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ARTICLE

The health benefits of air pollution control in India

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Abstract

This paper presents an overview of the health benefits of controlling ambient air pollution in India. We answer five questions: First, how high is ambient air pollution in different parts of India? Second, what are the morbidity and mortality consequences of ambient and household air pollution? Third, what are the health costs of pollution-related morbidity and mortality? Fourth, what are the primary sources of ambient air pollution in India and what are their implications for policies to control air pollution? Finally, what are the health benefits and costs of reducing air pollution from coal-fired power plants?

Keywords Ambient air pollution · Household air pollution · Coal-fired power plants · Air pollution in India · Health effects of PM2.5

JEL Classification Q51 · Q53 · I15

This paper provides an overview of the evidence on the health benefits of air pollution control in India, based on the research that we and our collaborators have conducted over the last several years. We answer five main questions: First, how high is ambient air pollution in different parts of India? Second, what are the morbidity and mortality consequences of ambient and household air pollution? Third, what are the health costs of pollution-related morbidity and mortality? Fourth, what are the primary sources of ambient air pollution in India and what are their implications for policies to control air pollution? Finally, what are the health benefits and costs of reducing air pollution from coal-fired power plants?

Indian Economic Review public lecture, delivered on September 28, 2022 by Maureen Cropper, Professor of Economics, University of Maryland and Senior Fellow at Resources for the Future.

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A common metric used to measure air pollution is PM2.5, which refers to airborne particulate matter less than two and one half microns in diameter. These fine particles are capable of penetrating the lung deeply. Long-term exposure is associated with higher risk of cardio-pulmonary disease (Burnett et al., 2018). There are two major sources of exposure to PM2.5. The first is outdoor (ambient) air, but the second, and less well recognized, is indoor air pollution. In many states of India, PM2.5 exposure to indoor pollution from burning solid fuels for cooking, and sometimes for heating, is much higher than from the outdoor air.

1 Air pollution in India

There are three methods used to measure ambient air pollution. The first is ground-based monitors: it is important to consider what is happening on the ground, both in terms of fine particles as well as other air pollutants. The Central Pollution Control Board operates over 800 monitoring stations across the country. But we are also interested in parts of the country where monitoring stations are sparsely distributed. Therefore, to analyze the impact of a policy or to build a counterfactual, it is necessary to model ambient air pollution. The second method uses estimates from atmospheric chemistry models. This requires data on emissions inventories and meteorological data. Examples of this approach include work by the International Institute for Applied Systems Analysis (IIASA) in Vienna, which has developed the GAINS model (IIASA, 2019). Work by Urban Emissions Info. in India (Guttikunda & Jawahar, 2014) also falls in this category. The third way to measure ambient air pollution is to use satellite data on aerosol optical depth and combine it with atmospheric chemistry modeling. This approach is used by the Global Burden of Disease study (Global Burden of Disease Collaborative Network, 2021). Satellite-based modeling is also used by Sagnik Dey at IIT Delhi (Dey et al., 2020).

Figure 1 (World Bank, 2022) shows estimated average annual PM2.5 ambient air pollution levels in 2018 from IIASA's GAINS model. Areas in red and orange have higher levels of ambient annual PM2.5. For example, in the Indo-Gangetic plain, the annual average PM2.5 has been estimated to exceed 90 µg per cubic meter. The orange areas in Rajasthan and Gujarat and the eastern states correspond to annual averages of approximately 50–60 µg per cubic meter. The eastern part of India is also home to many power plants. The southern regions see much lower ambient concentrations, on the order of 30 µg per cubic meter.

Comparing this with the results of the Global Burden of Disease analysis for 2019 in Fig. 2 (Members of the India State-Level Disease Burden Initiative Air Pollution Collaborators, 2021), the broad picture is quite similar, although there are differences. The states depicted in red (Uttar Pradesh, Bihar, Haryana) were estimated to have population-weighted ambient concentrations greater than one hundred micrograms per cubic meter in 2019. In Rajasthan, Jharkhand and Punjab population-weighted PM 2.5 was estimated between 80 and 100 µg. PM2.5 levels were slightly lower in Madhya Pradesh and West Bengal. In Karnataka and Tamil Nadu, levels were estimated to be 30 µg or less.

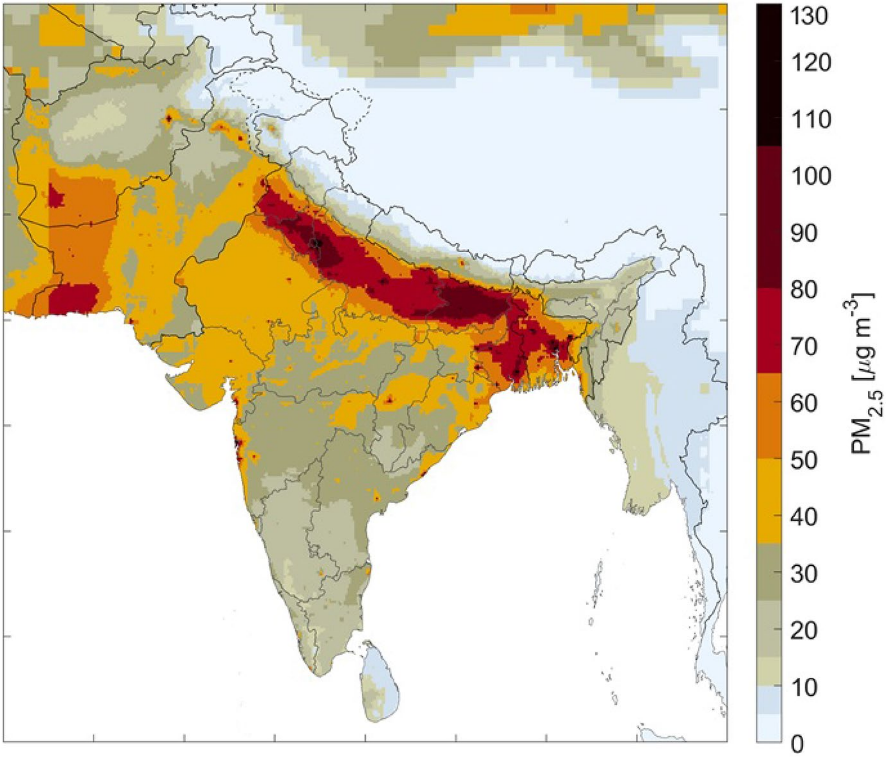

Fig. 1 2018 Annual average PM2.5 based on GAINS model. Source: World Bank (2022)

