

# Economic-boom-driven electricity demand linked to urban air pollution and health in India

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Basudev Swain<sup>1</sup>✉, Aishwarya Singh<sup>2</sup>✉, Debashis Tripathy<sup>3</sup>, Rui Song<sup>1</sup>, Adrien Deroubaix<sup>4</sup>, Marco Vountas<sup>5</sup>✉, Pritanjali Shende<sup>6</sup>, Chenchen Huang<sup>7</sup>, Luca Lelli<sup>8</sup> & Ankit Tandon<sup>9</sup>

Rapid economic growth in India since 2000 has been accompanied by rising electricity demand and worsening urban air pollution. Here we show that a threefold increase in GDP per capita was associated with a nearly fourfold rise in electricity demand, with coal supplying approximately 76% of total generation. This coal-dependent expansion increased energy-sector SO<sub>2</sub> emissions and contributed to a twofold increase in urban aerosol loading, with sulfate accounting for approximately 46% of the urban aerosol burden. Urban PM<sub>2.5</sub>-attributable deaths increased from approximately 0.7 million in 2000 to 0.9 million in 2020, with increasing contributions from power-sector emissions. Meanwhile, rising incomes increased clean-cooking access from approximately 25% to 75%, accompanied by declining household air-pollution deaths but increasing outdoor air-pollution deaths. These findings highlight contrasting indoor and outdoor air-pollution health consequences of coal-dependent economic growth. This underscores the urgency of decarbonizing electricity generation to improve urban air quality and public health as well as maintaining sustainable economic growth.

Over the past three decades, India has undergone rapid economic growth, particularly following the economic reforms initiated in 1991, which accelerated industrialization, liberalized trade, and expanded domestic and global markets<sup>1–3</sup>. These reforms marked a structural shift in India's economy, setting the stage for sustained increases in productivity, income and consumption. As economic activity expanded, India experienced rapid urbanization, with population and economic production increasingly concentrated in and around major cities<sup>1,2,4</sup>. This urban transition reshaped patterns of energy use, as industrial output, commercial activity and household consumption intensified in urban areas<sup>5–7</sup>.

Together, economic growth and urbanization have driven a sharp and sustained rise in electricity demand across industrial, commercial and residential sectors, making reliable electricity supply a central pillar of India's development model and a key constraint on continued economic expansion<sup>7–10</sup>. To meet this growing energy demand, India has relied predominantly on coal-based electricity generation. Despite recent growth in renewable capacity, coal remains the backbone of India's power sector, supplying the majority of electricity consumed nationwide<sup>7,11–13</sup>. As electricity consumption increased, coal-fired thermal power plants expanded generation along the extensive margins of the electricity system, frequently operating at higher capacity

<sup>1</sup>NCEO, Atmospheric, Oceanic and Planetary Physics, University of Oxford, Oxford, UK. <sup>2</sup>Aerosol Chemistry Department, Max Planck Institute for Chemistry, Mainz, Germany. <sup>3</sup>Yusuf Hamied Department of Chemistry, University of Cambridge, Cambridge, UK. <sup>4</sup>Max-Planck-Institut für Meteorologie, Hamburg, Germany. <sup>5</sup>Institute of Environmental Physics, University of Bremen, Bremen, Germany. <sup>6</sup>Department of Civil Engineering, Indian Institute of Technology Hyderabad, Hyderabad, India. <sup>7</sup>School of Management, University of Bath, Bath, UK. <sup>8</sup>Remote Sensing Technology Institute, German Aerospace Centre (DLR), Wessling, Germany. <sup>9</sup>Department of Environmental Sciences, Central University of Jammu, Samba, India.

✉e-mail: [basudev.swain@physics.ox.ac.uk](mailto:basudev.swain@physics.ox.ac.uk); [a.singh@mpic.de](mailto:a.singh@mpic.de); [vountas@iup.physik.uni-bremen.de](mailto:vountas@iup.physik.uni-bremen.de)

utilization to meet short-run demand fluctuations<sup>7,14</sup>. These plants emit large quantities of air pollutants, including sulfur dioxide (SO<sub>2</sub>), nitrogen oxides, black carbon (BC) and organic carbon (OC), which play a central role in shaping ambient air pollution<sup>15,16</sup>.

SO<sub>2</sub> emissions from coal combustion are of particular importance, as they undergo atmospheric oxidation to form sulfate aerosols, one of the dominant components of fine particulate matter (PM<sub>2.5</sub>) in India<sup>8,17–19</sup>. Sulfate aerosols persist in the atmosphere and are transported over large spatial scales, contributing to regional haze and widespread population exposure<sup>17–20</sup>. In addition, the incomplete combustion of coal produces BC and OC aerosols, which further increase air pollutant concentrations, degrade visibility and exacerbate cardiopulmonary health risks<sup>20,21</sup>. Together, these primary emissions and secondary aerosol formation processes link coal-based electricity generation to urban and regional air pollution far beyond the immediate vicinity of power plants<sup>20–23</sup>.

Paradoxically, although India continues to achieve rapid economic growth, air pollution across its urban regions has worsened over time, emerging as one of the most severe environmental threats to human health<sup>20,21,23</sup>. Economic growth has expanded population access to electricity and accelerated its adoption for household energy needs, facilitating a transition away from traditional solid fuels (such as wood, dung and coal) for cooking and reducing exposure to harmful indoor air pollution<sup>7,14</sup>. At the same time, the coal-based electricity system required to sustain this growth has increased emissions of SO<sub>2</sub>, BC, OC and secondary particulate matter, degrading outdoor air quality and elevating population exposure to outdoor air pollution, particularly in densely populated urban areas<sup>20,21,23</sup>.

Thus, it is critical to understand the extent to which surging electricity demand met largely by coal-fired thermal power plants during this ongoing period of rapid economic expansion has contributed to worsening urban air pollution and adverse health outcomes. This dual transition of reduced indoor air pollution alongside rising outdoor ambient pollution driven by sulfate-rich and carbonaceous aerosols from coal combustion creates complex and heterogeneous exposure patterns that are central to evaluating the environmental consequences of India's economic development pathway.

Understanding this trade-off is essential for assessing the sustainability of economic growth under a fossil-fuel-dependent energy system. It is worth noting that although numerous studies have examined air pollution sources, atmospheric processes and their associated health impacts across India<sup>8,20–26</sup>, there remains a critical gap in quantitatively connecting rapid economic growth, urbanization, electricity demand, coal-based electricity generation, SO<sub>2</sub> emissions, electricity access, clean-cooking transitions, air pollution and health outcomes within a single analytical study. As India undergoes one of the world's largest socioeconomic and energy transitions<sup>7,11,12</sup>, understanding how these interconnected processes evolve simultaneously is critical for evaluating the environmental and health consequences of rapid economic development.

To address this knowledge gap, we provide a comprehensive, unprecedented cross-sectoral approach of how growth-driven electricity demand propagates through the energy system to influence air pollution and human health across urban India. We show that electricity demand increased nearly fourfold after 2000, whereas coal consistently supplied approximately 76% of the total electricity generation. This expansion was accompanied by a substantial deterioration in urban air quality, with aerosol loading increasing from less than 0.2 to more than 0.4 and sulfate aerosols accounting for approximately 46% of the total aerosol burden. Simultaneously, rising incomes and increasing access to clean-cooking fuels and technologies, including natural gas, clean cookstoves and electricity-expanded clean-cooking adoption from approximately 25% of the population in 2000 to more than 75% in 2020. This transition contributed to a reduction in household air-pollution deaths from approximately 1.25 million in 2000 to 1.05 million in 2020. However, deaths attributable to ambient air pollution increased sharply from approximately 0.3 million to nearly

1.0 million over the same period, offsetting much of these indoor health gains, whereas urban air-pollution-related deaths increased from approximately 0.7 million to 0.9 million.

Together, these findings reveal a previously underappreciated environmental and health cost of growth-driven, coal-dependent electrification and underscore the importance of aligning economic development with rapid decarbonization of the power sector to protect urban air quality, public health and sustainable future growth.

## Results

### Rapid economic growth surges electricity demand and coal-driven thermal power plant expansion

India's rapid economic growth following the 1991 economic reforms was accompanied by a profound transformation of its energy system, with GDP per capita, electricity demand and electricity generation accelerating particularly after 2000 (Fig. 1a). GDP per capita increased from approximately US\$600–700 in 2000 to more than US\$2,000 by 2020, whereas electricity demand rose nearly fourfold from approximately 450 TWh to almost 2,000 TWh. Electricity generation increased at a similar rate, indicating that growing demand was met largely through increased domestic production. Over the same period, population access to electricity increased from approximately 60% to more than 95%, whereas urban aerosol optical depth (AOD) increased from less than 0.2 to more than 0.4 (Fig. 1a).

The increase in electricity demand was met predominantly through coal-based generation, which consistently supplied approximately 75%–80% of the total electricity production (Fig. 1b). In 2020, coal accounted for 75.9% of generation, followed by hydropower (7.7%), wind (6.6%), solar (4.0%), nuclear energy (2.8%), natural gas (2.7%) and oil (0.2%). Although renewable generation expanded substantially after 2010, coal remained the principal source of electricity supporting demand growth.

Coal-fired power infrastructure expanded accordingly (Fig. 1c). India operated 71 coal-fired power plants before 2000, with an additional 182 commissioned during 2001–2024, bringing the total to 253 by 2024. These facilities are concentrated predominantly across the Indo-Gangetic Plain and the Horseshoe Belt, which also encompass major urban agglomerations, industrial centers and economic corridors. Between 2000 and 2020, these regions experienced substantial population and urban growth, with population-density increases exceeding 300–500 persons per square kilometer in several areas, alongside pronounced increases in GDP (purchasing power parity (PPP)) (Fig. 1d). The spatial overlap among population growth, urbanization, economic activity and coal-fired power infrastructure places rapidly growing urban populations in proximity to major power-sector emission sources.

The relationship between economic growth and electricity demand is further supported by the econometric analysis described in the Methods section. The log–linear regression shows a highly significant positive relationship between GDP per capita and electricity demand ( $\beta = 1.139$ , 95% confidence interval (CI) of 1.112–1.167,  $P < 0.001$ ; Supplementary Table 2), with high explanatory power ( $R^2 = 0.996$  and adjusted  $R^2 = 0.996$ ). Specifically, a 1% increase in GDP per capita was associated with an approximately 1.14% increase in electricity demand, indicating that electricity consumption increased slightly faster than economic output. These temporal, spatial and statistical relationships show that India's post-2000 economic expansion was accompanied by rapidly increasing electricity demand that was met predominantly through continued reliance on coal-fired generation.

