

Who Breathes Worse?

Socio-economic Deprivation and PM_{2.5} in India

Simran Koul

Bren School of Environmental Science & Management, University of California, Santa Barbara, USA
Email: skoul@bren.ucsb.edu

October 13, 2026

Abstract

Air pollution in India has intensified rapidly, alongside substantial population growth across regions with highly uneven socioeconomic and developmental conditions. Ambient fine particulate matter (PM_{2.5}) is among the leading environmental contributors to premature mortality in India, where national average concentrations exceed the World Health Organization guideline by an order of magnitude. National-scale studies have further documented that this burden falls unevenly, with socially disadvantaged populations concentrated in districts recording higher PM_{2.5} concentrations, making the unequal distribution of exposure an issue of environmental inequity as well as public health. Existing studies of this disproportionate exposure, however, have relied on outdated census-based sociodemographic data or on sample surveys that lack sufficient geographic coverage and spatial granularity. My study addresses these limitations by employing gridded datasets that integrate high-resolution satellite and sociodemographic data to examine how social deprivation is associated with district-level concentrations of total and source-specific PM_{2.5} across 635 districts in India. I use five of the six indicators from the Global Gridded Relative Deprivation Index (GRDI), a globally standardized measure of multidimensional social deprivation, and implement multiscale geographically weighted regression, allowing each association to vary across space. The associations vary in strength and direction across districts rather than following a single national gradient. The most consistent is the trend in nighttime light intensity, which is negative in 85% of districts, so concentrations tend to be higher where recent development has been slower. Built-up area is negative in three quarters of districts, indicating that, compared with their neighbors, less built-up districts carry comparable or higher exposure. The association with infant mortality divides regionally and is positive across the northern plains, where national concentrations are highest. The same spatial variability holds within each of the nine emission source categories, with the strongest deprivation-aligned associations found for residential PM_{2.5}. These findings indicate that the relationship between social deprivation and PM_{2.5} exposure in India is regionally structured, and support the case for equitable air quality policies matched to regional source profiles.

Keywords: Environmental inequality, air pollution, PM_{2.5} exposure, social deprivation, India

1 Introduction

1.1 Air Pollution Burden in India

Air pollution has emerged as one of the world's largest environmental health concerns and was the second largest risk factor for death globally in 2021, when it was linked to 8.1 million deaths, with ambient fine particulate matter (PM_{2.5}) accounting for 58% of these deaths and household air pollution for 38% ([Health Effects Institute, 2024](#)). In addition, exposure to PM_{2.5} has been

causally linked to a range of adverse health outcomes, including stroke, lung cancer, lower respiratory infections among others (Cohen et al., 2017). Health risk assessments in South Asian urban settings have examined these exposures and their consequences for both adults and children (Madani et al., 2026). Despite these well-established connections and health risks, national and regional air quality standards frequently fail to maintain levels recommended for human health and safety. These standards are generally based on annual average concentrations of PM_{2.5}, with the World Health Organization (WHO) recommending a limit of 5 $\mu\text{g}/\text{m}^3$. However, according to the 2024 World Air Quality Report, only 12 countries and territories worldwide recorded PM_{2.5} concentrations below this guideline (IQAir, 2024).

Among the countries falling short of these WHO guidelines, India reports some of the highest annual surface PM_{2.5} concentrations globally, with a national average of 50.6 $\mu\text{g}/\text{m}^3$, more than ten times the WHO’s recommended limit of 5 $\mu\text{g}/\text{m}^3$. According to the IQAir World Air Quality Report (2024), India was home to six of the nine most polluted cities in the world (IQAir, 2024). This extreme exposure is not just a statistic; it translates into real human costs. In 2019, exposure to air pollution was responsible for an estimated 1.67 million premature deaths in India, accounting for 17.8% of the country’s total mortality (Pandey et al., 2021). This burden is concentrated in early life. District-level analysis reports that PM_{2.5} concentrations above India’s National Ambient Air Quality Standard are associated with substantially elevated neonatal and postneonatal mortality risk (Adhikary et al., 2024), and a population-based analysis of approximately 224,000 children under five found a monotonic relationship between exposure and respiratory illness that persisted below India’s own standard (George et al., 2024). In response, India has adopted targeted policy measures such as National Clean Air Programme (NCAP), launched in 2019 and aimed to reduce PM_{2.5} levels by 20–30% in over 100 non-attainment cities by 2024. The program emphasized strengthening air quality monitoring, developing city-specific action plans, and promoting inter-agency coordination across local, state, and national levels (Ministry of Environment, Forest & Climate Change, Government of India, 2019). Assessments of the programme’s early years have identified structural limitations. A review of 102 city action plans found that transport and road dust accounted for roughly half of all proposed action points while domestic cooking and heating accounted for 2%, and that only a quarter of plans drew on source apportionment evidence when selecting measures (Ganguly et al., 2020). A subsequent assessment covering 2019–2023 reported that the share of cities above 120 $\mu\text{g}/\text{m}^3$ fell from 30% to 20% while more than half remained between 60 and 120 $\mu\text{g}/\text{m}^3$, and recommended shifting evaluation from individual cities to regional airsheds (Guttikunda et al., 2024).