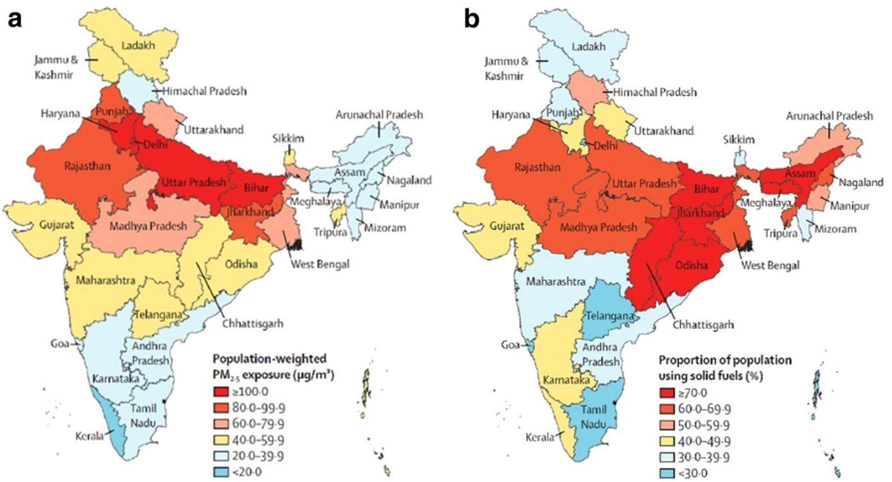

Fig. 2 GBD 2019 Estimates. **a** Annual average ambient PM2.5. **b** Percent households burning solid fuels. Source: Members of the India State-Level Disease Burden Initiative Air Pollution Collaborators (2021)

Figure 2 also presents information on the percentage of households that burned solid fuels for cooking, in 2019, by state. In Odisha, Jharkhand, Chhattisgarh, Bihar, and Assam over 70% of households burned solid fuels for cooking. Between 60 and 70% of households burned solid fuels in Rajasthan, Madhya Pradesh and Uttar Pradesh. The percentage of households burning solid fuels was much lower in southern India. These patterns have important consequences for controlling ambient air pollution in the Indo-Gangetic Plain, where household air pollution is an important source of ambient air pollution.

2 Health impacts of ambient and household air pollution

We used the methodology followed by the 2019 Global Burden of Disease to calculate the impacts of PM2.5 on premature mortality in 2018. We calculated health impacts for geospatial grid squares of 0.1 degree by 0.1 degree, for six diseases: ischemic heart disease, stroke, lower respiratory infection, chronic obstructive pulmonary disease, type two diabetes and lung cancer. In calculating the health impacts of PM2.5, the risk of death depends on all sources of PM2.5 exposure, both indoor and outdoor. For each grid square, we estimated population exposure to both indoor and outdoor air pollution, and calculated the fraction of deaths attributable to total PM2.5 exposure. We allocated deaths to ambient PM2.5 by multiplying total deaths attributable to PM2.5 in each grid square by the fraction of total PM 2.5 due to ambient sources. Deaths attributable to household air pollution were calculated similarly.

An important fact is that health risks of PM2.5 per microgram decrease as exposure increases (Burnett et al., 2018). In other words, the concentration response function relating relative risk of death to annual average PM2.5 is concave. This implies that the impact of a reduction in a microgram of ambient exposure will be lower if people are exposed to indoor air pollution than if they are not. Thus, if two areas have the same ambient PM2.5 levels, the one with the higher household air pollution exposure will have a lower death rate due to ambient PM 2.5, other things equal. This has implications for the design of pollution control methods.

By way of illustration, Fig. 3 (Global Burden of Disease Collaborative Network, 2021) presents a concentration response function for ischemic heart disease among people aged 70 to 75. It demonstrates that the impact on the relative risk of dying from ischemic heart disease by inhaling an addition microgram of PM 2.5 declines with higher levels of exposure. This is consistent with evidence on active smoking that marginal impacts decrease as smoking increases, and with epidemiological evidence on PM2.5 (Burnett et al., 2018). In the context of air pollution, one consequence is that—holding population and baseline death rates constant—the marginal benefits from reducing ambient air pollution will be smaller in areas where exposure levels are already high (say 100 µg, perhaps due to household air pollution) than in areas with a lower level of total PM2.5 exposure.

Figure 4 (first panel) presents the total number of deaths per grid square due to ambient PM2.5. Other things equal, there are more deaths in areas with higher ambient PM2.5; thus, there is a concentration of deaths in Indo-Gangetic plain, especially in Uttar Pradesh and Bihar, and also in West Bengal. There are also more deaths

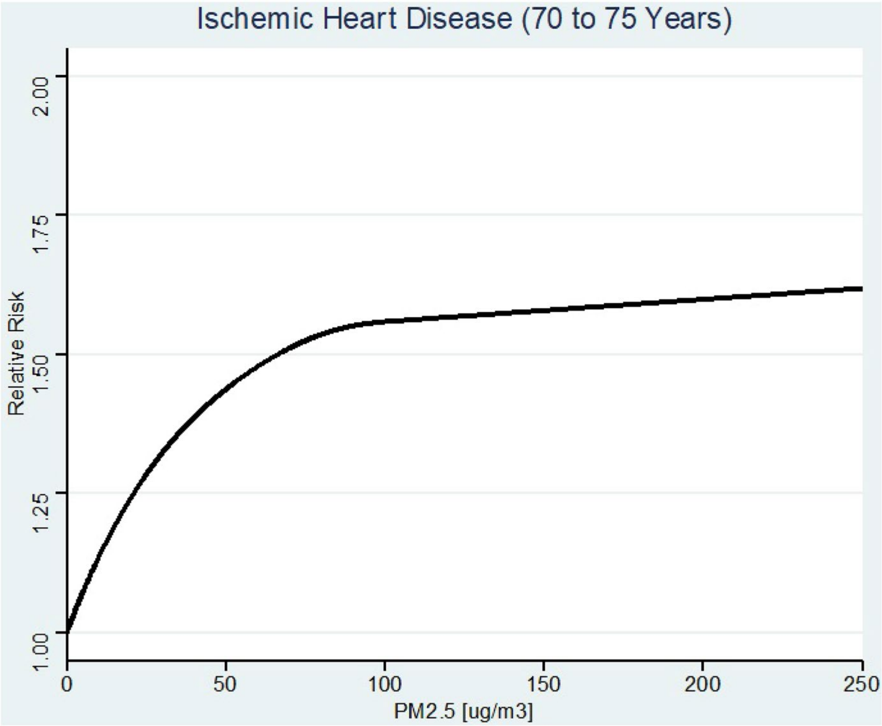

Fig. 3 Impact of PM2.5 on relative risk of ischemic heart disease. Source: Author's calculation from Global Burden of Disease Collaborative Network (2021)

