analysis show an increase in NO_2 levels for the period 2005–19. The distribution peaks at $\sim$ 1% CAGR, with a vast majority of districts (75%) having rates of increase in the range $0 - 2\%$. A total of 105 districts (14%) show a decline in NO_2 levels, and there is a strong spatial signature in the spread of these districts, with 40 of them (38%) belonging to the seven north-eastern states of India. These 40 districts account for 37% of all districts in the north-eastern states. Kurung Kumey district in the north-eastern state of Arunachal Pradesh shows the highest annual decline at -7.7% and Jharsuguda in Odisha shows the highest increase at 6.3%. The districts comprising some of India's largest metropolises, such as New Delhi, Mumbai City, Kolkata, and Chennai, are clustered close to 0% CAGR (Fig. 3). However, in 2005, all of these cities had high NO_2 levels above $40\mu mol/m^2$.

Impact of urbanization on NO_2 concentration

Given the observed increase in NO_2 levels for the large metropolitan districts, we now turn to a deeper examination of the relationship between urbanization rates and NO_2 levels for India's districts. The urbanization rate of a district is defined as the proportion of the urban population to the total population of the district.

Using data on urbanization rates at the level of the 640 districts in India's Census of 2011, we study the relationship between urbanization rates and NO_2 levels. We find no clear emergent patterns - average NO_2 levels are in the range $31.3 - 32.8\mu mol/m^2$ for districts in the following urbanization buckets: $< 10\%$, $10 - 20\%$, $20 - 30\%$, and $40 - 50\%$; $36.8\mu mol/m^2$ for districts in the $30 - 40\%$ urbanization range; and $42.5\mu mol/m^2$ for districts at $> 50\%$ urbanization.

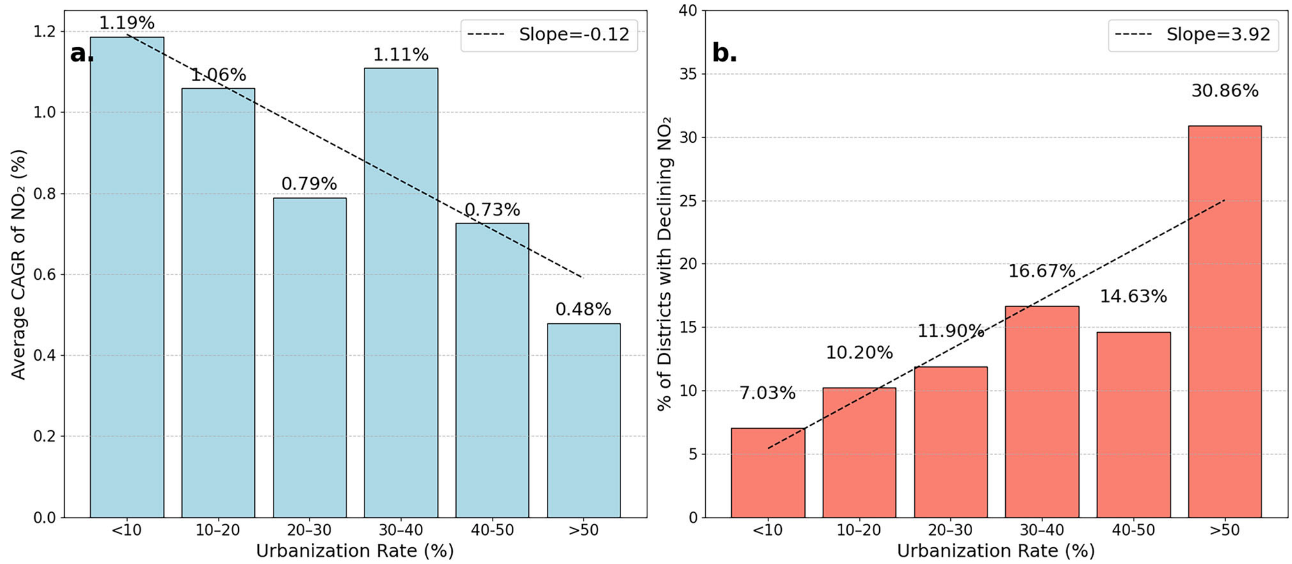
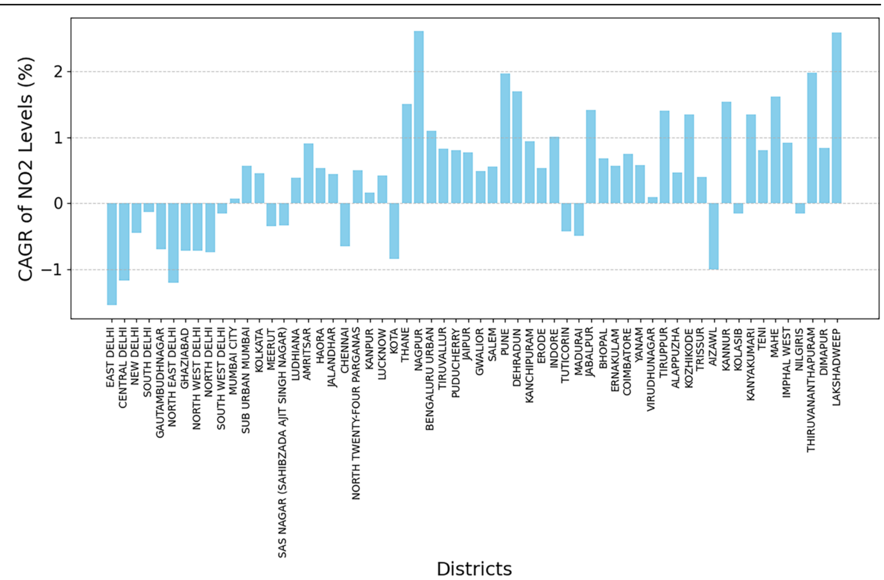