### Sulfate aerosols dominate the increase in urban aerosol loading

The aerosol products were evaluated against independent ground-based observations across major urban regions of India (Methods and Supplementary Figs. 1–4). Modern-Era Retrospective Analysis for Research and Applications, version 2 (MERRA-2) reproduced Aerosol Robotic

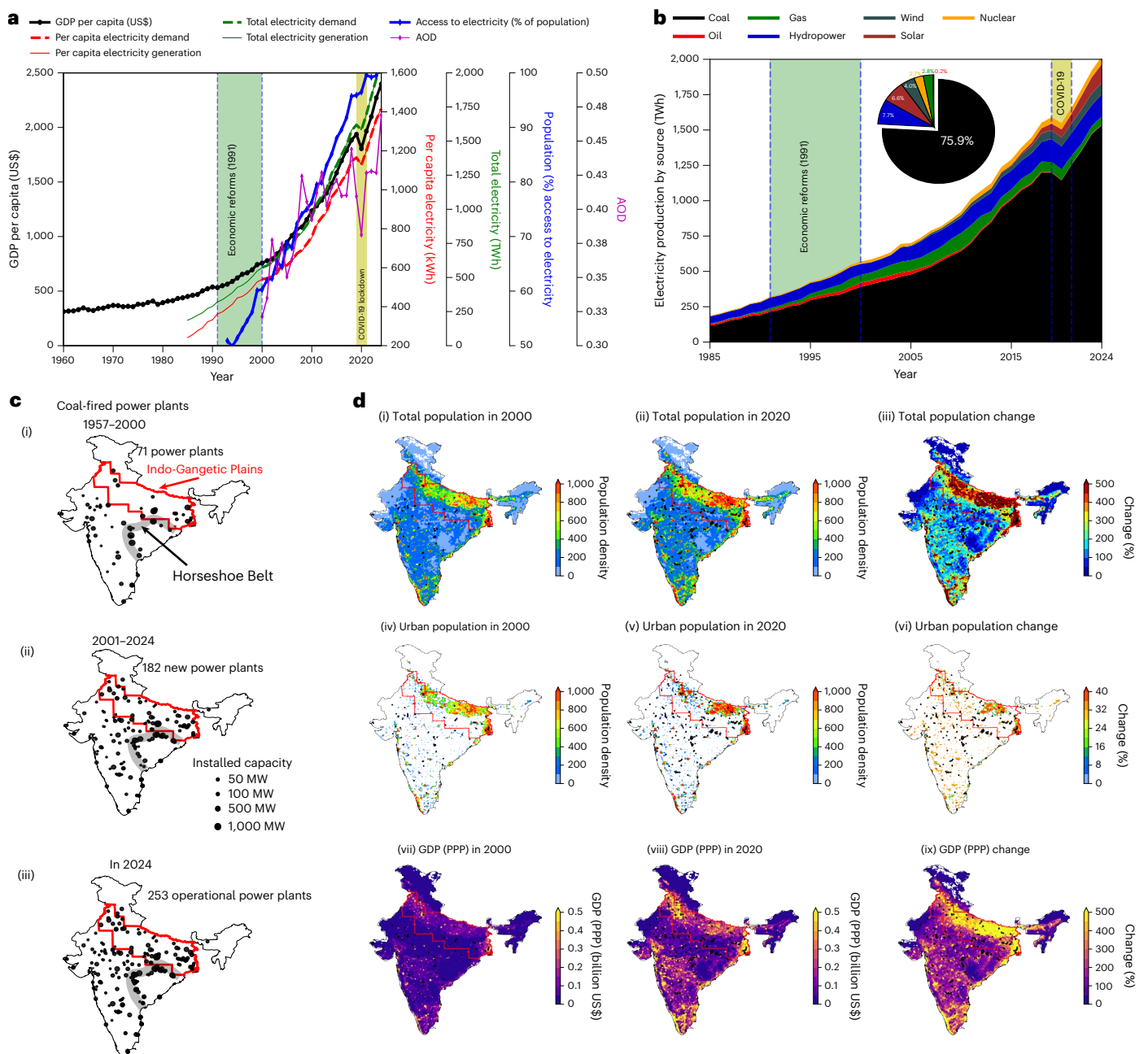


**Fig. 1 | Economic expansion drives rapid growth in electricity demand and coal-based power generation in India. a**, Post-reform acceleration of economic growth following the implementation of the 1991 economic reforms, reflected in rising GDP per capita, electricity demand and generation, expanding population access to electricity and increasing urban AOD. **b**, Electricity generation by source from 1985 to 2024, highlighting the persistent dominance of coal despite the expansion of renewable energy capacity. The pie chart in the inset shows the composition of electricity generation in 2020, with coal contributing approximately 76% of total generation. **c**, Spatial distribution of coal-fired power plants commissioned before 2000 (i), showing 71 operational power plants;

between 2001 and 2024 (ii), showing 182 newly commissioned power plants; and the cumulative distribution of operational power plants in 2024 (iii), totaling 253 facilities. Coal-fired power plants are concentrated within the Indo-Gangetic Plain and the Horseshoe Belt, two major economic and population corridors of India. **d**, Spatial distribution of total population, urban population and economic activity (GDP in PPP units) in 2000 and 2020, together with their corresponding changes over the study period. Regions experiencing the largest increases in population, urbanization and economic activity coincide with areas characterized by dense coal-fired power infrastructure, highlighting the strong spatial coupling between economic growth, urban expansion and electricity demand.

Network (AERONET) AOD with relatively high agreement ( $R^2 = 0.73$ ,  $RMSE = 0.12$ ,  $N = 415$ ), whereas GEOS-Chem showed strong agreement with available observations ( $R^2 = 0.92$ ,  $RMSE = 0.05$ ,  $N = 13$ ) and Moderate Resolution Imaging Spectroradiometer Multi-Angle Implementation of Atmospheric Correction (MAIAC) also captured the observed variability ( $R^2 = 0.65$ ,  $RMSE = 0.15$ ,  $N = 388$ ) (Supplementary Fig. 2). Intercomparison among MODIS, MERRA-2, GEOS-Chem and CMIP6 further showed

consistent urban aerosol loading, with strong agreement between MERRA-2 and GEOS-Chem AOD ( $R^2 = 0.84$ ; Supplementary Fig. 3), supporting the robustness of the observed long-term changes.

Urban AOD increased markedly during the period of rapid economic and electricity-demand growth (Fig. 2a). Before 1950, urban AOD remained approximately 0.15–0.18 and increased gradually through 1990. After 2000, AOD rose sharply, exceeding 0.3 by the mid-2000s

and reaching approximately 0.42–0.45 by 2024. A temporary decline during the 2020 COVID-19 lockdowns was followed by a rapid rebound, consistent with the strong influence of anthropogenic activity on urban aerosol loading.

Sulfate aerosols dominated this increase (Fig. 2b(i),(ii)). Their contribution to the total urban AOD increased from approximately 35.5% in 2000 to 46.4% in 2020, whereas dust declined from 30.4% to 21.5%. Organic aerosol contributions remained comparatively stable (19.8% to 18.6%), whereas BC accounted for 8.4% and 7.8% in 2000 and 2020, respectively; sea salt contributed 5.9% in 2000. The increasing sulfate fraction is consistent with rising  $\text{SO}_2$  emissions associated with the expansion of coal-based electricity generation.

Spatially, MERRA-2 AOD increased from generally below 0.15 in 2000 to approximately 0.35–0.45 across extensive urban regions of northern and eastern India by 2020, with absolute increases of 0.05–0.10 and relative increases of 30% to more than 100% across major urban corridors (Fig. 2b(i)–(iv)). Independent MODIS MAIAC observations show comparable increases, frequently exceeding 30%–50% across the Indo-Gangetic Plain and the Horseshoe Belt (Fig. 2b(v)–(viii)). GEOS-Chem sectoral simulations further attribute a substantial fraction of this growth to power-sector emissions: power-sector AOD increased from generally below 0.08 in 2000 to more than 0.16–0.20 across large parts of northern and eastern India by 2020, with relative increases exceeding 200% in several urban regions (Fig. 2b(ix)–(xii)). The largest changes coincide with dense clusters of large coal-fired power plants ( $\geq 1,500$  MW).

Statistically significant urban AOD trends during 2000–2023 similarly concentrate over the Indo-Gangetic Plain and central and eastern India, reaching approximately +0.02 to +0.04 AOD per decade, compared with generally less than +0.01 AOD per decade or insignificant trends across southern and less industrialized regions (Fig. 2b(xiii)–(xvi)). GEOS-Chem simulations indicate that industrial emissions also contributed substantially to aerosol growth, particularly across northern and eastern urban regions, whereas transportation-related AOD remained comparatively small and localized around major metropolitan areas (Supplementary Fig. 5).

Aerosol composition further supports the predominance of anthropogenic sources (Supplementary Fig. 6). Dust and sea-salt AOD changed relatively little between 2000 and 2020, generally by less than 0.05 in absolute magnitude and 20% in relative terms. By contrast, BC AOD increased locally by approximately 0.01 and OC AOD by up to 0.04, with relative increases exceeding 60% across parts of northern and central India. These increases expanded across the Indo-Gangetic Plain and the Horseshoe Belt alongside the growth of coal-fired power infrastructure.

Together, the observational, reanalysis and model results show that the post-2000 increase in urban aerosol loading was dominated by sulfate and concentrated across regions with dense coal-fired power infrastructure, supporting a major contribution from growth-driven coal-based electricity generation.

### Power-sector $\text{SO}_2$ emissions drive sulfate aerosol growth

The increasing dominance of sulfate in urban aerosol loading suggests an important role for sulfur emissions from coal combustion (Fig. 2).

We, therefore, examined changes in sulfate aerosol optical depth ( $\text{SO}_4$  AOD), satellite-derived  $\text{SO}_2$  and GEOS-Chem sectoral contributions (Fig. 3).

MERRA-2 shows a substantial increase in urban sulfate AOD between 2000 and 2020 (Fig. 3a(i)–(iv)). Values generally below 0.05–0.10 in 2000 increased to more than 0.10–0.15 across northern and eastern India by 2020, locally approaching 0.20. Absolute increases exceeded 0.05–0.10 across large portions of the Indo-Gangetic Plain and eastern India, whereas relative increases frequently exceeded 50%–100%, indicating a doubling of sulfate loading across many urban regions. The strongest increases coincide with dense clusters of coal-fired power plants.

Independent TROPospheric Monitoring Instrument (TROPOMI) observations reveal pronounced  $\text{SO}_2$  hotspots across the same regions (Fig. 3a(v),(vi)).  $\text{SO}_2$  columns frequently exceed 0.3–0.5 DU across the Indo-Gangetic Plain, eastern India and the Horseshoe Belt, with local urban enhancements exceeding 0.5 DU near clusters of large coal-fired power plants ( $>1,500$  MW). Their spatial correspondence with elevated sulfate AOD provides independent observational evidence linking sulfur-emission hotspots with increasing sulfate aerosol loading.