1.2 PM_{2.5} Exposure and Environmental Inequality

Despite growing public concern and increased policy attention, critical questions remain about who benefits most from air quality improvements and who continues to be left behind in terms of exposure reduction and health protection (Chakraborty & Basu, 2021; Kawano et al., 2025). National and state-level initiatives like NCAP mark an important shift, but their standardized, city-level targets are not designed to capture the highly uneven exposure patterns produced by caste- and class-based residential segregation, informal and peri-urban settlements, and the siting of major pollution sources within and across cities. Consequently, without targeted equity considerations, such programs can risk improving air quality primarily for more socially advantaged groups, potentially exacerbating existing disparities. Studies have begun to show that although socially marginalized groups frequently bear a disproportionate share of the air pollution burden, these disparities remain underexamined in both research and policy (Chakraborty & Basu, 2021; deSouza et al., 2023). Evidence from other national contexts indicates that such disparities are structured by emission source rather than distributed uniformly. In the United States, nearly all major emission sectors expose racial and ethnic minority populations to above-average PM_{2.5} concentrations (Tessum et al., 2021), and source-apportioned analyses across urban areas attribute those disparities to particular sectors, including heavy fuel oil,

industrial and metal processing, agricultural, and motor vehicle emissions (Knobel et al., 2023). Work in the same setting suggests that geographically targeted reductions in a small share of national emissions could substantially reduce exposure inequality (Wang et al., 2022).

1.3 Social Deprivation and Unequal Pollution Burden

While few quantitative studies on the environmental justice implications of air pollution have focused on India, recent empirical work has documented spatial and social inequalities in the distribution of air pollution exposure at the national scale. Chakraborty and Basu (2021) conducted a district-level analysis that integrated annual average PM_{2.5} concentrations for 2010 and their change through 2016, derived from satellite observations and a chemical transport model calibrated to ground measurements, with sociodemographic data from the 2011 Census of India. Their findings revealed widespread inequities in air pollution levels and related increases: over 85% of socially disadvantaged populations, including Scheduled Castes (SCs), children aged six or under, and households without toilet facilities resided in districts where PM_{2.5} concentrations exceeded international air quality standards. These overall exposure disparities were compounded by trends in increasing PM_{2.5} pollution over the 2010–2016 period. Specifically, districts with higher proportions of SCs, young children, and households without toilets were significantly more likely to experience increases in PM_{2.5} concentrations over time. These associations remained robust in multivariable models, suggesting that social disparities in exposure were not solely attributable to economic development or demographic characteristics.

In related work, deSouza et al. (2023) linked satellite-derived 2010–2015 PM_{2.5} data to more than 28,000 geocoded clusters from the National Family Health Survey (NFHS-4), a component of the global Demographic and Health Survey. They used multilevel modeling to examine the relationship between air pollution and social composition at the neighborhood level (villages in rural areas and census blocks in urban areas), focusing on the share of historically marginalized communities, such as SCs, Other Backward Classes (OBCs), and Muslims. Their results indicated that clusters with higher proportions of SC and OBC households were exposed to higher ambient PM_{2.5} concentrations, while associations for Scheduled Tribe, Muslim, and poorer households ran in the opposite direction, and directions differed between urban and rural clusters and across emission sources, leading the authors to argue for a more nuanced environmental justice framework for India. Their analysis also incorporated source-wise disaggregated pollution data. More recent work linking the fourth and fifth rounds of the NFHS to 1 km satellite-derived PM_{2.5} reports that exposure disparities across wealth and caste groups widened in urban areas between 2015–2016 and 2019–2021 even as average concentrations declined, indicating that aggregate improvement in air quality does not necessarily produce a more equal distribution of exposure (Sarkar et al., 2026).