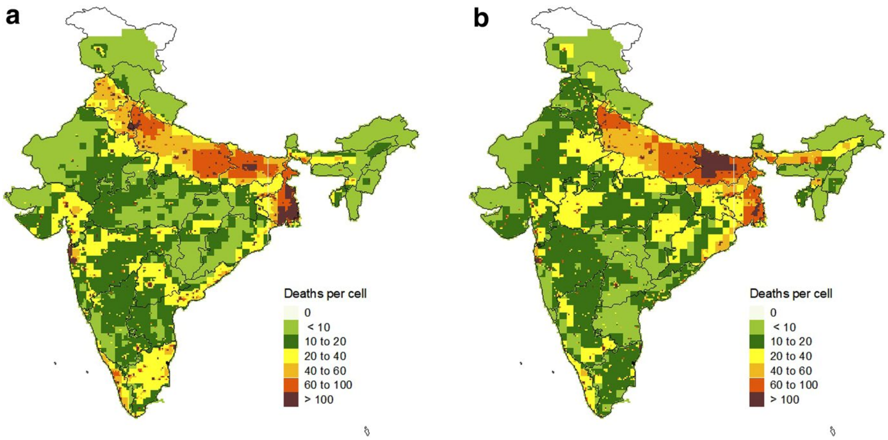

Fig.4 **a** Ambient PM2.5 deaths 2018. **b** HAP PM2.5 deaths 2018. Source: Author's calculation

in densely populated areas, such as Tamil Nadu and the east coast of India. In the aggregate, the number of deaths we attributed to ambient PM2.5 exceeded 740,000 in 2018. The largest contribution was from the Indo-Gangetic Plain (325,000 deaths), followed by 124,000 deaths in Gujarat and Maharashtra. The southern Indian states of Andhra Pradesh, Telangana and Tamil Nadu together accounted for 110,000 deaths.

The second panel in Fig. 4 presents the results for household air pollution (HAP). We estimated that in 2018, the total number of deaths arising from direct exposure to burning of solid fuels for cooking within the household was 660,000, largely coming from north and central India. What is particularly noteworthy is that in 18 states, for those persons exposed to household air pollution, household exposure to PM2.5 was greater than PM2.5 exposure from ambient air pollution.

Once one controls for population and looks at death rates (Fig. 5), the interaction between household and ambient air pollution becomes apparent. The highest mortality rate due to ambient PM2.5 occurred in Punjab and Haryana, states with high levels of ambient PM2.5, but with a lower percentage of households burning solid fuels than in Uttar Pradesh and Bihar. The higher death rates due to ambient PM2.5 in the central part of India occurred because Gujarat, Maharashtra and Telangana do not have such high burning of indoor solid fuels for indoor cooking. The death rates due to household air pollution in each grid square were the highest in Jharkhand, Madhya Pradesh, Chhattisgarh, and Odisha, areas where over half of people's PM2.5 exposure came from household air pollution.

Seven states in India: Punjab, Haryana, Uttar Pradesh, Bihar, Jharkhand, West Bengal, and Delhi, accounted for almost half of the ambient air pollution deaths in 2018. They also accounted for about half of the household air pollution deaths. It is also the case that the emissions from household air pollution accounted for a large fraction of ambient pollution in these states. Indeed, the proportion of ambient PM2.5 deaths attributable to household air pollution was 34% in Bihar and West Bengal, 21% in Delhi, Uttar Pradesh, Jharkhand, and 15% in Haryana and Punjab.

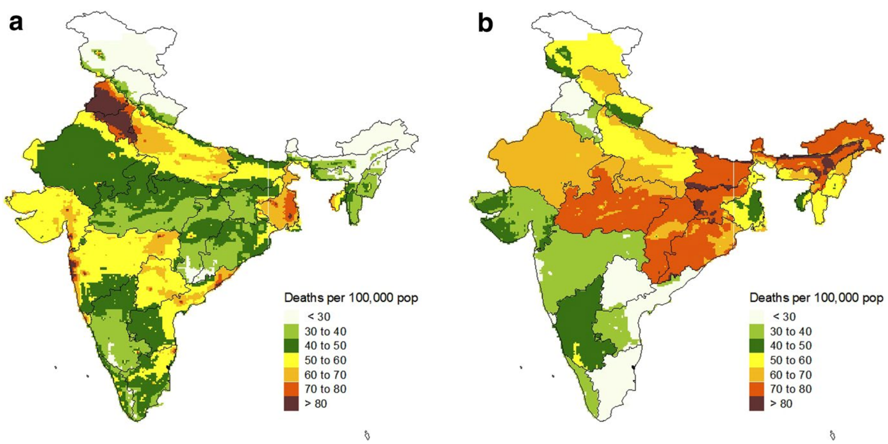

Fig. 5 **a** Ambient air pollution death rate 2018. **b** HAP death rate 2018. Source: Author's calculation

This implies that there is a double dividend to reducing household air pollution: it reduces the direct exposure of household members to PM2.5 but also reduces ambient air pollution.

If one could reduce ambient air pollution in the seven states from 2018 levels to 35 µg per cubic meter, and simultaneously halve the percentage of households that burn solid fuels for cooking, this would result in 160,000 fewer deaths in these states. If one could further reduce ambient air pollution to 10 µg per cubic meter and again halve the percentage of households burning solid fuels, one could eliminate almost 300,000 deaths in the seven states.

3 Health costs of ambient and household air pollution

In this section, we summarize evidence on the economic costs of air pollution, based on work that was published in The Lancet Planetary Health (2021) authored by the India State-Level Disease Burden Initiative Air Pollution Collaborators (Members of the India State-Level Disease Burden Initiative Air Pollution Collaborators, 2021). To quantify the health costs of PM2.5, we estimated the indirect costs of illness, measured as the output that is lost due to illness or premature death. To compute this, we used the Global Burden of Disease measure of morbidity, years lived with disability (YLDs). YLDs measure the fraction of healthy time lost due to a year with a debilitating ailment (e.g., chronic lung disease or ischemic heart disease). We valued YLDs using lost output per worker in 2019 and valued premature mortality in 2019 by taking the present value of lost output.

To value worker output in 2019 in state i, average output per worker was calculated as

$$W_i = \frac{(\text{Labor}'\text{s share of output in India})(\text{GSDP}_i)}{\#\text{workers in state } i}.$$

We adjusted W_i for the probability of working, using the ratio of workers to population, and for non-market output. For an individual of age j in state i:

$$W_{ij} = (WPR_{ij} + \lambda(1 - WPR_{ij}))W_i,$$

where W_{ij} is expected output of an individual of age j in state i, WPR_{ij} is the worker-population-ratio at age j in state i, and λ (=0.3) is the ratio of non-market to market output.

The present discounted value of lost market and non-market output for a person who died in 2019 at age j in state i, PV_{ij}, was calculated as

$$PV_{ij} = \sum_{t=j}^{84} \pi_{ij,t} \left(\frac{1+g}{1+r}\right)^{t-j} W_{it},$$

where $\pi_{ij,t}$ is the probability of survival to age $t>j$ for a j year-old in state i, estimated using GBD India lifetables; g is the annual growth rate of output per worker

(=4.83%) and r is the annual discount rate, chosen as 6% to reflect the annual the yield on 10-year government bonds in 2019.