Sulfate AOD trends during 2000–2023 are persistent and statistically significant across northern and eastern urban India, frequently reaching +0.02 to +0.04 AOD per decade and locally approaching +0.06 AOD per decade (Fig. 3a(vii),(viii)). By contrast, southern urban regions generally exhibit trends below +0.01 AOD per decade or statistically insignificant changes. The close correspondence between sulfate and total AOD trends (Fig. 2b(xiii),(xvi)) indicates that secondary sulfate formation is a major contributor to the long-term increase in urban aerosol loading.

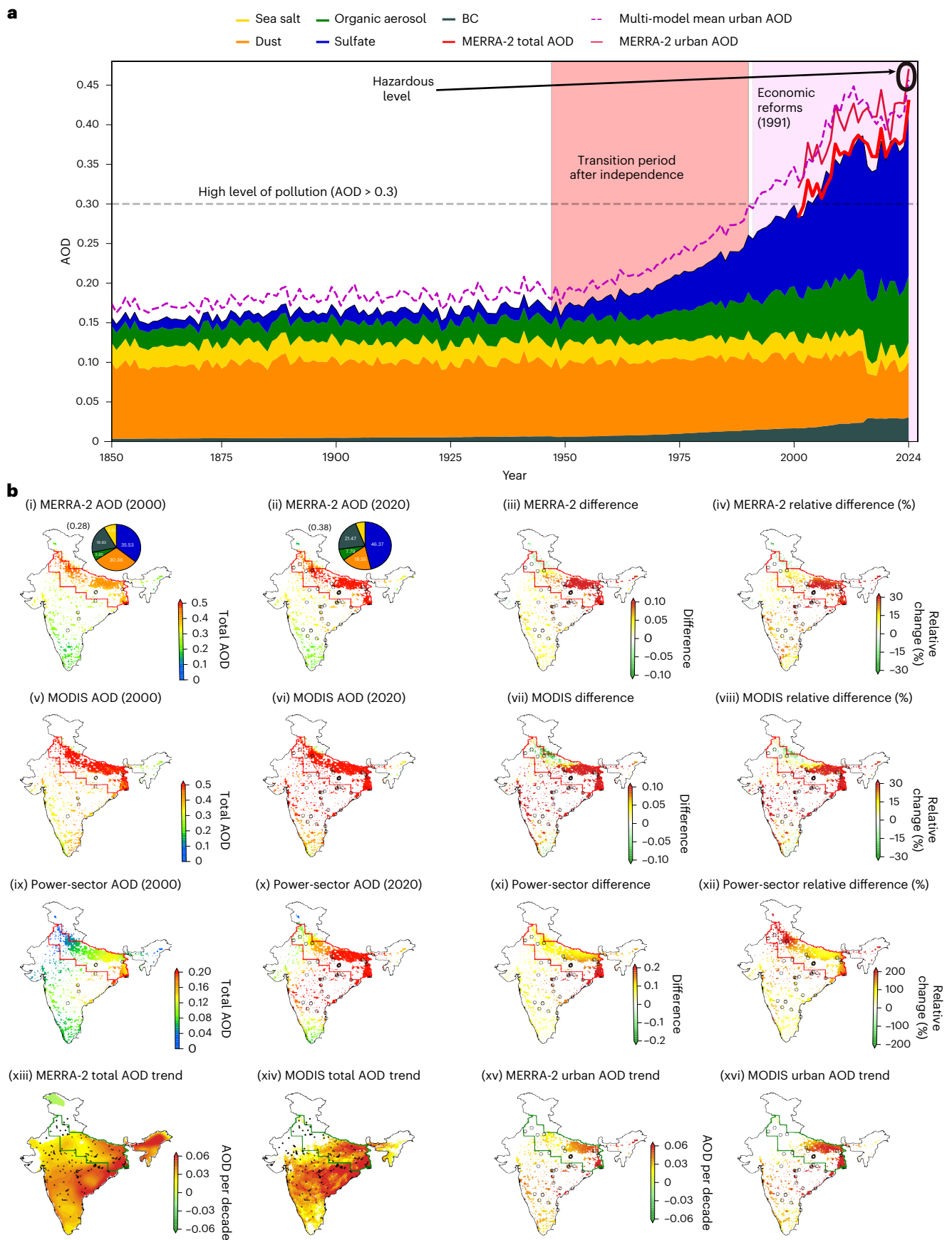
GEOS-Chem sectoral simulations further quantify the contribution of power-sector emissions (Fig. 3b). The power-sector contribution to total urban AOD increased from approximately 16% in 2000 to 36% in 2020, becoming the largest anthropogenic contributor, whereas industry accounted for approximately 32% in 2020. Between 2000 and 2020, power-sector and industrial AOD increased by approximately 125% and 130%, respectively, whereas transportation and other sectors showed comparatively smaller changes (Fig. 3b(i)–(iii)). Together with the comparatively small changes in dust and sea salt and increases in combustion-related aerosols (Supplementary Fig. 6), these results identify power-sector sulfur emissions as a major contributor to sulfate aerosol growth over urban India and establish a mechanistic pathway linking growth-driven electricity demand, coal combustion,  $\text{SO}_2$  emissions and increasing urban aerosol loading.

### Expansion of coal-based electricity generation increases urban $\text{PM}_{2.5}$ exposure

MERRA-2 and GEOS-Chem  $\text{PM}_{2.5}$  were evaluated against independent Central Pollution Control Board (CPCB) observations and through direct intercomparison (Methods and Supplementary Figs. 2(iv),(v) and 3(v)). Both products reproduce observed urban  $\text{PM}_{2.5}$  variability, with GEOS-Chem showing slightly stronger agreement ( $R^2 = 0.57$ ,  $\text{RMSE} = 28.67 \mu\text{g m}^{-3}$ ,  $N = 95$ ) than MERRA-2 ( $R^2 = 0.51$ ,  $\text{RMSE} = 52.72 \mu\text{g m}^{-3}$ ,  $N = 372$ ) (Supplementary Fig. 2(iv),(v)). MERRA-2 and

**Fig. 2 | Coal-based electricity generation intensifies urban aerosol loading across India. a**, Long-term evolution of urban AOD from 1850 to 2024, showing the temporal evolution of total aerosol loading and its major components derived from CMIP6 and MERRA-2. Sulfate aerosols emerge as the dominant contributor to the post-2000 increase in urban AOD, coinciding with rapid economic growth and expansion of coal-based electricity generation. The dashed line indicates the high-pollution threshold (AOD = 0.3), whereas the shaded region highlights the transition period following Indian independence. **b**, Spatial distribution of total AOD from MERRA-2 ((i)–(iv)), MODIS MAIAC ((v)–(viii)) and GEOS-Chem power-sector AOD ((ix)–(xii)) for 2000 and 2020, together with their absolute and relative changes. Pi charts show the fractional contribution of

major aerosol species to the total AOD in 2000 and 2020. The strongest increases in aerosol loading occur over the Indo-Gangetic Plain and the Horseshoe Belt, regions characterized by dense coal-fired power infrastructure and rapid urban growth. Spatial trends in total AOD derived from MERRA-2 (xiii) and MODIS MAIAC (xiv), together with trends in urban AOD from MERRA-2 (xv) and MODIS MAIAC (xvi). Only statistically significant trends ( $P < 0.05$ ) are shown. Consistent positive trends across independent satellite, reanalysis and model products indicate a widespread increase in aerosol loading over urban regions during the study period. The black circles indicate the locations of large coal-fired power plants with installed capacities exceeding 1,500 MW, illustrating the expansion of major power-generation infrastructure between 2000 and 2020.