1.4 Source-Specific PM_{2.5} and Spatial Heterogeneity

Total PM_{2.5} concentrations aggregate emissions from sources that differ in spatial distribution and in the populations they reach. In India, residential energy use has been estimated to account for approximately half of population-weighted ambient PM_{2.5} (Conibear et al., 2018), and sectoral attribution for South Asia assigns the largest shares of PM_{2.5}-attributable mortality to residential combustion, industry, and power generation (Chatterjee et al., 2023). These sources are unevenly distributed across the country, with concentrations and their composition varying substantially between the Indo-Gangetic Plain and southern and central India (David et al., 2019; Guttikunda & Ka, 2022). In India, one such analysis has addressed a single sector. Combining modelled dispersion from coal plant locations with census demographics, Kopas et al. (2020) found that marginalized and poorer populations were more likely to be exposed to emissions from coal-fired power generation. Because social deprivation is itself spatially structured, indicators of disadvantage may relate differently to concentrations originating in

household sources than to those from industrial or transport sources, a distinction that analyses of total PM_{2.5} alone cannot recover.

1.5 Gaps in Existing Research

While these studies provide important insights on the social distribution of air pollution in India, they are characterized by specific limitations that I seek to address in my study. First, [Chakraborty and Basu \(2021\)](#)'s study relied on sociodemographic data from the 2011 Census of India which may not provide the best temporal match with more recent air pollution estimates. Second, [deSouza et al. \(2023\)](#) and [Sarkar et al. \(2026\)](#) both used geocoded data from the National Family Health Survey, which is subject to spatial displacement and anonymization protocols that limit fine-grained spatial precision and may not be as comprehensive as the national census in terms of geographic coverage. Third, all three studies have largely focused on categorical social identities such as caste, religion, or household amenities as proxies for vulnerability, often overlooking broader structural and developmental dimensions of deprivation. Finally, [deSouza et al. \(2023\)](#) did incorporate source-specific PM_{2.5} estimates and related them to socioeconomic characteristics in mutually adjusted models, though as supplementary analyses alongside a main analysis of total PM_{2.5}, and [Sarkar et al. \(2026\)](#), like [Chakraborty and Basu \(2021\)](#), examined only total PM_{2.5}; in all three studies, moreover, the socioeconomic measures were derived from survey clusters or census data rather than from a source with complete national administrative coverage produced independently of either. The measures of disadvantage used across these studies therefore derive either from the decennial census or from a sample survey, each carrying the constraints described above. Gridded sociodemographic products offer one route past the temporal and coverage constraints of census- and survey-based measures, since they are produced independently of the decennial census and provide continuous surfaces that can be aggregated to any administrative unit. A further constraint is one of measurement. Deprivation is conventionally represented either by a single socioeconomic indicator or by membership in a social category, whereas multidimensional approaches count deprivations jointly and give priority to those experiencing several at once, on the reasoning that disadvantages accumulate and that a summary along one axis can conceal them ([Alkire & Foster, 2011](#)). India's National Multidimensional Poverty Index applies this logic at the district level across twelve indicators spanning health, education, and standard of living ([NITI Aayog, 2021](#)). Analyses of exposure disparity have not generally adopted this framing, so it remains unclear whether particular dimensions of deprivation are associated with particular pollution sources. Examining component indicators separately, rather than collapsing them into a single composite score, is what makes that distinction visible.

1.6 Contribution and Significance

Recently developed global, gridded datasets that integrate high-resolution sociodemographic and satellite data offer a new empirical foundation for characterizing multiple dimensions of social deprivation and addressing gaps in previous research on social inequalities in the distribution of air pollution. The Global Gridded Relative Deprivation Index (GRDI) represents one such advancement, providing subnational insights into social deprivation by incorporating variables such as built-up areas, infant mortality, child dependency ratios and nighttime light intensity, including changes over time. In this study, I assess the six distinct economic, social, and developmental indicators that comprise the GRDI, five of which are retained as predictors after assessing local collinearity (Subsection 2.4), to develop a more systematic understanding of how different dimensions of deprivation relate to air pollution exposure from multiple emission sources in India. These indicators are linked to district-level estimates of both total and source-specific PM_{2.5} concentrations to determine how particular indicators of social deprivation are associated with both overall PM_{2.5} pollution and those from specific source categories.