Output loss associated with YLDs in 2019 for persons of age j in state i is given by

$$M_{ij} = W_{ij} YLD_{ij}.$$

Total output loss in state i is obtained by summing over output loss due to premature deaths and YLDs at each age

$$\sum_j (\text{Deaths}_{ij} PV_{ij} + M_{ij}).$$

For India as a whole, in 2019, there were estimated to be over 5.5 million YLDs and 1.6 million premature deaths associated with air pollution, both indoor and outdoor. These translated to an output loss attributable to air pollution of USD 36.8 billion, or approximately 1.36 percent of GDP. Of this, USD 28.7 billion, or 1.06 percent of GDP, was attributed to mortality, and USD 8 billion, or about three tenths of a percent, to output lost due to YLDs. There were, however, wide variations across states. Figure 6 (Members of the India State-Level Disease Burden Initiative Air Pollution Collaborators, 2021) indicates that states that had the highest losses stated as a percent of gross state domestic product (GSDP) included Uttar Pradesh with losses equal to over 2% of GSDP due to both indoor and outdoor air pollution, Bihar (losses equal to 1.95% of GSDP), Rajasthan and Madhya Pradesh (equal to 1.70 of GSDP) and Chhattisgarh (equal to 1.55% of GSDP). The states with small losses were largely in the north-east, places that were relatively clean and where many households did not burn solid fuels.

To emphasize the role that household air pollution plays in output losses, Fig. 7 shows losses as a percentage of state GSDP attributable to outdoor air pollution in blue; the orange bars represent losses as a percentage of state GSDP attributable to indoor air pollution. In four of the states—Bihar, Chhattisgarh, Madhya Pradesh and Rajasthan—half or more of the losses were due to household air pollution. In the other states that had high losses, including Punjab, Uttarakhand, Gujarat, Haryana, Delhi, losses were due primarily to outdoor air pollution. Ambient ozone pollution losses, also included in Fig. 7, were small.

To summarize, in the aggregate, the losses from YLDs and premature mortality in 2019 were high: the morbidity losses alone were about three tenths of a percent of GDP for the country. Household air pollution accounted for about 36% of these economic losses. In eight states, the losses were in excess of one and a half percent of GSDP. Note further that economic losses from air pollution far exceed what has been quantified here and do not include direct costs of illness, or the impacts of PM2.5 on agriculture or on ecosystems. What has been quantified are conservatively estimated impacts on lost output.

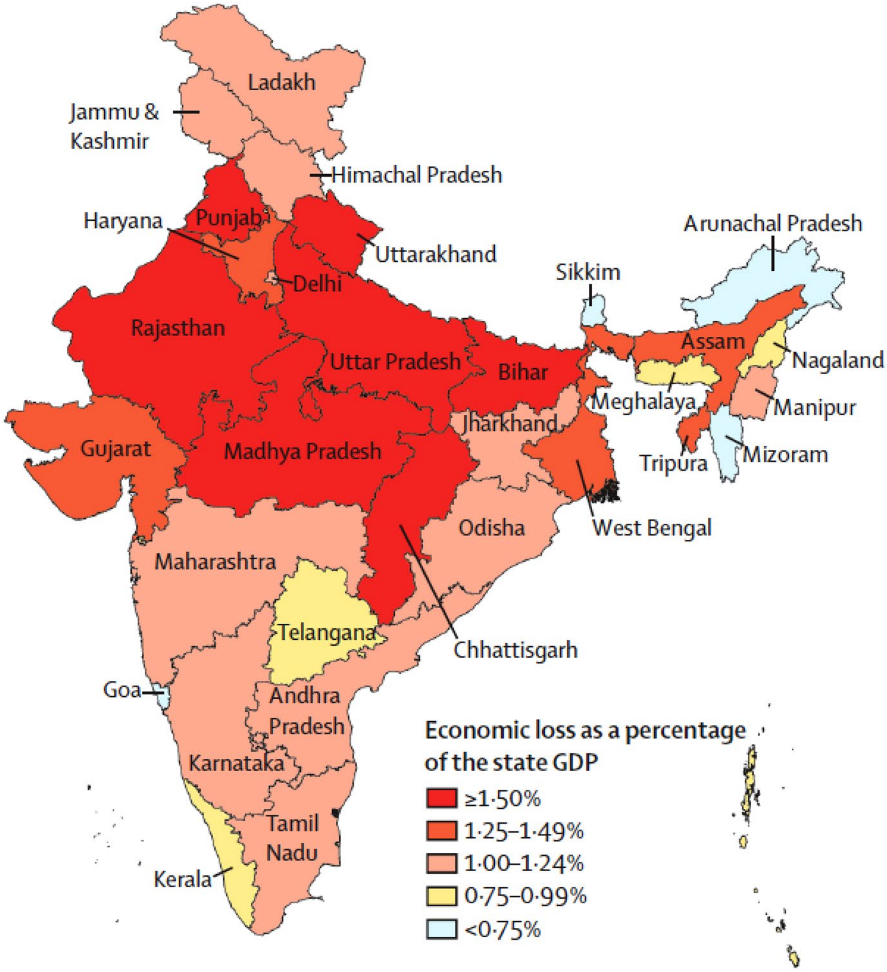

Fig. 6 Output loss as a % of GSDP by state/UT. Source: Members of the India State-Level Disease Burden Initiative Air Pollution Collaborators (2021)

4 Ambient sources of air pollution

Since household sources of air pollution are better understood, we turn next to identifying the sources of ambient air pollution and what they imply for pollution control. Results based on the GAINS model are presented in Fig. 8; note that the legend on the right-hand side has a logarithmic scale. The panel on power plants and their impact on ambient PM 2.5 indicates that in 2018, they accounted for between 3.16 and 10 μg of PM2.5 (orange). The yellow colors in the panel on large industries indicate impacts on ambient PM 2.5 that were between 1 and 3.16 μg. Blue and green colors represent smaller contributions to PM2.5. It is clear that ambient concentrations from power plants were significant. These were especially large in

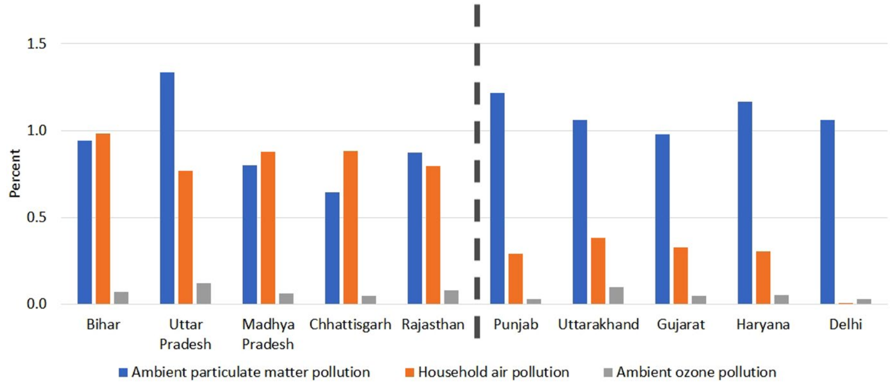

Fig. 7 Output loss as a % of GSDP attributed to different types of air pollution—selected states/UTs. Source: Author's calculation