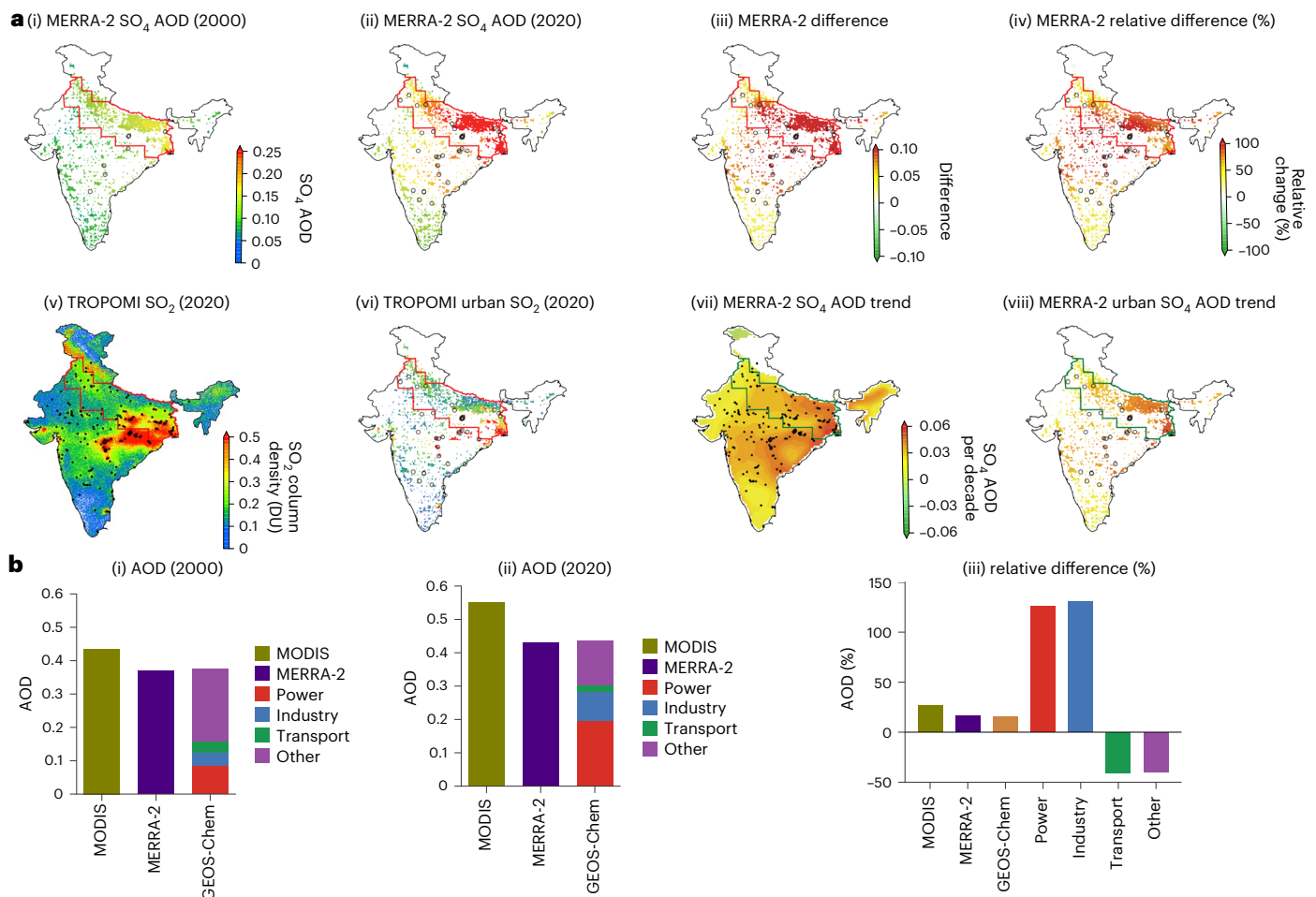


**Fig. 3 | Power-sector emissions drive the increase in sulfate aerosols and urban aerosol loading across India.** **a**, Spatial distribution of SO<sub>4</sub> AOD from MERRA-2 in 2000 and 2020 ((i) and (ii)), together with their absolute and relative changes ((iii) and (iv)). TROPOMI SO<sub>2</sub> column density observations for 2020 (v) and urban SO<sub>2</sub> distributions (vi) highlight major sulfur-emission hotspots associated with coal-based electricity generation. Statistically significant trends in total sulfate AOD and urban sulfate AOD during 2000–2023 ((vii) and (viii)). Only statistically significant trends ( $P < 0.05$ ) are shown. The largest increases in sulfate aerosol loading occur over the Indo-Gangetic Plain and the Horseshoe Belt, coinciding with regions of dense coal-fired power infrastructure and elevated SO<sub>2</sub> concentrations. **b**, Comparison of total AOD derived from

MODIS, MERRA-2 and GEOS-Chem for 2000 (i) and 2020 (ii), together with the sectoral decomposition of GEOS-Chem AOD. Relative change in total AOD and the contribution of individual emission sectors between 2000 and 2020 (iii). Power-sector and industrial emissions exhibit the largest increases in aerosol loading, whereas transportation and other sectors contribute comparatively smaller changes. The strong correspondence between sulfate AOD, TROPOMI SO<sub>2</sub> observations and GEOS-Chem source attribution indicates that coal-based electricity generation is a major contributor to the observed increase in urban aerosol loading over India. The black circles indicate the locations of large coal-fired power plants with installed capacities exceeding 1,500 MW, illustrating the expansion of major power-generation infrastructure between 2000 and 2020.

GEOS-Chem also show strong consistency in urban PM<sub>2.5</sub> spatial patterns ( $R^2 = 0.81$ ; Supplementary Fig. 3(v)), supporting their use for long-term trend and sectoral analyses.

Consistent with the increase in sulfate-rich aerosol loading (Figs. 2 and 3), mean urban PM<sub>2.5</sub> increased from approximately 35–38  $\mu\text{g m}^{-3}$  in 2000 to more than 40–45  $\mu\text{g m}^{-3}$  by 2020, with several years after 2015 exceeding 45  $\mu\text{g m}^{-3}$  (Fig. 4a). Sulfate remained one of the largest PM<sub>2.5</sub> components and exhibited the strongest increase. Urban PM<sub>2.5</sub> temporarily declined during the 2020 COVID-19 lockdowns before rebounding, consistent with the response observed for aerosol loading.

Spatially, MERRA-2 PM<sub>2.5</sub> increased from generally below 30–40  $\mu\text{g m}^{-3}$  across many urban regions in 2000 to more than 60–80  $\mu\text{g m}^{-3}$  across extensive areas of northern and eastern India by 2020, substantially exceeding national and World Health Organization air-quality guidelines<sup>27</sup> (Fig. 4b(i)–(iv)). Absolute increases frequently exceeded 10–20  $\mu\text{g m}^{-3}$  and relative increases reached 20%–50%, with the largest changes concentrated across the Indo-Gangetic Plain and the Horseshoe Belt.

GEOS-Chem sectoral simulations attribute a substantial fraction of this increase to power-sector emissions (Fig. 4b(v)–(viii)). Power-sector PM<sub>2.5</sub> increased from generally below 5  $\mu\text{g m}^{-3}$  in 2000 to 10–20  $\mu\text{g m}^{-3}$  across large portions of northern and eastern India by 2020, locally approaching 20–25  $\mu\text{g m}^{-3}$ . Absolute increases frequently exceeded 5–10  $\mu\text{g m}^{-3}$ , whereas relative increases reached 100%–400% in several urban regions, particularly near dense clusters of large coal-fired power plants ( $\geq 1,500$  MW).

Statistically significant PM<sub>2.5</sub> trends during 2000–2023 are similarly concentrated across northern and eastern India, frequently exceeding +5 to +10  $\mu\text{g m}^{-3}$  per decade in major urban and thermal power corridors, with weaker trends across southern and less industrialized regions (Fig. 4b(ix),(x)). Their spatial correspondence with sulfate trends (Fig. 3a(vii),(viii)) further supports an important contribution from secondary sulfate formation to increasing urban PM<sub>2.5</sub>.

Sectoral attribution further shows that the overall 2000–2020 PM<sub>2.5</sub> increase of approximately 20%–30% in GEOS-Chem is broadly consistent with MERRA-2, but differs markedly among sectors

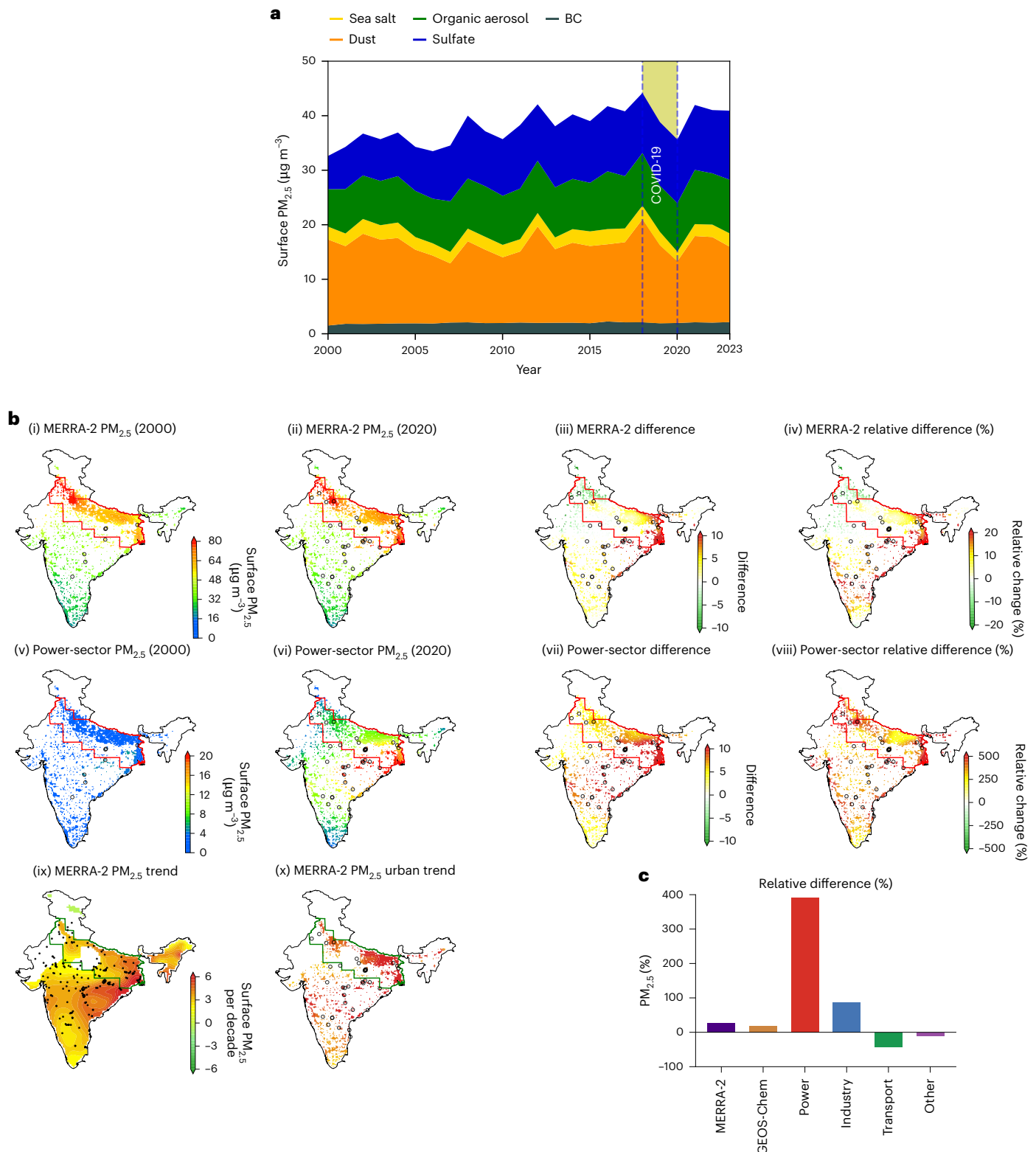


**Fig. 4 | Power-sector emissions substantially increase urban  $PM_{2.5}$  concentrations across India. a**, Temporal evolution of surface  $PM_{2.5}$  concentrations and their major aerosol components derived from MERRA-2 during 2000–2023. Sulfate aerosols constitute a major fraction of the total  $PM_{2.5}$  and exhibit a pronounced increase during the period of rapid economic growth, with a temporary decline during the COVID-19 lockdown period. **b**, Spatial distribution of surface  $PM_{2.5}$  concentrations from MERRA-2 in 2000 and 2020 ((i) and (ii)), together with their absolute and relative changes ((iii) and (iv)). GEOS-Chem-derived  $PM_{2.5}$  attributable to power-sector emissions in 2000 and 2020 and the corresponding absolute and relative changes ((v)–(viii)). Statistically significant trends in total  $PM_{2.5}$  and urban  $PM_{2.5}$  during 2000–2023 ((ix) and (x)).

Only statistically significant trends ( $P < 0.05$ ) are shown. Black circles indicate the locations of large coal-fired power plants with installed capacities exceeding 1,500 MW operating in 2000 and 2020, respectively. The largest increases in  $PM_{2.5}$  concentrations occur over the Indo-Gangetic Plain and the Horseshoe Belt, coinciding with regions characterized by dense coal-fired power infrastructure and rapid urban expansion. **c**, Relative changes in total  $PM_{2.5}$  concentrations derived from MERRA-2 and GEOS-Chem between 2000 and 2020 together with the sectoral decomposition of GEOS-Chem  $PM_{2.5}$ . Power-sector emissions exhibit the largest increase in  $PM_{2.5}$  burden, followed by industrial emissions, whereas transportation and other sectors contribute comparatively smaller changes.