Fig. 4 | Urbanization and the rate of increase in NO_2. a Average NO_2 CAGR (2005–19) vs. urbanization rate. Increase in NO_2 declines with urbanization, on average. **b** Districts with declining NO_2 CAGR vs. urbanization rate. About one-third of the districts that are more than 50% urbanized have seen a decline in NO_2. Dashed lines indicate trendlines.

Fig. 5 | Rate of increase in NO_2 for India's 50 most urbanized districts. Over 74% of these districts show less than 1% annual increase in NO_2.



However, we find that there is some evidence for an inverse relationship between rate of increase of NO_2 and urbanization (Fig. 4a). Districts with an urbanization rate less than 10% have, on average, a NO_2 increase of 1.19% (compared to the mean increase rate of 0.93%), while districts with urbanization rates greater than 50% have a mean increase of 0.48%. It is also important to point out that districts at intermediate levels of urbanization, 30 − 40%, show a higher NO_2 increase than expected (1.11%), just as the same set of districts were outliers in terms of NO_2 levels.

When we consider the relation of urbanization with the decline in NO_2 levels, we find, on average, that there is a greater likelihood of decline in NO_2 in the more urbanized districts (Fig. 4b). For instance, only 7.03% of districts that are less than 10% urbanized experience a decline in NO_2, while 30.86% or districts that are more than 50% urbanized experience decline in NO_2.

Overall, these analyses indicate that higher urbanization corresponds to lower rates of increase in NO_2. To further explore this phenomenon, we zoom into the 50 most urbanized districts in India (in 2019), and find that 19 of them (38%) show a decline in NO_2, while only 13 (26%) show more than 1% CAGR (Fig. 5). Among the top 20 urbanized districts, the trends are even starker, with 14 (70%) of them showing a decrease in NO_2 concentration, including the core cities of New Delhi and Chennai. Kolkata and Mumbai show very low increase in NO_2, below 0.5%.

Spatial patterns of NO_2 and PM_{10} concentration in Indian cities

From the district level, we now turn our attention to a different level of spatial aggregation—the city. The Central Pollution Control Board (CPCB) has installed ground-level monitoring stations in a cross-section of Indian cities to measure concentration levels of NO_2 (since 2010) and PM_{10} (since 2016) (details in the Methods section).