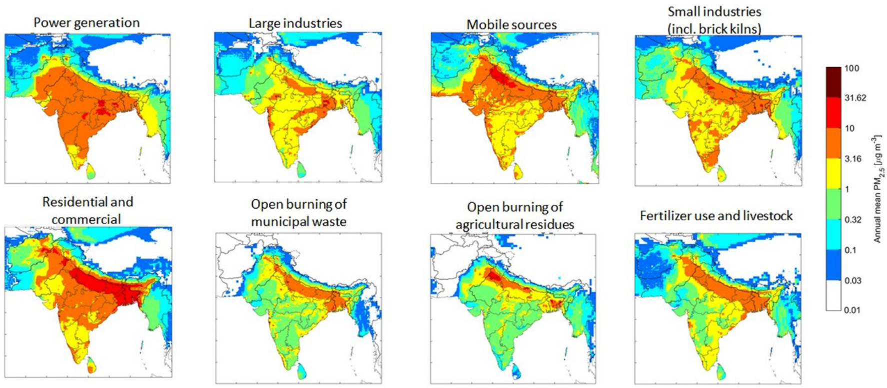

Fig. 8 Sectoral contributions to $PM_{2.5}$ in ambient air—2018. Source: World Bank (2022)

the eastern part of India, for example, in Chhattisgarh and Jharkhand. And, in states where power plants are concentrated, there were also impacts of large industries. Mobile sources were especially important in the Indo-Gangetic plain, especially in Delhi and Haryana. The lower left panel points to the substantial impacts of household air pollution on ambient air pollution. A key takeaway is that there are substantial variations in sources of ambient PM2.5 across geographies within India. Before designing mitigation strategies for controlling ambient air pollution in a region, it is necessary to understand what are the main sources of ambient PM2.5.

Figure 9 presents the main sources of pollution in the seven states that, by our estimates, accounted for half of the ambient and household air pollution deaths in 2018. As might be expected, the last two bars, representing emissions from agriculture, were important sources of outdoor air pollution in Haryana and Punjab. In Bihar, West Bengal and Jharkhand, household air pollution was important. Transport accounted for a large share of ambient PM2.5 in Delhi, Haryana and Punjab than in

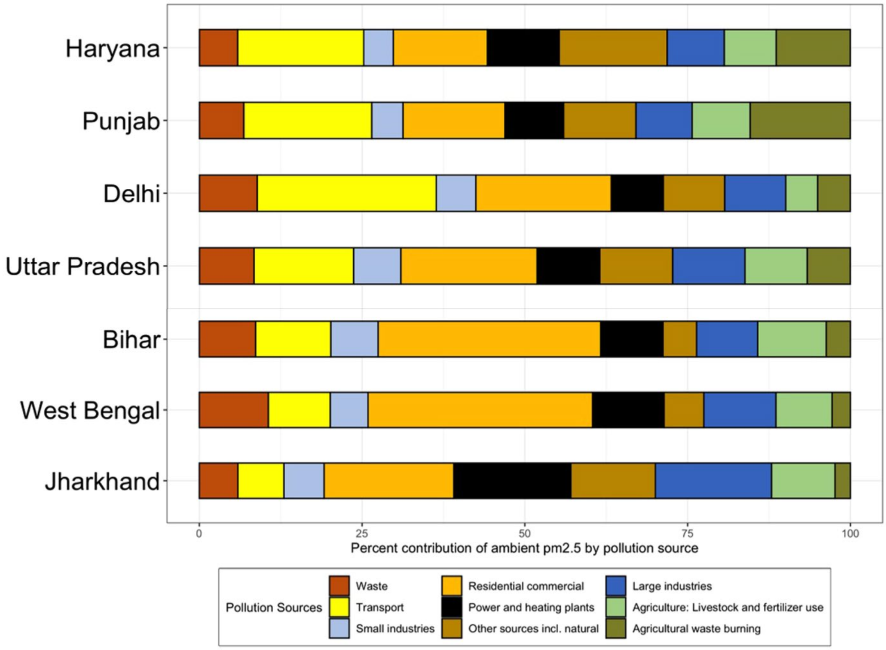

Fig. 9 Proportion of ambient air pollution by source. Source: World Bank (2022)

the other four states. Each of the seven states, however, had a variety of sources contributing to ambient PM2.5.

Figure 10 (World Bank, 2022) drills down further to the Delhi national capital region (upper panel) and Kolkata (lower panel). Each panel presents not only the sources of pollution but the geographic location of the source (other countries, other states, neighboring states, natural sources and the same state and city). Of the over 90 μg annual average PM2.5 in Delhi in 2018, a little over 20 μg originated in Delhi itself. All the other components of the 90 μg came from other states, or other countries. A similar pattern obtained in Kolkata: of the over 90 μg annual average PM2.5 in 2018, approximately 25 μg were generated within the city itself; the rest were from outside the city. The important implication is that pollution control cannot occur solely within cities.

The right panel in both graphs distinguishes between primary versus secondary particles. Our focus thus far has been on PM2.5, some of which is directly emitted when biomass is burned or coal is burned (primary PM2.5). But PM2.5 also comes from what are known as secondary particles, which are created when power plants emit sulfur dioxide, or nitrogen oxides are emitted from motor vehicles and power plants. These gases combine in the atmosphere with ammonia and other substances to form secondary particles. The graphs suggest that secondary are important sources of pollution—it will not be enough to control only the direct emission of fine particles. Again, the primary implication is that knowledge of the sources of ambient air pollution has important implications for control strategies, at the