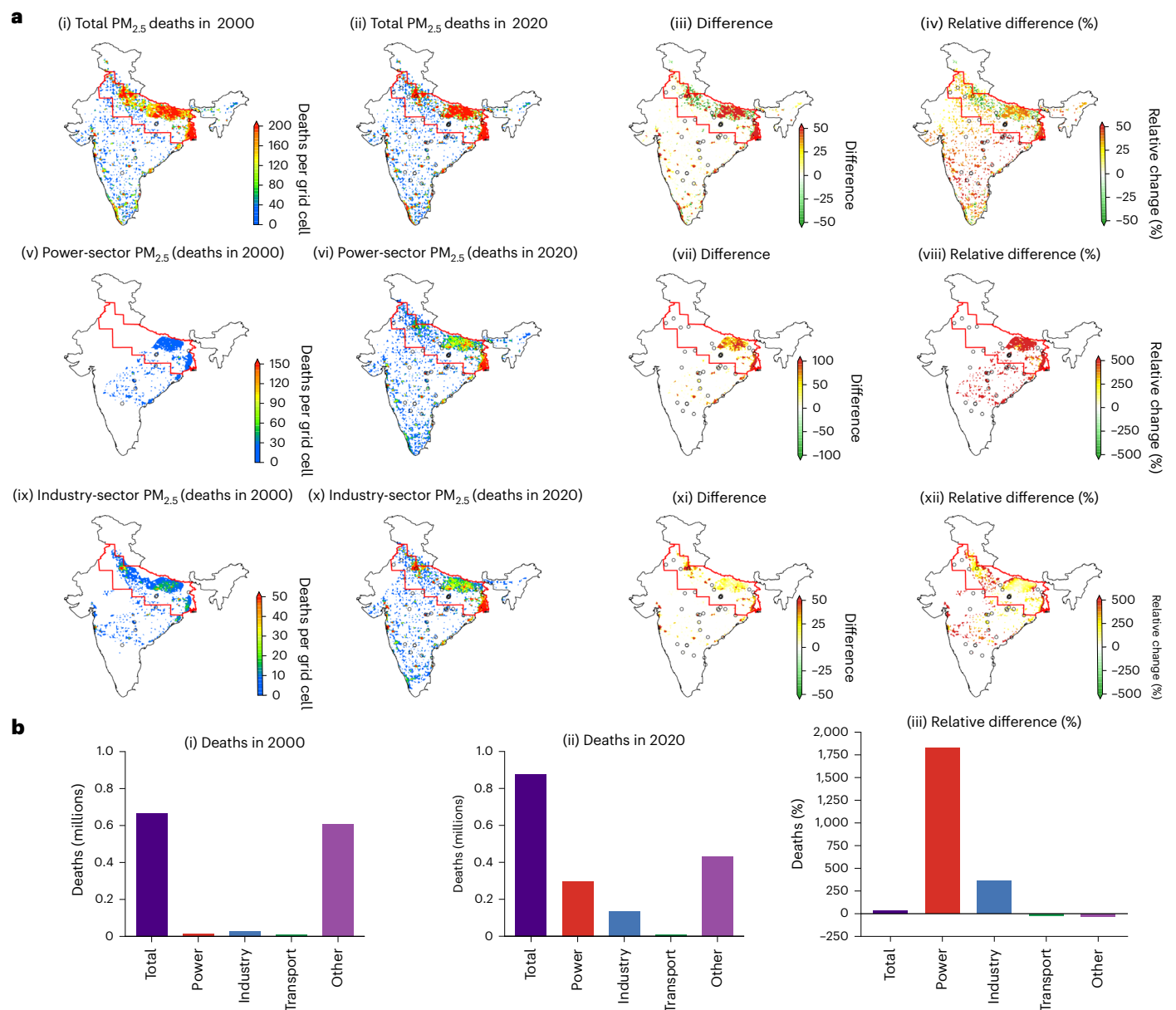


**Fig. 5 | Expansion of coal-based electricity generation increases PM<sub>2.5</sub>-attributable deaths across urban India. a**, Spatial distribution of total PM<sub>2.5</sub>-attributable deaths in 2000 and 2020 ((i) and (ii)), together with their absolute and relative changes ((iii) and (iv)). PM<sub>2.5</sub>-attributable deaths associated with power-sector emissions in 2000 and 2020 and the corresponding absolute and relative changes ((v)–(viii)). Equivalent contribution from industrial emissions ((ix)–(xii)). Black circles indicate the locations of large coal-fired power plants with installed capacities exceeding 1,500 MW operating in 2000 and 2020. The largest increases in PM<sub>2.5</sub>-attributable deaths occur over the Indo-Gangetic Plain and the Horseshoe Belt, coinciding with regions characterized by dense coal-

fired power infrastructure, rapid urbanization and increasing PM<sub>2.5</sub> exposure. **b**, Sectoral decomposition of PM<sub>2.5</sub>-attributable deaths in 2000 (i) and 2020 (ii), together with their relative changes over the study period (iii). Power-sector emissions exhibit the largest increase in attributable deaths, followed by industrial emissions, whereas transportation and other sectors contribute comparatively smaller changes. The strong increase in deaths attributable to power-sector emissions indicates that growth-driven expansion of coal-based electricity generation has become a major contributor to the urban health burden associated with PM<sub>2.5</sub> exposure in India.

(Fig. 4c and Supplementary Fig. 7). Power-sector PM<sub>2.5</sub> increased by approximately 400%, the largest relative increase, compared with approximately 90% for industrial emissions; transportation-related PM<sub>2.5</sub> declined by approximately 40%, whereas other sectors changed only modestly. Thus, although industry remains an important secondary contributor, the magnitude and spatial distribution of power-sector PM<sub>2.5</sub> growth, together with the corresponding sulfate trends, identify coal-based electricity generation as a major contributor to increasing urban PM<sub>2.5</sub> exposure across India.

### Coal-based electricity generation increases PM<sub>2.5</sub>-attributable deaths across urban India

Using the Global Exposure Mortality Model (GEMM)<sup>28</sup> framework (Methods), annual PM<sub>2.5</sub>-attributable deaths were estimated for each urban grid cell by combining PM<sub>2.5</sub> concentrations, population exposure and cause-specific concentration–response functions (Supplementary Table 1). The largest health burdens were concentrated within the Indo-Gangetic Plain and the Horseshoe Belt, where high population densities coincide with elevated PM<sub>2.5</sub> concentrations and extensive coal-fired power infrastructure (Fig. 5a).

Between 2000 and 2020, both the magnitude and spatial extent of urban  $\text{PM}_{2.5}$ -attributable deaths increased substantially across northern and eastern India (Fig. 5a(i)–(iv)). Several urban grid cells exceeded 120–200 deaths in 2000, whereas absolute increases by 2020 frequently exceeded 25–50 deaths per grid cell and relative increases reached 25%–50%. These patterns closely resemble the spatial distributions of sulfate aerosols and urban  $\text{PM}_{2.5}$  concentrations (Figs. 3 and 4).

GEOS-Chem sectoral simulations show a particularly large increase in deaths attributable to power-sector emissions (Fig. 5a(v)–(viii)). Power-sector-attributable deaths increased from generally below 30–60 deaths per grid cell in 2000 to more than 90–150 deaths per grid cell across several northern and eastern urban and industrial corridors by 2020. Absolute increases frequently exceeded 50–100 deaths per grid cell, whereas relative increases reached 250%–500%, with the largest changes concentrated across the Indo-Gangetic Plain and the Horseshoe Belt. Industrial emissions also contributed substantially (Fig. 5a(ix)–(xii)), with absolute increases exceeding 25–50 deaths per grid cell and relative increases exceeding 250% in several locations, although their magnitude and spatial extent remained smaller than those associated with power-sector emissions.

Aggregated estimates further highlight the growing urban health burden (Fig. 5b). Total urban  $\text{PM}_{2.5}$ -attributable deaths increased from approximately 0.67 million in 2000 to 0.87 million in 2020, an increase of approximately 30%. Over the same period, power-sector-attributable deaths increased from approximately 0.015 million to nearly 0.30 million, corresponding to an approximately 1,800% increase, whereas industrial-attributable deaths increased from approximately 0.03 million to 0.14 million, or approximately 350%. Transportation emissions contributed comparatively little and changed only modestly.

Together, the increase in total and sector-specific  $\text{PM}_{2.5}$ -attributable deaths, particularly across regions with dense coal-fired power infrastructure, identifies growth-driven coal-based electricity generation as a major contributor to the increasing urban air-pollution health burden.

### Economic growth increases access to clean cooking as urban and outdoor air-pollution deaths continue to rise

Long-term sectoral  $\text{SO}_2$  emissions reveal a major transformation of India's emission profile following the economic reforms initiated in 1991 (Fig. 6a). Emissions from all sectors remained generally below 0.1 million tons per year before 1950 and increased gradually thereafter. Following rapid electricity-demand growth after 2000, energy-sector  $\text{SO}_2$  emissions rose from less than 1 million tons per year in the late 1990s to approximately 7–8 million tons per year by the early 2020s, becoming the dominant sulfur-emission source. Industrial emissions also increased to approximately 3–4 million tons per year, whereas contributions from buildings, transport, agriculture and waste remained comparatively small. Figure 6b places these energy-system changes in the context of clean-cooking access, urbanization and pollution-related health burdens. Household and outdoor air-pollution deaths are obtained from independent health datasets and were not estimated in this study (Methods), whereas urban  $\text{PM}_{2.5}$ -attributable deaths were calculated using the GEMM framework, MERRA-2  $\text{PM}_{2.5}$  and gridded urban population data. Between 2000 and 2023, access to clean fuels and technologies for cooking increased from approximately 25% to nearly 75%, whereas the urban population share increased from approximately 27% to 35% and the rural share declined from approximately 73% to 65%. Household air-pollution deaths declined from approximately 1.25–1.30 million per year around 2010 to approximately 1.0 million per year by 2023, whereas outdoor air-pollution deaths increased from approximately 0.22 million in 1990 to nearly 0.95 million by 2023. Urban  $\text{PM}_{2.5}$ -attributable deaths estimated in this study similarly increased from approximately 0.7 million in 2000 to 0.9 million in 2020. Temporary declines during the COVID-19 lockdown period are consistent with the corresponding reductions in aerosol loading and  $\text{PM}_{2.5}$  (Figs. 2 and 4).

The household energy ladder provides a conceptual framework for these contrasting trends (Fig. 6c). Rising incomes facilitate transitions from traditional solid fuels such as crop residues, dung, wood, charcoal and coal toward liquefied petroleum gas, natural gas, electricity and other clean-cooking technologies, reducing household emissions and exposure. However, where electricity generation remains coal dominated, increasing electrification also increases the importance of emissions from centralized power generation.