Before we delve into our analysis, we address the issue of consistency between the satellite data used for districts and ground-level measurements for cities. In order to ensure that these data are broadly compatible, we regress the satellite data for a set of highly urbanized districts (with

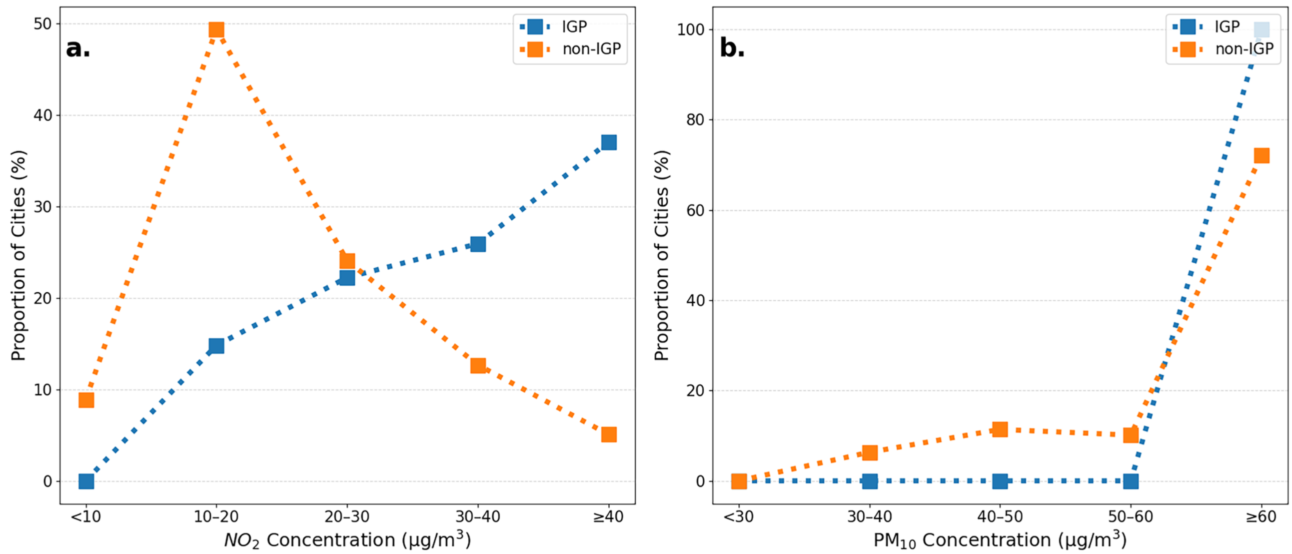


Fig. 6 | Distributions of cities by NO_2 and PM_{10} concentration (μg/m^3). a Distribution of cities—IGP and non-IGP - based on NO_2 concentration. **b** Distribution of cities—IGP and non-IGP - based on PM_{10} concentration. NO_2 concentration is particularly acute in the IGP cities.