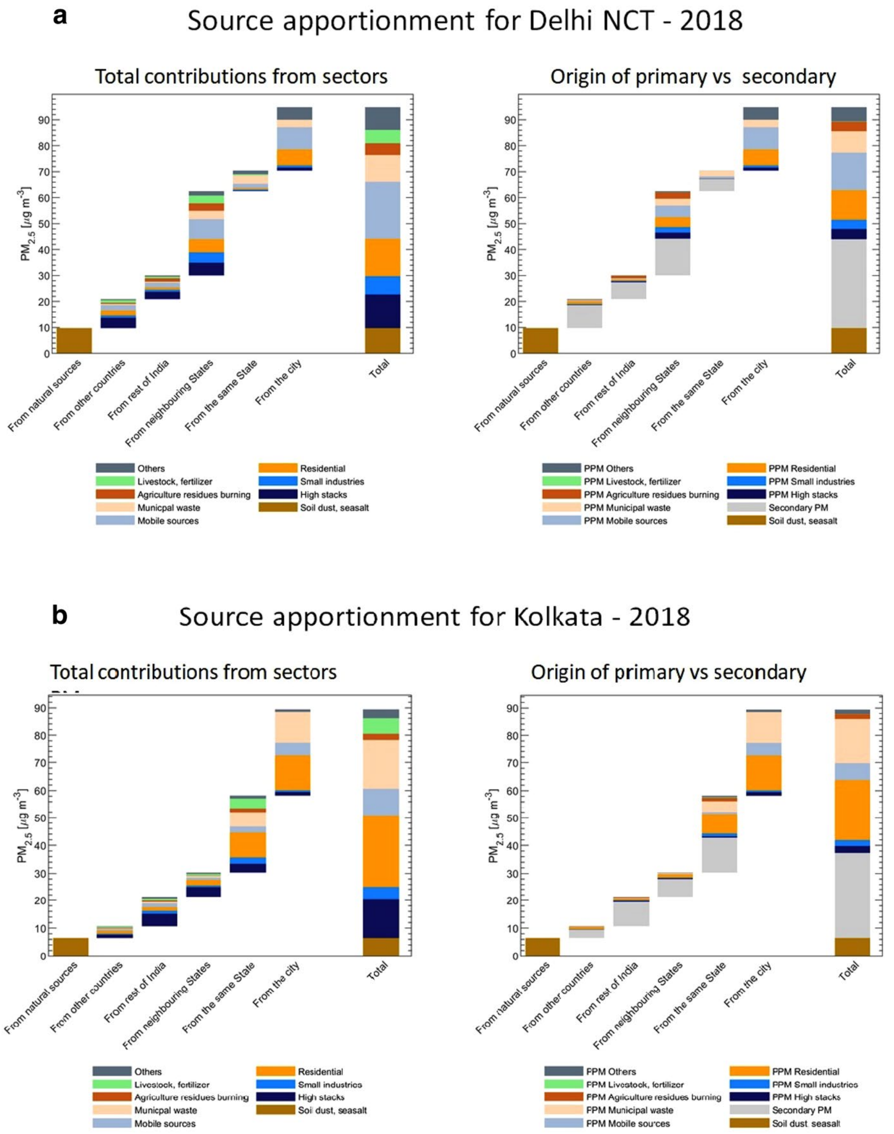

Fig. 10 **a** Source apportionment for Delhi NCT—2018. **b** Source apportionment for Kolkata—2018. Source: World Bank (2022)

appropriate level of government, to minimize leakage effects and spill overs. These methods of control also need to be cost effective.

5 Pollution control in the electricity sector

As seen in the previous section, power plants in India are a major source of ambient PM2.5. In 2015, about a third of greenhouse gas emissions came from coal-fired electricity generation. In 2018, there were a little over 200 gigawatts of coal-fired installed capacity. About 95 gigawatts were in the planning stages as of 2019, an increase in capacity of 50%. In 2018, coal-fired power plants generated 75% of electricity in India, although they constituted 56% of installed generation capacity. Much of existing capacity is concentrated in North and Central India, but much of the planned expansion is on the eastern coast. Figure 11 (Cropper et al., 2021b) presents a map of the location of current and planned installed capacity.

In this section, we quantify the benefits in terms of avoided CO_2 emissions and reduced PM2.5 mortality from not building the planned plants. We also examine the ability of pollution controls installed on coal-fired power plants to reduce local air pollution and ask whether they pass the benefit–cost test. The results in this section are based on our PNAS (Cropper et al., 2021a) work.

We have modeled the impacts of current (2018) and planned plants on ambient PM2.5 and, taking account of household exposure to solid fuels, the impact of power plants on health. We first constructed emission factors for each plant operating in 2018 and for plants that were in the planning stages in 2019. These were added to a baseline emissions inventory and ambient PM 2.5 was modeled at a 0.25 degree by 0.25 degree resolution. The modeled impacts on ambient air pollution are presented in Fig. 12 (Cropper et al., 2021a) with darker shades

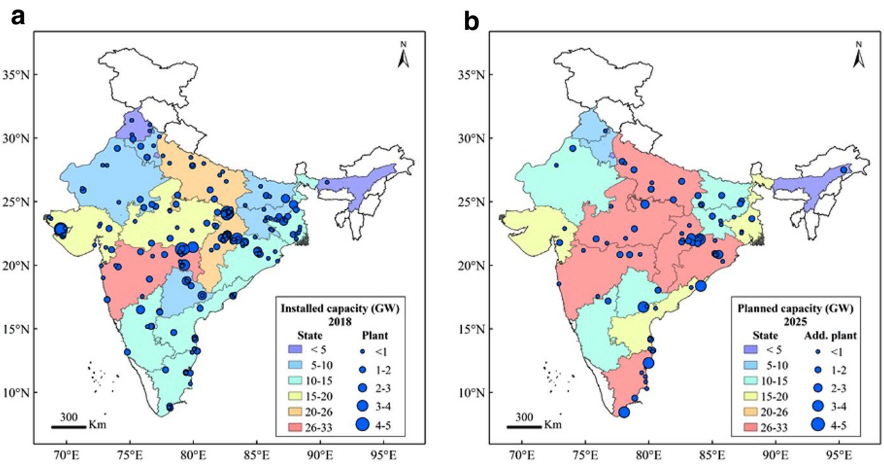

Fig. 11 Location of current and planned plants. **a** 2018 Plants. **b** New plants. Source: Cropper et al. (2021b)

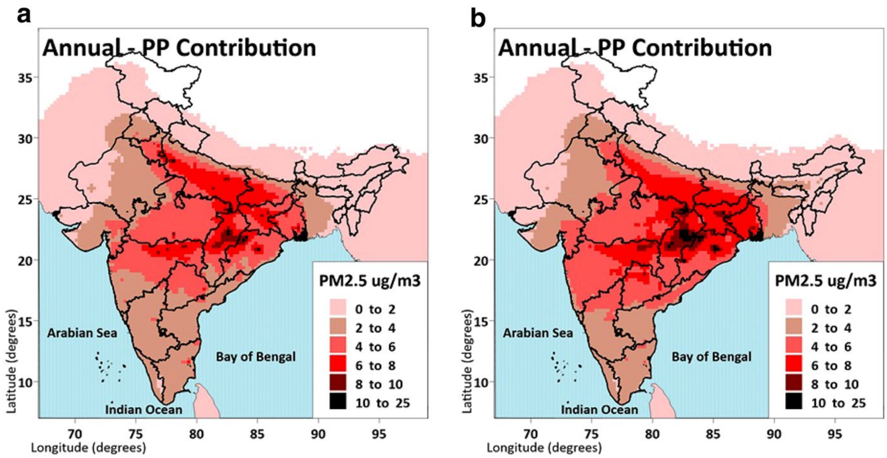

Fig. 12 Impact of plants on ambient PM2.5. **a** Impact of 2018 plants. **b** Impact of 2018 plants and new plants. Source: Cropper et al. (2021a)

representing more particulate matter coming from coal power plants. Note that Tamil Nadu, despite having planned increases in installed coal power plant capacity, does not contribute as much to increased emissions largely because of its location: emissions from plants located here blow into the Indian Ocean. Wind direction thus plays an important role in deaths attributable to coal-fired power plants.