Changes in India's income distribution illustrate the scale of this socioeconomic transition (Fig. 6d). More than 90% of the population belonged to the very low-income category (<US\$2,000  $\text{yr}^{-1}$ ) in 1985, declining to approximately 20%–25% by 2025. Over the same period, the middle-income population increased from less than 10% to nearly 40%, whereas the high-income population increased from approximately 1% to 10%. Given India's population of approximately 1.25–1.4 billion<sup>29</sup>, these changes represent several hundred million people moving up the income ladder and gaining greater access to modern household energy.

The econometric analysis further quantifies these relationships (Supplementary Table 2). GDP per capita was strongly associated with clean-cooking access ( $\beta = 1.116$ , 95% CI of 1.028–1.204,  $R^2 = 0.979$ ,  $P < 0.001$ ), such that a 1% increase in GDP per capita corresponded to an approximately 1.12% increase in clean-cooking access. Electricity demand was positively associated with power-sector  $\text{SO}_2$  emissions ( $\beta = 0.796$ , 95% CI of 0.743–0.850,  $R^2 = 0.980$ ,  $P < 0.001$ ), whereas  $\text{SO}_2$  emissions were associated with higher urban AOD ( $\beta = 0.238$ , 95% CI of 0.180–0.296,  $R^2 = 0.753$ ,  $P < 0.001$ ) and  $\text{PM}_{2.5}$  concentrations ( $\beta = 0.208$ , 95% CI of 0.153–0.264,  $R^2 = 0.650$ ,  $P < 0.001$ ). Urban  $\text{PM}_{2.5}$  was positively associated with outdoor air-pollution deaths ( $\beta = 3.676$ , 95% CI of 2.742–4.611,  $R^2 = 0.562$ ,  $P < 0.001$ ), whereas clean-cooking access was negatively associated with household air-pollution deaths ( $\beta = -0.098$ , 95% CI of -0.180 to -0.015,  $p = 0.020$ ).

Together, these results show contrasting health patterns accompanying India's economic and energy transition: rising incomes and clean-cooking access coincided with declining household air-pollution deaths, whereas growth in coal-dependent electricity demand was accompanied by higher  $\text{SO}_2$  emissions, sulfate aerosol formation, urban  $\text{PM}_{2.5}$  exposure, and increasing outdoor and urban air-pollution health burdens.

## Discussion

India's rapid economic growth following the 1991 economic reforms transformed its energy system, atmospheric environment and public-health landscape. Electricity demand increased nearly fourfold between 2000 and 2020, whereas coal consistently supplied approximately three-quarters of total generation. The resulting expansion of coal-based electricity was accompanied by increasing  $\text{SO}_2$  emissions, sulfate aerosols, urban  $\text{PM}_{2.5}$  concentrations and  $\text{PM}_{2.5}$ -attributable deaths, establishing a pathway linking economic growth, electricity demand, power generation, air pollution and urban health.

Sulfate emerged as the dominant contributor to increasing urban aerosol loading, rising from approximately 35.5% of total urban AOD in 2000 to 46.4% in 2020. TROPOMI observations identify strong  $\text{SO}_2$  hotspots over the Indo-Gangetic Plain and the Horseshoe Belt, whereas GEOS-Chem sectoral simulations show a rapidly increasing contribution from power-sector emissions. The correspondence among  $\text{SO}_2$  hotspots, sulfate trends and source-attribution simulations provides mechanistic evidence that sulfur emissions from coal combustion are a major contributor to worsening urban air quality.

Multiple independent datasets support this interpretation. MERRA-2, MODIS MAIAC and GEOS-Chem reproduce the observed aerosol variability against AERONET, whereas MERRA-2 and GEOS-Chem capture major urban  $\text{PM}_{2.5}$  patterns observed by CPCB. MERRA-2 and GEOS-Chem also show strong agreement for AOD ( $R^2 = 0.84$ ) and  $\text{PM}_{2.5}$  ( $R^2 = 0.81$ ), increasing confidence that the observed

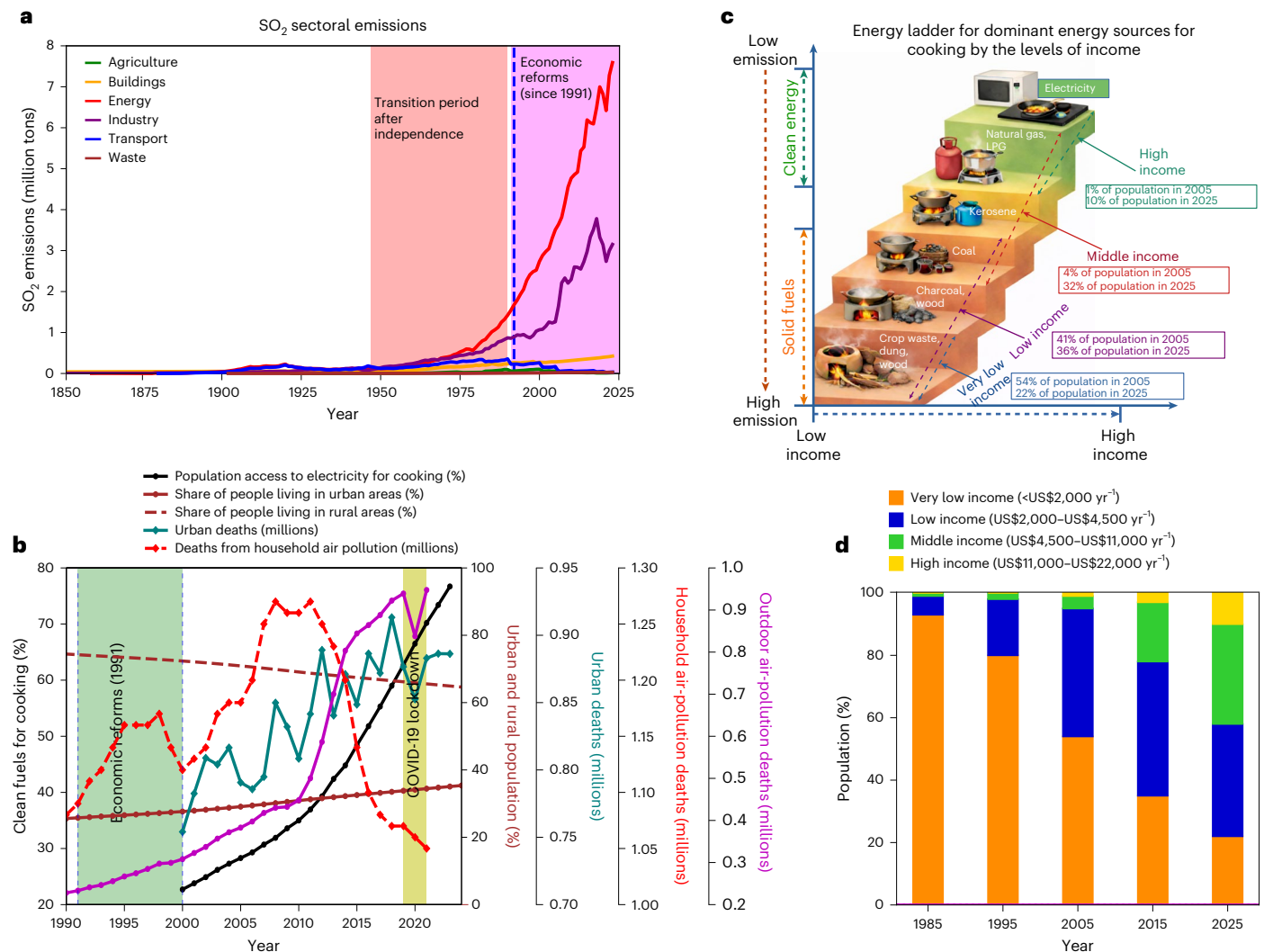


**Fig. 6 | Economic growth and electrification shift pollution-related health burdens from indoor to outdoor environments. a**, Long-term evolution of sectoral SO<sub>2</sub> emissions in India, showing the rapid increase in emissions from the energy sector following the implementation of the 1991 economic reforms. Energy-sector emissions become the dominant source of SO<sub>2</sub>, substantially exceeding contributions from buildings, transport, agriculture and waste. **b**, Temporal evolution of access to clean fuels and technologies for cooking, urban and rural population shares, urban PM<sub>2.5</sub>-attributable urban deaths, deaths attributable to household air pollution and deaths attributable to outdoor air pollution. Increasing access to clean cooking is accompanied by a decline in household air-pollution deaths, whereas deaths attributable to outdoor air pollution increase substantially over the same period. **c**, Conceptual

representation of the energy ladder, illustrating the transition from traditional solid fuels (crop residues, dung, wood, charcoal and coal) to cleaner energy sources (kerosene, liquefied petroleum gas (LPG), natural gas, clean cookstoves and electricity) with increasing income. The figure also highlights the changing population distribution across income groups between 2005 and 2025. **d**, Evolution of population income distribution from 1985 to 2025, showing a decline in the proportion of population living in very low-income conditions and a corresponding expansion of middle- and high-income groups. This income transition increases access to clean fuels, including electricity for cooking, contributing to reduced household air pollution and simultaneously increasing dependence on centralized electricity generation.

changes are robust across independent observational, reanalysis and modeling frameworks.

Although the long-term observations of speciated aerosols over India remain limited, previous evaluations indicate that MERRA-2 reproduces the spatial and temporal variabilities of major aerosol species, including sulfate, over South Asia, whereas uncertainties remain in absolute concentrations because of emissions, aerosol processes and reanalysis resolution<sup>30,31</sup>. Sulfate estimates should, therefore, be interpreted primarily in terms of long-term changes rather than precise absolute concentrations. Their attribution is strengthened by independent GEOS-Chem sector-specific simulations and TROPOMI SO<sub>2</sub> observations.

The associated urban health burden increased substantially. Urban PM<sub>2.5</sub>-attributable deaths rose from approximately 0.7 million

in 2000 to 0.9 million in 2020, whereas power-sector-attributable deaths increased from approximately 0.015 million to nearly 0.30 million. Industrial emissions also contributed to the health burden, but their influence remained smaller than that of the power sector, highlighting the growing health consequences of coal-dependent electricity generation.

An important limitation is that the health-impact assessment uses MERRA-2 PM<sub>2.5</sub>, which may underestimate absolute concentrations over densely populated urban areas despite capturing temporal variability reasonably well<sup>30,31</sup>. Because GEMM exposure–response functions depend on absolute PM<sub>2.5</sub> concentrations, this low bias may result in conservative estimates of PM<sub>2.5</sub>-attributable deaths. The absolute health estimates should, therefore, be interpreted accordingly, whereas the long-term trends and relative changes are supported by

their consistency with satellite observations, GEOS-Chem simulations and ground-based measurements.