By examining how multiple dimensions of deprivation relate to both overall and major sources of PM_{2.5} concentrations across Indian districts, my analysis provides more detailed insights on social inequalities in air pollution exposure than prior studies that relied on other data sources and social indicators. I assess whether total and source-specific PM_{2.5} concentrations are higher in districts with greater GRDI-based social deprivation, and, using a spatially explicit model, whether those associations hold uniformly across the country or vary from region to region.

2 Materials and Methods

2.1 Data Sources

This is a district-level ecological study, in which annual PM_{2.5} estimates and gridded indicators of social deprivation are linked at the district scale and analyzed as area-level averages rather than individual exposures. To investigate how social deprivation relates to both overall and source-specific PM_{2.5} concentrations, my analysis integrates district-level estimates of total and source-apportioned PM_{2.5} for 2017 with deprivation indicators from the GRDI. The GRDI is a ~1 km, globally standardized index that combines subnational human development (socioeconomic status), infant mortality and child dependency ratios (demographic and health disadvantage), the ratio of built-up to non-built-up area (infrastructural and urban development), and both the level and growth of nighttime lights (economic activity and development intensity). My use of districts as the unit of analysis aligns with previous national-scale studies on environmental injustices in India (Basu & Chakraborty, 2016; Chakraborty & Basu, 2021). The following subsections describe the data integration processes, variable definitions, and statistical modeling approaches used in this study.

2.2 Dependent Variables

The dependent variables for my district-level analysis comprise: (a) total annual average PM_{2.5} concentrations and (b) nine source-specific contributions to PM_{2.5} concentrations available for the year 2017, compiled by Guttikunda and Ka (2022). The underlying PM_{2.5} concentration estimates were originally developed by the Atmospheric Composition Analysis Group (ACAG) at Washington University in St. Louis, by integrating satellite-derived Aerosol Optical Depth (AOD) data from NASA’s Moderate Resolution Imaging Spectroradiometer (MODIS), Multi-angle Imaging SpectroRadiometer (MISR), and Sea-viewing Wide Field-of-view Sensor (SeaWiFS) instruments with global chemical transport modeling using the GEOS-Chem-CEDS system, so named for its coupling of the GEOS-Chem model to the Community Emissions Data System (CEDS). These modeled PM_{2.5} concentrations were subsequently calibrated to ground-level air quality measurements following established methods (e.g., van Donkelaar et al., 2021).

Guttikunda and Ka’s (2022) compiled PM_{2.5} concentration estimates are provided at a native spatial resolution of approximately 0.01 degrees (~1 km), and for exposure analysis were aggregated to 0.1 degrees (~10 km grid size) and summarized to 640 districts as defined by the 2011 Census of India. My study includes 638 districts, since two districts (Lakshadweep and Cuddalore) were recorded as zero across total and source-specific PM_{2.5} in the compiled dataset and therefore had no valid exposure estimate; both were excluded as data-availability gaps, and neither exclusion is related to district deprivation levels. A further three districts in the Andaman and Nicobar Islands were excluded from the modeled analysis, because the spatial weights used in the statistical models are defined by shared district boundaries and these island districts lie outside the mainland landmass to which that structure applies. The analytical sample for all models reported here is therefore 635 districts, drawn from the 640 districts of the 2011 Census of India. Sources of PM_{2.5} concentrations in this study are grouped into 10 major emission categories, nine of which are analyzed here. These categories are based on aggregating

the original 20 source sectors in the CEDS Global Burden of Disease–Mapping Air Pollution Sources (GBD-MAPS) inventory into broader, policy-relevant groups, following the framework recommended by [Guttikunda and Ka \(2022\)](#). These broad source groups are anthropogenic dust, wind erosion, waste burning, residential (commercial and residential cooking, lighting, and heating), transport (excluding aviation), energy generation, industrial (including solvent and product use), biomass burning, agriculture, and miscellaneous sources. Two boundaries between these groups matter for interpretation. Agricultural waste burning, including crop residue burning, falls within the biomass burning group rather than the agriculture group, so the agriculture group comprises non-combustion agricultural activities such as fertilizer, soil, and manure management. The source names used throughout the text correspond to the column headings in Table 3. The ‘miscellaneous’ category (classified as ‘OTHER’ in GBD-MAPS) which represents a small share of national $\text{PM}_{2.5}$ ($\sim 4\%$, though a larger share in some states), was excluded from my analysis due to its limited relevance for targeted air quality management interventions. For my district-level analysis, concentrations of pollution estimates disaggregated by source were computed by multiplying each source’s percentage contribution by the total $\text{PM}_{2.5}$ concentration within each district. These source-attributed values are absolute concentrations ($\mu\text{g}/\text{m}^3$) rather than each source’s relative share of total $\text{PM}_{2.5}$. Because each is derived from the district’s total concentration, the source-specific outcomes are mechanically related to the total, so their associations with the GRDI indicators partly reflect the overall spatial pattern of total $\text{PM}_{2.5}$ in addition to any source-specific patterning.