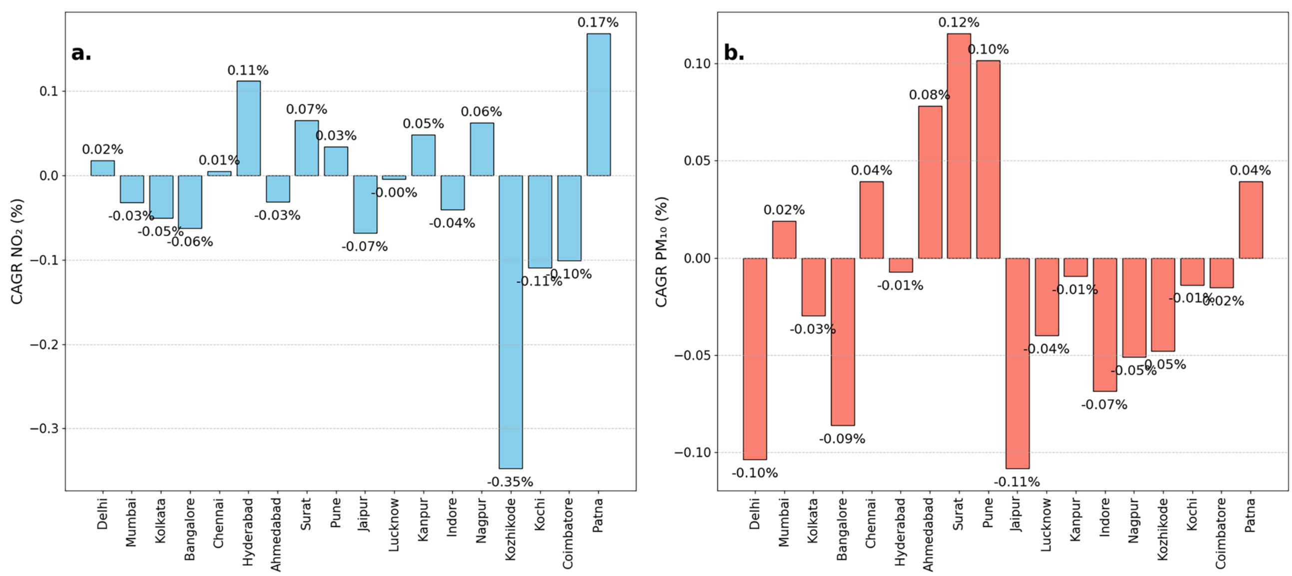


Fig. 7 | Annual NO_2 and PM_{10} growth rates for 18 Indian cities with a population >2 million (2016–19). a NO_2 CAGR (2016–19) shows that nine cities have a negative CAGR. **b** PM_{10} CAGR (2016–19) shows that 12 cities have negative CAGR.

urbanization rates $>66\%$) against the ground-level data for the cities that correspond to those districts. We set this urbanization criterion to include only highly urbanized districts whose pollution profiles are predominantly influenced by a single major city. However, it must be noted that both data sets are based on different measurement systems—the satellite data integrates spatially and contains NO_2 tropospheric vertical column densities, while the in-situ data comprises mass concentrations of NO_2 in ambient air measured near the ground. We find that the satellite and ground readings are quite consistent with one another, characterized by a linear relation between these measures, with $R^2 = 0.79$ (see Methods section).

Using data for 106 cities from 2016 to 2019, we analyse NO_2 and PM_{10} concentration levels, and find that the average city-level NO_2 is $25.2\mu g/m^3$, with 13.2% of cities above the national air quality standard of $40\mu g/m^3$. Average PM_{10} is 105.8 $\mu g/m^3$, which is significantly higher than the national air quality standard of $60\mu g/m^3$; 80.2% of cities are above this standard. For comparison, levels of PM_{10} concentration in large global metropolises such as London, Los Angeles, Frankfurt, and Seoul, are 21, 22, 20, and $42\mu g/m^3$, respectively[30]. Thus, the secularly high levels of PM_{10} across a wide spectrum of Indian cities—ranging between $33\mu g/m^3$ (Shimoga, in the state of Karnataka) and $295\mu g/m^3$ (Gorakhpur, in the IGP state of Uttar Pradesh), with a mean of 107.8 $\mu g/m^3$—present a significant environmental and health concern.

Just as in the case of districts, we find that there is a spatial pattern to NO_2 and PM_{10} concentration levels in urban India. Cities in the Indo-Gangetic Plain (IGP) are, on average, more likely (37.0%) to have NO_2 concentrations $>40\mu g/m^3$ than other non-IGP cities (5.1%), and much less likely (14.8%) to be in the $10-20\mu g/m^3$ range than non-IGP cities (50.6%) (Fig. 6a). Similarly, even as most cities in India exceed PM_{10} standards, 100% of cities in the IGP fall afoul of the standard, compared to 73.4% of non-IGP cities (Fig. 6b).

When we consider the rate of increase of pollutants between 2016 and 2019, we find that NO_2 and PM_{10} increase in only 47.2% and 36.8% of cities, respectively. This is in sharp contrast to the case of districts, where NO_2 increased in 86% of cases. It should be reiterated that because the