Economic growth was also accompanied by substantial changes in household energy access. Between 2000 and 2023, access to clean fuels and technologies for cooking increased from approximately 25% to nearly 75%, whereas household air-pollution deaths declined from approximately 1.25 million to nearly 1.0 million per year. The middle-income population increased from less than 10% to nearly 40%, representing—given India's population exceeding 1.25 billion—several hundred million people gaining greater access to modern household energy. By contrast, outdoor air-pollution deaths increased from approximately 0.3 million to nearly 1.0 million, alongside the increase in urban PM<sub>2.5</sub>-attributable deaths estimated here.

The econometric analysis supports these contrasting pathways. GDP per capita was positively associated with clean-cooking access ( $\beta = 1.116$ ), whereas electricity demand was positively associated with SO<sub>2</sub> emissions ( $\beta = 0.796$ ). SO<sub>2</sub> emissions were, in turn, associated with urban aerosol loading ( $\beta = 0.238$ ) and PM<sub>2.5</sub> concentrations ( $\beta = 0.208$ ), and urban PM<sub>2.5</sub> was positively associated with outdoor air-pollution deaths ( $\beta = 3.676$ ). Together, these relationships indicate that rising incomes expanded access to cleaner household energy, whereas growth in coal-dependent electricity demand increased ambient air-pollution burdens.

These findings have important implications for rapidly developing economies dependent on coal-based power generation. Decarbonizing electricity systems will be critical to ensuring that future economic growth and improvements in energy access are accompanied by sustained gains in urban air quality and public health.

## Methods

### Economic activity

Economic activity is measured using the annual gross domestic product (GDP)<sup>32</sup> per capita for India. GDP represents the total value added produced by all resident economic units within a given year and is compiled by national statistical agencies following internationally standardized accounting frameworks under the System of National Accounts. National GDP estimates are constructed using a combination of production-, income- and expenditure-based approaches that integrate sectoral output statistics, administrative records, enterprise surveys and household consumption data. Nominal GDP estimates are converted to real terms using country-specific GDP deflators to remove the effects of inflation, and GDP per capita is obtained by normalizing real GDP by total population. GDP per capita is expressed in constant 2015 US dollars and is used here for within-country temporal analysis rather than cross-country welfare comparisons. GDP per capita data spanning 1960–2024 are obtained from ref. 33, which harmonizes estimates from national statistical organizations and central banks, the Organisation for Economic Co-operation and Development (OECD) national accounts and World Bank staff estimates. Harmonization procedures reconcile revisions across national accounts vintages, ensuring consistency in base-year pricing and currency units<sup>33</sup>.

### Electricity demand, generation and production mix

Data for annual electricity demand and electricity generation are used to characterize trends in electricity consumption and supply in India. Electricity demand refers to the total electrical energy consumed within a year, whereas electricity generation represents the gross quantity of electricity produced by all power plants, including central utilities and independent power producers. Both total and per capita measures are used to capture aggregate electricity use and changes in electricity intensity associated with economic growth and urbanization. Electricity generation is disaggregated by source, including coal, natural gas, oil, nuclear, hydropower, wind, solar and other renewable technologies. Generation shares by source are computed to characterize changes

in the electricity production mix and the persistence of coal as the dominant source of electricity supply. Electricity demand, generation and generation-by-source data are obtained from ref. 34, by using the corresponding datasets for electricity demand<sup>34</sup>, electricity generation<sup>35</sup> and electricity production by source<sup>36</sup>. These datasets compile and harmonize statistics from the International Energy Agency, the US Energy Information Administration, the Ember Global Electricity Dataset, the Energy Institute's Statistical Review of World Energy and national electricity authorities. Data are reported on an annual basis in terawatt-hours (TWh), with per capita values expressed in kilowatt-hours per person. The most recent observations (2024) represent the latest available complete annual data and may be subject to minor revisions as national energy balances are updated<sup>34</sup>.

### Electricity access and clean cooking

Electrification and household clean-cooking transitions are characterized using annual data on population access to electricity and access to clean fuels and new innovations for cooking. Electricity access is defined as the share of the population with a household electricity connection that provides a basic level of supply for lighting and household energy services. Access to clean cooking captures the share of the population whose primary cooking fuel is natural gas, electricity and clean cookstoves. These indicators are obtained from Our World in Data<sup>37</sup> using the datasets for population access to electricity<sup>38</sup> and access to clean fuels and new innovations for cooking<sup>39</sup>. Underlying estimates draw on the World Bank's Global Electrification Database and the Energy Sector Management Assistance Program, which integrate nationally representative household surveys (for example, Demographic and Health Surveys and Multiple Indicator Cluster Surveys), population censuses and administrative records. Survey-based observations are interpolated across years using population-weighted methods to generate continuous annual time series. These indicators measure access rather than the quality, reliability, or intensity of electricity or cooking fuel use.

### Spatial distribution of power plants, total and urban population and economic activity

To examine the spatial alignment between electricity generation infrastructure, population exposure and economic activity, we compile geospatial datasets on coal-fired power plant locations, population distribution, urban population density and economic activity across India. All spatial datasets are harmonized to a common geographic coordinate system to enable consistent spatial analysis. Locations of coal-fired power plants are obtained from the Global Power Plant Database maintained by the World Resources Institute (<https://datasets.wri.org/>). This dataset provides georeferenced locations, installed capacity, fuel type and operational status for individual power plants, based on national energy statistics, utility disclosures and satellite verification. Power plants are treated as point sources and overlaid on gridded population and economic datasets to assess spatial collocation. Gridded total and urban population data at approximately 1-km spatial resolution are obtained from the NASA Socioeconomic Data and Applications Center<sup>40</sup>. These data are produced by disaggregating census-based population totals to grid cells using ancillary geospatial covariates such as built-up area, land cover and settlement patterns. Urban population grids identify populations residing in areas classified as urban based on built-environment characteristics rather than administrative boundaries<sup>40</sup>. Spatial economic activity is characterized using gridded GDP data expressed in PPP units from the global subnational GDP dataset<sup>41</sup>. These data report GDP in billions of PPP-adjusted currency units and represent the spatial intensity of economic production rather than individual income or household welfare. National GDP is downscaled to grid cells using a combination of population distribution, nighttime lights intensity and ancillary socioeconomic indicators<sup>41</sup>.

## AOD and its composition from MERRA-2 and CMIP6

Spatial and temporal patterns of AOD and its chemical composition are analyzed using the MERRA-2 (ref. 42) aerosol reanalysis and Coupled Model Intercomparison Project Phase 6 (CMIP6)<sup>43</sup> Earth system model simulations. AOD represents the column-integrated extinction of solar radiation by aerosols and serves as a proxy for ambient particulate pollution. All analyses are conducted at a common spatial resolution of  $0.5^\circ \times 0.625^\circ$ . MERRA-2 assimilates satellite observations, including MODIS<sup>44</sup>, Multi-angle Imaging SpectroRadiometer<sup>45</sup> and AERONET<sup>46</sup> observations, into a global chemical transport model to produce physically consistent aerosol fields<sup>42</sup>. MERRA-2 provides the total AOD as well as speciated AOD contributions from sulfate, BC, OC, dust and sea salt. Monthly outputs are aggregated to annual means for consistency with socioeconomic and health datasets. The CMIP6 aerosol outputs are used to complement the reanalysis data and assess robustness across modeling frameworks<sup>43</sup>, as the CMIP6 models operate at varying native spatial resolutions and provide one of the few datasets capable of representing the long-term evolution of AOD since 1850; all CMIP6 aerosol fields are conservatively regridded to the MERRA-2 grid to ensure spatial comparability and the preservation of spatially aggregated aerosol load using the Climate Data Operator<sup>47</sup>. It should be noted that CMIP6 outputs are used exclusively to examine long-term historical changes in aerosol loading and composition, whereas the analysis of urban air pollution relies primarily on MERRA-2 reanalysis and higher-resolution satellite products, which are better suited for resolving aerosol variability over densely populated urban regions.

A central focus of the analysis is the comparison between the years 2000 and 2020. The year 2000 represents a baseline period following the effective implementation of the 1991 economic reforms but before the rapid expansion of coal-fired electricity generation. By contrast, 2020 constitutes a unique observational year due to the COVID-19 pandemic, during which widespread lockdowns substantially reduced emissions from transportation, construction and many industrial activities, whereas large coal-fired thermal power plants largely continued operating to meet residual electricity demand<sup>21,48</sup>. This asymmetric reduction in emissions provides a quasi-natural experiment that enhances the ability to isolate changes in aerosol loading and composition associated with coal-based electricity generation. To ensure robustness, the 2000–2020 comparison is complemented by multi-decadal analyses using the full MERRA-2 record and cross-validation with regridded CMIP6 multi-model ensembles.

## High-resolution (1-km-scale) AOD from MODIS MAIAC

To complement the MERRA-2 reanalysis and better characterize urban aerosol loading, we used AOD at 550 nm from the MODIS MAIAC product (MCD19A2, Collection 6.1)<sup>49</sup>. MAIAC combines Terra and Aqua MODIS observations to provide daily AOD retrievals at approximately 1-km spatial resolution from February 2000 onward, making it well suited for urban-scale air-pollution analyses. The data were accessed and processed using the Google Earth Engine. To minimize retrieval uncertainty, we retained only high-quality observations using the MAIAC AOD<sub>QA</sub> flags, including cloud-free pixels, pixels unaffected by cloud adjacency and best-quality aerosol retrievals. Daily AOD retrievals were aggregated to monthly means and subsequently to annual means for consistency with the socioeconomic, emissions and health datasets used in this study. The MAIAC product was used primarily to characterize urban-scale spatial variability in aerosol loading and to evaluate the robustness of patterns identified using MERRA-2. Although MERRA-2 provides aerosol composition and long-term consistency, MAIAC provides substantially improved spatial detail over densely populated urban regions.