Second, we computed health effects from power plants, using concentration response functions from the Global Burden of Disease applied to each grid cell. Deaths attributable to coal power plants were calculated as the fraction of the deaths caused by ambient PM2.5 multiplied by the fraction of ambient PM2.5 attributed to coal power plants. We estimated the aggregate number of deaths attributable to coal power plants in 2018 to be 78,000. Deaths attributable to coal-fired power plants would increase to 112,000 after planned plants were operating. To put these numbers in perspective, 7,444,000 people died in India in 2018.

We also quantified the premature mortality that could be *avoided* by not building the planned plants. We treated not building planned plants as a marginal decision—reducing concentrations of PM2.5 from a world in which current and future plants exist. In terms of health impacts, it is important to distinguish between attributable fractions and avoidable fractions, as these matter to the evaluation of alternative policies. Due to the concavity of exposure–response functions, deaths *avoidable* are much smaller than deaths *attributable* to planned plants. In the aggregate, of the 34,000 deaths attributable to planned plants (= 112,000–78,000 deaths), 19,000 deaths would be avoidable by not building planned plants. Note, however, that over 40-years plant lifetimes, deaths avoided will grow: both because of population growth and because of reductions in household air pollution exposure that move the impacts of power plants toward the steeper part of the concentration response function. At least 844,000 lives would be saved over 40 years by not building planned plants.

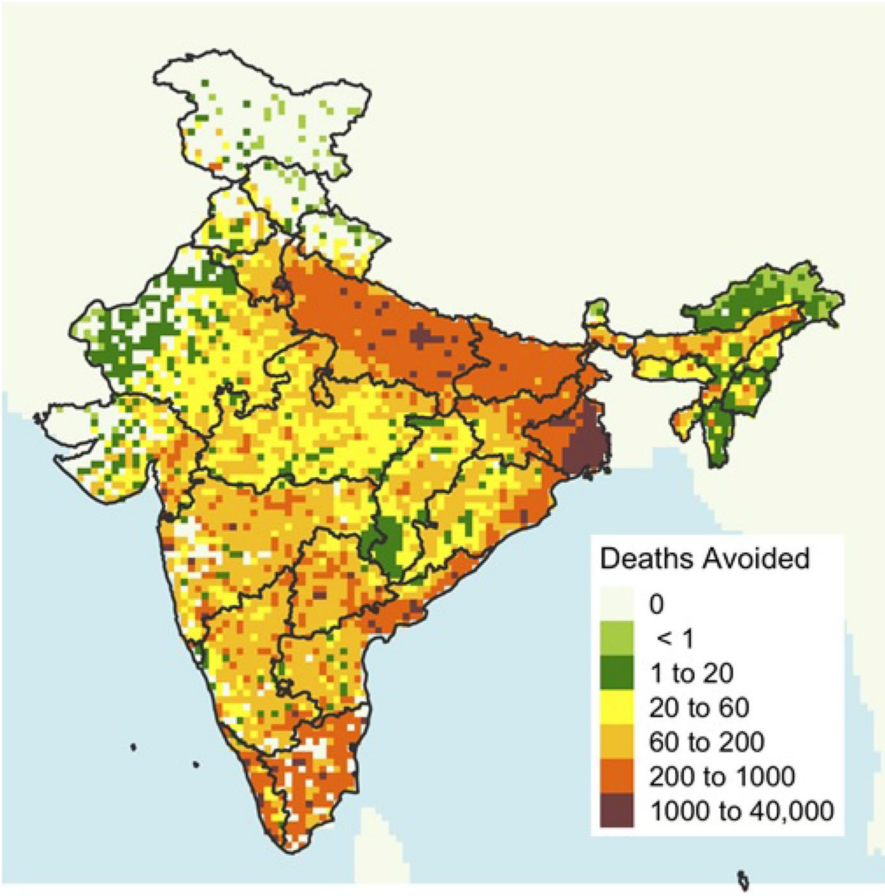

Fig. 13 Deaths avoidable by not building new plants, assuming 40-year plant life. Source: Cropper et al. (2021a)

Figure 13 (Cropper et al., 2021a) shows the avoidable deaths from not building planned plants, assuming they were to operate for 40 years. Effects vary by location: almost half the deaths avoided are in Uttar Pradesh, Bihar, and West Bengal. West Bengal and Bihar account for only ten gigawatts of planned capacity, but because of the way the wind blows and the fact that they are located downwind from areas where large increases in installed capacity are planned, they suffer disproportionately. States with 50% of planned capacity expansion account for only 20% of the deaths associated with planned plants.

The calculations we have presented thus far have been based on the actual usage of pollution control equipment in 2018. Another strategy that could be employed is to retrofit existing plants with flue gas desulfurization (FGD) units to reduce sulfur dioxide emissions and to use selective catalytic reduction (SCR) to reduce nitrogen dioxide emissions. Research suggests (Cropper et al., 2021a) that 70% of the deaths associated with both existing plants and new ones could be avoided by installing pollution controls.

In 2015, the Ministry of Environment, Forests and Climate Change issued stringent emissions standards (Ministry of Environment, Forest and Climate Change, 2015) for coal-fired power plants in India, but their implementation has been delayed. These emissions standards would, effectively, require installing FGDs on coal-fired plants. In the remainder of this section, we look at the costs and benefits of retrofitting coal-fired plants with pollution control equipment. This draws from our earlier work (Cropper et al., 2017) which looked at the costs and benefits of retrofitting all coal-fired power plants that were operating in 2008 with FGDs and a recent paper (Cropper et al., 2019) which calculated the benefits and costs of retrofitting plants at eight locations in India with a scrubber.

Both papers involved plant-by-plant analyses: modeling a given plant with and without a scrubber. We considered the effects of the scrubber on emissions, on ambient concentrations and on mortality, over the 20-years life of the equipment. To measure costs, we estimated the present value of the cost of installing and operating the equipment for 20 years. To measure benefits, we valued reductions in mortality using a value per statistical life (VSL)—the sum of what people would pay for small reductions in the probability of dying that together sum to one statistical life.