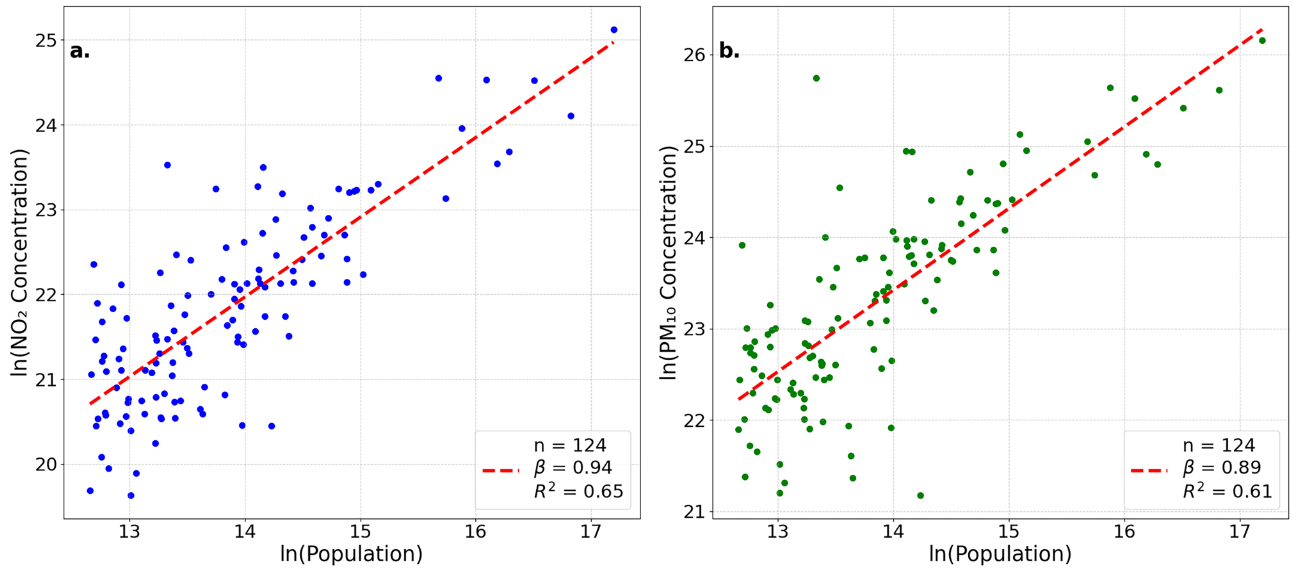


Fig. 8 | Scaling of pollutants in Indian cities by city size. a logNO_2 (2019) vs. log N shows sublinear scaling with exponent 0.94 ± 0.12. **b**. logPM_{10} (2019) vs. log N shows sublinear scaling with exponent 0.89 ± 0.13.

Table 1 | Scaling analysis of NO_2 for IGP and non-IGP cities shows spatial heterogeneity in how air pollution varies with city size

Year	IGP cities			All other cities		
	Y_0	β (R^2)	n	Y_0	β (R^2)	n
2019	7.38	1.04 (0.71)	39	9.44	0.89 (0.62)	85
2014	8.36	0.99 (0.77)	24	8.65	0.96 (0.66)	77
2010	10.78	0.81 (0.71)	19	8.79	0.95 (0.63)	66

absolute levels of PM_{10} have been so high in Indian cities (average of 109.3$\mu g/m^3$ in 2016), even with the negative growth between 2016 and 19, the vast majority of them are significantly above the air quality standard for India.

We zoom into the largest Indian cities, with population > 2 million (as per Census 2011) and find that out of these 18 cities, nine have seen a decline in NO_2 and 12 in PM_{10} between 2016 and 2019 (Fig. 7). Of particular concern are the cities of Hyderabad, Patna, Ahmedabad, Surat, and Pune, which all show high growth rate for at least one of these pollutants.

Urban scaling of NO_2 and PM_{10}

In order to systematically quantify the effect of city size on air pollution, we now present a scaling analysis of NO_2 and PM_{10} concentrations for Indian cities. This data were obtained from ground monitoring stations installed across Indian cities by the Central Pollution Control Board of India (details in Methods section)

Urban scaling is a study of how city properties vary with city size[53,54]. Urban scaling theory models cities as networks and makes predictions for the forms of these dependences, usually as scale-invariant functions (power laws)[54]. Empirical studies have broadly confirmed the predictions of urban scaling theory [53,55–59].

According to theory, a property $Y(t)$, such as urban GDP or length of road network, at time t, is related to the city size or population at that time, $N(t)$, through the power-law relation (Eq. 1):

$$Y(t) = Y_0 N(t)^{\beta} e^{\epsilon(t)} \qquad (1)$$

Here, Y_0 is the baseline provision of the quantity Y (level of provision when $N = 1$); β is the scaling exponent that describes how the property changes with size—$\beta < 1$ indicates sublinear scaling or the existence of economies of scale and is predicted for physical network infrastructures like roads and street lights, $\beta = 1$ indicates linear scaling or change proportional to population and is predicted for household properties like electricity and water usage, and $\beta > 1$ indicates superlinear scaling or change that is more than proportional to population and is predicted for social network phenomenon like income and innovation; and ϵ is the residual which is independent of city size and captures the extent of deviation from the scaling law that is established by β.