## GEOS-Chem simulations and sectoral attribution of AOD and PM<sub>2.5</sub>

To quantify the contribution of the power sector to aerosol loading and surface particulate matter pollution, we performed simulations

using the GEOS-Chem chemical transport model (v. 14.6.3)<sup>50</sup>. Simulations were conducted in the aerosol mode, which explicitly represents the transport, chemical transformation and scavenging of major aerosol species. The model was driven by MERRA-2 meteorological reanalysis data and operated at a horizontal resolution of  $0.5^\circ \times 0.625^\circ$  with 47 vertical layers extending from the surface to approximately 0.01 hPa. To examine changes in aerosol distributions during the period of rapid economic growth and expansion of electricity demand, simulations were performed for the years 2000 and 2020. Each experiment included a spin-up period to minimize the influence of initial conditions, consisting of 6 months for simulations. For the regional nested configuration, boundary conditions are taken from the global simulation at  $2^\circ \times 2.5^\circ$  resolution. A baseline simulation was first performed to quantify the inputs of major emission sectors to AOD and PM<sub>2.5</sub> concentrations over India. Simulations were performed for the power, industrial and transportation sectors. The contribution of each sector was quantified by comparing the baseline simulation with the corresponding sector-removal experiment, thereby providing a source-resolved assessment of the relative importance of different emission sectors to aerosol loading and population exposure. Anthropogenic emissions were obtained from the Community Emissions Data System inventory<sup>51</sup>. Natural and biogenic emissions were represented using offline emission datasets for dust, biogenic volatile organic compounds, sea salt and soil nitrogen oxides<sup>52</sup>, whereas online emissions included sea-spray fluxes, volcanic emissions and biomass-burning emissions from the Global Fire Emissions Database version 4 (ref. 53).

The GEOS-Chem simulations were used to provide a mechanistic and source-resolved assessment of the contribution of the power sector to sulfate aerosol formation, total AOD and surface PM<sub>2.5</sub> concentrations over India. These simulations complement the observational analyses based on MERRA-2, MODIS MAIAC, AERONET and CPCB datasets, and provide a physically based framework for attributing changes in aerosol loading to specific emission sectors. The validation of all the datasets associated with AOD and PM<sub>2.5</sub> is presented in Supplementary Section 1.

## Calculation of trend significance

Long-term trends in AOD, PM<sub>2.5</sub> and other gridded variables were quantified using pixel-wise linear regression<sup>54</sup> applied to annual mean time series. For each grid cell, annual values were regressed against time to estimate the magnitude and direction of the long-term trend. Trend estimates were subsequently expressed on a per-decade basis to facilitate comparison across variables and regions. The statistical significance of each trend was evaluated using the *P* value associated with the regression slope. Trends were considered statistically significant at the 95% confidence level ( $P < 0.05$ ). Grid cells with non-significant trends were masked, and only statistically significant trends were retained in the final trend maps. This approach enables the identification of regions in which observed changes are unlikely to result from random interannual variability and, therefore, represent robust long-term changes over the study period. Trend calculations were performed independently for each grid cell using annual observations from 2000 to 2023. The resulting maps provide both magnitude of change per decade and spatial extent of statistically significant trends, allowing the assessment of regional patterns in aerosol loading and particulate matter concentrations across India.

## Sectoral SO<sub>2</sub> emissions

Annual sectoral SO<sub>2</sub> emissions data are used to characterize the sources of sulfur emissions relevant for sulfate aerosol formation. SO<sub>2</sub> emissions are reported for major sectors, including electricity and heat production, manufacturing and construction, transport, residential and commercial buildings, agriculture and waste-related activities. Sectoral SO<sub>2</sub> emissions data are obtained from the Community Emissions

Data System<sup>51</sup>, which combines activity data, fuel characteristics and emission factors to produce consistent historical emission inventories.

### High-resolution SO<sub>2</sub> observations from TROPOMI

To show the spatial distribution of SO<sub>2</sub> distribution over the study region, we used level-2 SO<sub>2</sub> column number density retrievals from the TROPOMI<sup>55</sup> onboard Sentinel-5P. TROPOMI provides high-spatial-resolution observations of atmospheric SO<sub>2</sub> columns and is well suited for identifying regional emission plumes and spatial contrasts associated with major anthropogenic sources, including coal-fired power plants and industrial corridors. The level-2 swath data were processed using the HARP Python package<sup>56</sup>. Only retrievals with high-quality measurements were retained by applying a validity threshold of greater than 50. The valid pixels were then regridded to a regular latitude–longitude grid using spatial binning at 0.01° resolution, corresponding to approximately 1 km, to produce high-resolution SO<sub>2</sub> maps. For each day, all available observations within the selected domain were aggregated to generate gridded SO<sub>2</sub> fields, and missing pixels were masked when no valid retrievals were available. TROPOMI SO<sub>2</sub> observations were used as an independent high-resolution satellite constraint to examine the spatial coherence of sulfur-rich plumes and to support the attribution of enhanced sulfur emissions over regions with dense coal-based electricity generation.

### Estimation of PM<sub>2.5</sub>-attributable deaths over urban regions

Urban PM<sub>2.5</sub>-attributable deaths were estimated by combining gridded urban population data with annual surface PM<sub>2.5</sub> concentrations from MERRA-2 and GEOS-Chem using the GEMM<sup>28</sup>. Population densities were converted into grid-cell population counts and combined with PM<sub>2.5</sub> exposure, cause-specific baseline mortality rates and GEMM concentration–response functions. A theoretical minimum-risk exposure level of 2.4 µg m<sup>-3</sup> was applied following ref. 28. Attributable deaths were calculated separately for chronic obstructive pulmonary disease, lung cancer, ischemic heart disease, stroke and lower respiratory infections, and subsequently summed across causes and urban grid cells. The same framework was applied to GEOS-Chem sector-specific PM<sub>2.5</sub> fields to quantify deaths attributable to individual emission sectors. Full equations, GEMM parameters, baseline mortality treatment and calculation method are provided in Supplementary Section 2.

### Deaths from indoor and outdoor air pollution

Health impacts are quantified using annual estimates of premature deaths attributable to household (indoor) and ambient (outdoor) air pollution. Premature deaths are defined as deaths occurring earlier than expected due to long-term exposure to air pollutants and are estimated using a comparative risk assessment framework that links population exposure to cause-specific mortality through epidemiologically derived exposure–response relationships<sup>57,58</sup>.

Deaths attributable to household air pollution reflects exposure to pollutants emitted from the use of solid fuels for cooking and heating, whereas outdoor ambient air-pollution deaths are dominated by long-term exposure to PM<sub>2.5</sub>, which is associated with elevated risks of cardiovascular and respiratory diseases and lung cancer<sup>28</sup>.

Mortality estimates are obtained from Our World in Data, which compiles results from the Global Burden of Disease study produced by the Institute for Health Metrics and Evaluation<sup>59</sup>. The Global Burden of Disease framework integrates satellite-derived and ground-based exposure estimates, atmospheric modeling, nationally reported cause-of-death data and integrated exposure–response functions to estimate pollution-attributable mortality<sup>60</sup>.

Death estimates are reported as annual population-level counts and represent aggregate health burdens rather than individual risk. Uncertainty intervals account for uncertainty in exposure estimation, relative risk functions and baseline mortality rates, although central estimates are used in the main analysis.

### Income distribution and the energy ladder for cooking

Shifts in population income distribution in India are characterized using published studies that integrate nationally representative household survey data with macroeconomic growth trajectories to estimate population shares across income brackets over time<sup>61,62</sup>. These studies combine micro-level income or expenditure distributions with aggregate economic growth implied by national accounts, allowing a consistent estimation of how households transition across income groups as the economy grows. We use these income-group distributions to contextualize changes in household energy access and cooking fuel choice over time.

Household cooking energy transitions are interpreted using the energy ladder framework<sup>63</sup>, which provides a structured representation of how dominant cooking fuels shift with rising income, from traditional solid fuels (such as fuelwood, crop residues and dung) and transitional fuels (such as charcoal and kerosene) to clean fuels and technologies (including liquefied petroleum gas and electricity). Although recognizing that households may engage in fuel stacking, the energy ladder framework captures the dominant cooking energy source within each income group and, thus, the prevailing exposure pathway to household air pollution. This framework is used to link income growth to reductions in indoor pollution exposure and to the corresponding upstream relocation of emissions toward centralized, and often coal-based, electricity generation.

### Econometric analysis and statistical evaluation

To quantify temporal associations among economic growth, electricity demand, sulfur emissions, air pollution and health outcomes, we applied log–linear time-series regressions using ordinary least squares<sup>64,65</sup> to annual observations. The analysis evaluated relationships between GDP per capita and electricity demand and clean-cooking access, electricity demand and power-sector SO<sub>2</sub> emissions, SO<sub>2</sub> emissions and urban AOD and PM<sub>2.5</sub> concentrations, urban PM<sub>2.5</sub> and outdoor air-pollution deaths, and clean-cooking access and household air-pollution deaths. Logarithmic transformations were applied to reduce skewness and allow regression coefficients to be interpreted as elasticities. Model performance and statistical robustness were evaluated using  $R^2$ , adjusted  $R^2$ , 95% confidence intervals and two-sided  $P$  values, with heteroskedasticity- and autocorrelation-consistent (Newey–West) standard errors applied where appropriate. Missing observations were removed pairwise for each model. Full model specifications, equations, statistical procedures and regression results are provided in Supplementary Table 2.

### Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

### Data availability

The datasets used in this study are publicly available from the following sources. GDP per capita is obtained from Our World in Data (GDP per capita). Electricity demand and electricity generation are obtained from Our World in Data (electricity demand) and Our World in Data (electricity generation). The percentage of population having access to electricity is obtained from Our World in Data (electricity access). Electricity production by sector is obtained from Our World in Data (electricity production by source). Spatial distribution of coal-fired power plants is obtained from Global Power Plant Database (World Resources Institute). Spatial distribution of the total and urban population is obtained from NASA Socioeconomic Data and Applications Center population datasets. Spatial distribution of economic activity (GDP in PPP) is obtained from Dryad Global Subnational GDP dataset. AOD and its components from CMIP6 are obtained from CMIP6 ESGF archive, and MERRA-2 aerosol reanalysis data are obtained from NASA MERRA-2 archive. Sectoral SO<sub>2</sub> emission data are obtained from Our

World in Data (sectoral SO<sub>2</sub> emissions). The percentage of the population having access to electricity for cooking is obtained from Our World in Data (clean-cooking access). Premature mortality from indoor and outdoor air pollution is obtained from Global Burden of Disease Results Tool. The energy ladder and dominant energy sources for cooking by income group are obtained from Our World in Data (energy ladder). Shifts in population income distribution over time are obtained from Banerjee and Dufo (income distribution) and Bhattacharya et al. (income projections).

## Code availability

All the plots are generated using Python (v. 3.5)<sup>66</sup>. The GOES-Chem model code is available via Zenodo at <https://zenodo.org/records/12807579> (ref. 67).

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## Author contributions

B.S., A.S., M.V. and D.T. designed the study, performed the data analysis and drafted the paper. All authors, B.S., A.S., D.T., R.S., A.D., M.V., P.S., C.H., L.L. and A.T., have contributed to shaping the paper.

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## Competing interests

All authors declare no competing interests.

## Additional information

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**Correspondence and requests for materials** should be addressed to Basudev Swain, Aishwarya Singh or Marco Vountas.

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