How is the value of a statistical life to be determined? A recent study in India (Chakravarty & Somanathan, 2021) recommends a value per statistical life that is 82 times per capita income. In 2013 dollars this translates into about $125,000 for the VSL in 2013. Another paper (Robinson et al., 2019) recommends 100 times per capita income, $152,000 in 2013 dollars. If the cost of saving a statistical life by installing is a scrubber is less than the VSL, then, on average, scrubbing passes the benefit–cost test.

We first looked at the impact of retrofitting 72 plants that operated in 2008 with scrubbers (Cropper et al., 2017). We estimated that the SO_2 emitted from the 72 plants resulted in approximately 18,000 deaths annually, of which 72% could be avoided by retrofitting scrubbers. (This assumed 90% scrubber efficiency and lags between emissions reductions and impacts on mortality.) These results are presented in Table 1. The number of lives saved by scrubbing (12,890) may seem small; however, the 72 plants accounted for only 68 gigawatts of installed capacity. The average cost per life saved was 131,000 USD. This masks considerable heterogeneity: the 30 plants with the lowest cost per life saved were in densely populated areas or

Table 1 Cost-effectiveness of FGD installation, 2008–2009. Source: Cropper et al. (2017)

	Annual lives saved	Annual cost (Mil.)	Average cost per life saved
72 Plants	12,890	$1691	$131,000
30 Plants with lowest CPLS	9196	$615	$67,000
30 Plants with most deaths	10,061	$965	$96,000
30 Largest plants (MW)	7901	$1164	$147,000

Cost unit: 2013 USD

areas where it was cheaper to install the scrubber. Focusing on these plants would have saved approximately 9000 lives, but would have cut the cost per life saved by half. Retrofitting the 30 largest plants would have saved approximately 8000 lives but would have raised the cost per life saved to $150,000. All these options met the benefit–cost test, although their cost-effectiveness varied.

This prompted us (Cropper et al., 2019) to explore the locations in India where retrofitting scrubbers would yield the largest net benefits. We did this by locating a model power plant in eight locations where there have been power plants: Dadri, Unchahar, Bakreswar, Talcher, Koradi, Dahanu, Rayalaseema, and Tuticorin (see Fig. 14). The costs of scrubbing vary by location (proximity to the sea), and the number of persons exposed to the plant varies with population density. Table 2 presents the benefit–cost ratios for each of these plants under various assumptions about the VSL and the discount rate used to compute the present value of costs and benefits. It is clear that

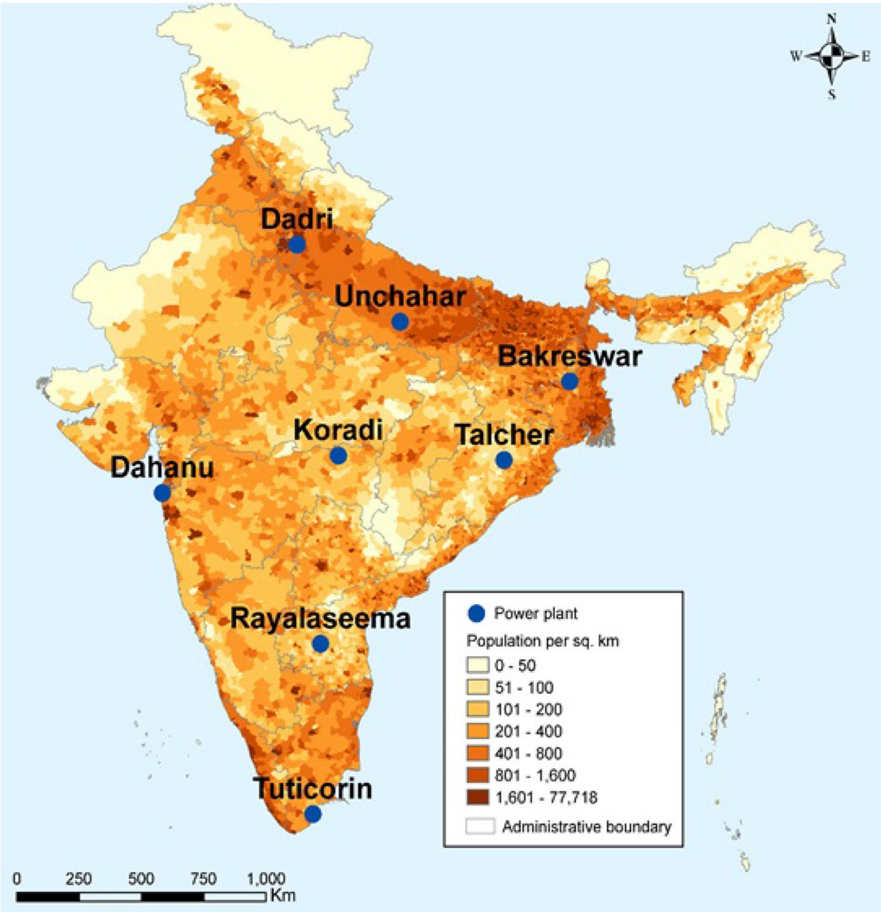

Fig. 14 Location of model plants. Source: Cropper et al. (2019)

Table 2 Benefit–cost ratios for FGD retrofits. Source: Cropper et al. (2019)

Plant name	VSL	\$160,000	\$256,000	\$256,000
	Discount rate	3%	3%	8%
Dadri		11	18	14
Unchahar		7.5	12	9.5
Bakreswar		3.4	5.5	4.3
Dahanu		2.4	3.8	3.0
Talcher		1.5	2.4	1.9
Koradi		1.0	1.6	1.3
Rayalaseema		0.56	0.89	0.70
Tuticorin		0.51	0.82	0.65

regardless of the VSL or the discount rate, plants in the Indo-Gangetic plain pass the benefit–cost test with high benefit–cost ratios. The Dahanu, Talcher and Koradi plants pass the benefit–cost test in all of the three cases shown here. But the plants in the south, which are not in as densely populated areas, do not pass the benefit–cost test. Note that benefits as calculated include only avoided mortality; not morbidity impacts, or impacts on agriculture or ecosystems. The Dahanu plant has actually been scrubbed for ecological reasons, by legal order. The benefit–cost ratios in Table 2 should be looked at as underestimates but do suggest where investments should be prioritized.

6 Concluding thoughts

This paper has answered five questions about the health benefits of controlling air pollution in India. With the exception of the power sector, we have not discussed the most effective policies for controlling air pollution or their costs. We have also not discussed what are the most politically acceptable methods of controlling different sources of air pollution. These questions should be addressed—and are being answered (World Bank, 2022; Greenstone et al., 2022). In addition to calculating the benefits of reducing air pollution, they are a necessary step in constructing cost-effective air pollution control strategies.

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Declarations

Conflict of interest The authors have no competing interests to declare that are relevant to the content of this article.

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