We now seek to understand how air pollution, specifically NO_2 and PM_{10} concentrations, scales in the Indian city system. Using data for 2019, we find that both NO_2 and PM_{10} scale sublinearly, with exponents of $0.94(95\%CI : [0.82 - 1.06])$ and $0.89(95\%CI : [0.76 - 1.02])$, respectively (Fig. 8a, b). This result is broadly consistent with the prior work on the scaling of air pollutants with city size in the USA, China, India, and Europe, and is generally attributed to the increase in energy efficiency that leads to a reduction in NO_2 emissions, across nations[13,15,60]. In their scaling analysis of NO_2 in Indian cities[13], find a scaling exponent of 0.36, which is substantially different from our findings (though both are sublinear). This discrepancy could be related to the very coarsely resolved population data at 0.25 × 0.25° in their study and the fact that they established city boundaries based on population density, which is an arbitrary criterion given the phenomenon of suburbanization, whereas urban scaling analysis requires a functional definition of the city—a “commute to work” network comprising places of work and residence.

The sublinear scaling for India means that the concentration of both these pollutants decreases (slightly) as we move to larger cities.

Finally, we explore the question of whether the scaling behavior also displays the spatial patterns that we have observed in our earlier analysis. We separate cities into two sets—in the Indo-Gangetic Plain (IGP cities) and all others (non-IGP cities)—and find that, in 2019, IGP cities display superlinear scaling ($\beta = 1.04$) while non-IGP cities display sublinear scaling ($\beta = 0.89$) (Table 1). This means that, in stark contrast to the rest of India, where larger cities see lower per capita pollution, in the Indo-Gangetic Plain, not only can larger cities have higher absolute NO_2 concentration (per unit volume), but they also see higher per capita NO_2 concentration.

Further, a temporal analysis (2010–19) of the scaling of NO_2 concentration in the Indo-Gangetic Plain reveals that the situation has worsened over the decade starting 2010, when IGP cities displayed sublinear scaling of NO_2 ($\beta = 0.81$), and now display superlinear scaling ($\beta = 1.04$) in 2019—meaning that larger IGP cities saw a disproportionate increase in terms of their intensity of air pollution (Table 1), relative to smaller cities in the same region.

Discussion

Our analysis indicates that the Indo-Gangetic Plain emerges as the region of particular concern in India from an air pollution perspective. This finding is consistent with prior studies on NO_2 pollution in India[33,51,52]. This is particularly significant because the IGP houses two of the largest states in India by population, Uttar Pradesh (200 million) and Bihar (104 million).

The concern around the IGP identified by our analysis is consistent with both anthropogenic and meteorological factors. The Indo-Gangetic Plain is home to a dense concentration of coal-fired thermal power plants (as of 2015, 49 out of India's 117 coal-fired power plants/stations were along the IGP); industrial and mining activity (the mineral rich north-eastern peninsular belt containing over 90% of India's iron ore and 84% of coal is at the eastern end of the IGP); transport and freight networks (the Eastern Dedicated Freight Corridor runs along the length of the IGP, from Punjab to West Bengal, a distance of 1839 km); intense agricultural activity (including the annual stubble burning during winter resulting in the haze observed over the IGP); and household-level burning of biofuels for cooking[61–68]. From the perspective of emissions, each and all of these sources of pollution should become the focus of mitigation efforts.

Climatically, the IGP is flanked by the Himalayas to the north and the Deccan Plateau to the south, creating atmospheric conditions over the low-humidity plain that result in enhancing the atmospheric lifetime of NO_2 from point sources such as power plants and industry, and its consequent dispersal over a broader area[52]. Seasonal variations have been observed in NO_2 concentrations, with higher values observed from December to May, and lower values during the monsoon (June to September)[33].

These trends in NO_2 pollution in the IGP are especially concerning since there will be significant intensification of economic activity in this region, given that the IGP remains one of the poorest regions in India—Uttar Pradesh and Bihar have the lowest per capita net domestic product among Indian states, at INR 93,514 (Indian rupee) and INR 60,337 for 2023–24 (compared to an all-India average of INR 184,205)[69].

The same concern also holds for many of the districts that exhibit a decline in NO_2 levels between 2010 and 2019. We observed that a disproportionate number of these districts are from the north-eastern region of India (38%). This high proportion of districts with declining NO_2 is consistent with the relatively lower intensity of economic activity in the north-eastern states of India[70,71]. However, over the last decade, the government of India has intensified its focus on the economic and infrastructure development of this region, reflected in a $2.5X$ increase in the budget allocation to the north-eastern states in the decade 2014–15 to 2024–25[72]. Thus, the economic growth of this region could meaningfully also increase its NO_2 burden in the future.

However, there is also a small note of hope in our results. The picture that emerges for the most urbanized districts in the country (urbanization rate $>50\%$) is that while these districts have the highest NO_2 levels, on average, they have also been able to contain the rate of increase in NO_2 in the period 2005–19 (in comparison to all other districts), including in some cases reducing NO_2 levels (such as in Delhi). The low rates of increase correspond to the fact that highly urbanized places are also at the center of the government's air pollution mitigation efforts, by being the first sites of implementation for vehicle regulations, industrial emission control, and improved monitoring systems[42].

Thus, there is a typology of challenges and possible policy actions suggested by these results. The two main challenges can be decomposed as follows:

1. Achieving systematic and steady improvements in the air quality of India's largest and most polluted cities; and
2. Avoiding pollution increases in initially poorer, less urban but fast-developing regions of the country, especially in the IGP.

The first challenge consists of high levels of pollution related to high population and activity density in large cities and relatively higher levels of economic development. As sources of emissions, this deals with higher spatial and temporal use intensity of conventional internal combustion vehicles, urban industrial activity, and higher power consumption. Possible solutions are suggested by those adopted in other large cities, most recently in China, but also in Europe and North America[73]. These include pollution controls (and relocation) of power generation and industry, and the adoption of less polluting vehicles. In both cases, effective traditional policies can now be substantially aided by emerging technologies for energy generation, storage, and electrification of transportation and industry. Substantial economic growth and innovation will also be produced by deploying these technologies (renewable energy production, storage, electric vehicles) in new ways at the scale and complexity of India's large cities.

In the case of developing regions, the challenges are quite different. They involve the adoption of new technologies in energy generation, but also in more traditional economic sectors such as agriculture and small-scale manufacturing and services. The opportunity here stems principally from creating new energy systems that can scale up with development, and indeed support it by removing limiting factors to more efficient agricultural production, education and training, transportation and basic service delivery. Success in these environments will need to be replicated in other less urbanized regions of the world, especially in Africa.

Looking ahead, our methods rely on sources of data that will continue to be collected, leading to meaningful longitudinal assessments of pollution mitigation and reduction, at different scales from cities to smaller regions and less urbanized districts. The tighter coupling of pollution mitigation assessments to policy making in the multi-level system of governance in India provides ample room for experimentation with approaches and new technologies towards more effective, sustainable, and context-appropriate solutions.

Methods

Satellite observations of NO_2 data

For district level NO_2 data, we leverage satellite-based observations from the Ozone Monitoring Instrument (OMI), aboard NASA's AURA satellite[74]. OMI is a nadir-looking spectrometer that operates in a near-polar and sun-synchronous orbit. It allows daily global monitoring of atmospheric trace gases, aerosols and clouds with a nominal spatial resolution of 13 km × 27 km. In particular, we use daily tropospheric NO_2 column densities on an equidistant grid of 0.125° latitude and 0.125° longitude spatial resolution (equivalent to areas of about 8.5km × 13.9km)[75]. The geophysical unit of the tropospheric column densities is $\mu mol/m^2$. Since the amount of NO_2 is modified by meteorological conditions, we derive annual means from the daily data to reduce the potential influence of these effects[76]. Due to this temporal aggregation, we expect meteorological influences to be minor. To comply with the objectives of the study, we have aggregated the annual data for each district using the polygons provided by the Survey of India (https://onlinemaps.surveyofindia.gov.in/Digital_Product_Show.aspx).

The satellite-based tropospheric NO_2 burden is a well-established proxy for local and regional anthropogenic emissions and directly captures spatio-temporal air pollution variability[60,76–79]. Due to the short lifetime of NO_2 in the boundary layer of several hours, it is, on average, not advected far downwind and reflects the source regions very well[80,81]. The temporal sensitivity of tropospheric NO_2 to anthropogenic emission activity is substantiated by reflecting weekly cycles with significantly lower NO_2 levels over the weekend, Sunday in particular[82,83]. Natural contributions to the NO_2 budget are confined to lightning[84], biomass burning[85] and soil processes[86].

The overall error budget of the tropospheric NO_2 retrievals is influenced by several parameters like cloud fraction, cloud pressure, surface albedo, surface pressure, the a priori NO_2 profile shape and NO_x emissions, as well as aerosol-related errors[87]. Over unpolluted areas and water bodies, the retrieval error is dominated by the spectral fitting errors, while over

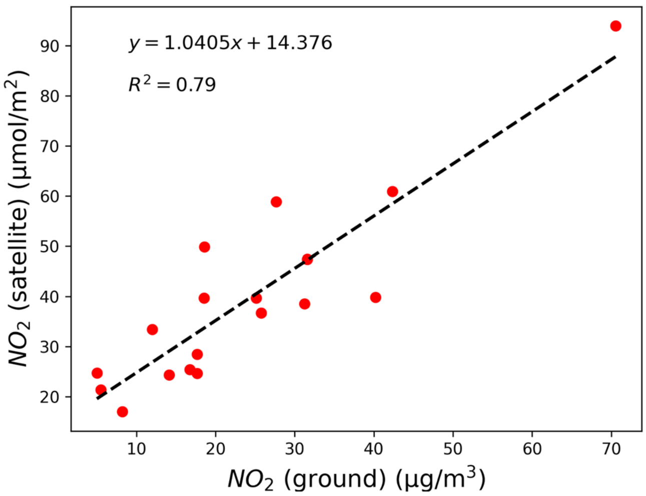


Fig. 9 | NO_2 (ground station, μg/m³) v. NO_2 (satellite, μmol/m²). There is good linear correlation, described by the equation $y = 1.0405x + 14.376$, between the ground and satellite readings ($R^2 = 0.79$).

polluted areas, air-mass factor errors contribute substantially to the overall error. However, by applying annual means in this study derived from daily observations, the uncertainty was significantly reduced[50].

District boundaries of India

For creating the maps, we have used the district boundaries from the DataMeet India community (https://datameet.org/)/. District boundaries are available at: https://github.com/datameet/maps (license: CC BY 4.0).

Ground observations of NO_2, PM_{10} data

For city-level data, we use mass concentrations ($\mu g/m^3$) of NO_2 and PM_{10} provided by ground monitoring stations installed by the Central Pollution Control Board (CPCB). NO_2 concentration data were available from 2010 to 2019, with the number of cities covered increasing from 85 in 2010 to 124 in 2019. PM_{10} data is available from 2016 to 2019, with the number of cities covered increasing from 108 in 2016 to 124 in 2019.

Computing compounded annual growth rate (CAGR)

The annual rate of increase in the pollutant—NO_2 or PM_{10}—levels for a time-period starting in year y_i with pollutant level $P(y_i)$, and ending in year y_f with pollutant level $P(y_f)$, is given by the compounded annual growth rate (CAGR), computed as (Eq. 2):

$$CAGR = \left[\frac{P(y_f)}{P(y_i)}\right]^{\frac{1}{y_f - y_i}} - 1 \quad (2)$$

Relationship between satellite and ground readings of NO_2

We have NO_2 concentration data from ground-level stations of the Central Pollution Control Board (CPCB) at city-level ($\mu g/m^3$), and from satellite data at the district level ($\mu mol/m^2$). To see if these data are broadly consistent with one another, we study the relationship between these readings for a set of 18 districts which are co-terminus with the cities within them (that is, the city comprises at least 2/3rd of the district's population), making the NO_2 readings comparable. Figure 9 shows that there is a strong positive relationship between the NO_2 readings from ground and satellite.

Data availability

Details of data sources and methods are provided in the Methods section.

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Author contributions
A.S. and L.M.A.B. conceived the study. A.S., N.K., T.E., M.W., H.T., and L.M.A.B. contributed to the analysis and reviewed and edited the manuscript. A.S. wrote the main manuscript text. All authors have read and approved the manuscript.

Competing interests
The authors declare no competing interests.

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