2.3 Independent Variables

Independent variables for my study are drawn from the six indicators that comprise the GRDI, formulated to provide a comprehensive measure of multidimensional social deprivation at a 1 square km spatial resolution. Originally developed by Columbia University’s Center for International Earth Science Information Network (CIESIN), GRDI integrates satellite-derived and sociodemographic data to quantify deprivation beyond purely economic indicators, encompassing broader social, infrastructural, and developmental aspects ([CIESIN, 2022](#)). Although GRDI has informed socioeconomic research globally (e.g., [Hassan & Ibrahim, 2024](#)), my study presents a novel application of the dataset by integrating it with high-resolution air pollution data to examine social inequalities.

The GRDI is a unitless indicator that includes the Built-up Area Index, Child Dependency Ratio, Infant Mortality Rate, Subnational Human Development Index (HDI), Nighttime Light Intensity, and the Trend in Nighttime Light Intensity. Each indicator captures a distinct dimension of deprivation, following the construction of the index ([CIESIN, 2022](#)). The Child Dependency Ratio is the ratio of the population aged 0 to 14 to the working-age population aged 15 to 64, and represents the size of the dependent population relative to those of working age. The Infant Mortality Rate, the number of deaths before age one per 1,000 live births, is a widely used summary measure of population health; child mortality serves the same function as a health indicator in India’s National Multidimensional Poverty Index ([NITI Aayog, 2021](#)). The Subnational Human Development Index summarizes education, health, and standard of living. The Built-up Area Index, the ratio of built-up to non-built-up area, distinguishes more rural from more urban settings, and is included on the basis that rural populations experience higher multidimensional poverty than urban populations, other things being equal. Nighttime Light Intensity is treated in the index as a proxy for anthropogenic activity, economic output, and infrastructure development ([CIESIN, 2022](#)); nighttime lights have been shown to correlate with local measures of household wealth, education, and health, on evidence from 29 African countries ([Bruederle & Hodler, 2018](#)). The Trend in Nighttime Light Intensity, the slope of annual light intensity over time, captures the direction of recent change in that activity. These GRDI indicators are constructed using scale metrics tailored to the nature of each variable, allowing for consistent and meaningful comparisons of relative deprivation both within and

across countries (CIESIN, 2022). CIESIN combines these six inputs into a single composite GRDI raster, but I do not use that composite value here. Each component indicator is assessed as its own predictor, so that the association between each dimension of deprivation and $PM_{2.5}$ can be estimated separately; as described in Subsection 2.4, one of the six, Subnational HDI, is subsequently excluded from the final models for local collinearity with Infant Mortality Rate, so five component indicators are retained as predictors. All references to “GRDI indicators” in this paper therefore denote the six components, not the composite index, unless otherwise specified as the five retained predictors. Each indicator enters the models in its native measured direction rather than being recoded to a common deprivation scale, so each coefficient must be read against that indicator’s own direction of deprivation. For the Infant Mortality Rate and Child Dependency Ratio, higher values indicate greater deprivation, whereas for the Built-up Area Index, Subnational HDI, Nighttime Light Intensity, and its trend, lower values indicate greater deprivation. Table 1 summarizes the dependent and independent variables, units of measurement, and the direction of deprivation for each.

The $PM_{2.5}$ concentrations and their source contributions, available in tabular format at the district level, were joined to the 2011 Census of India district boundaries to create a geographically referenced dataset, using the `geopandas` package in Python. Each of the six GRDI indicators was obtained as global raster GeoTIFF layers and aggregated to the district scale by computing mean values within each district polygon using the `exactextract` package in Python. The resulting dataset included total $PM_{2.5}$, source-specific $PM_{2.5}$ concentrations, and the six GRDI deprivation indicators for each district. Descriptive statistics for both dependent and independent variables described previously are presented in Table 1.

2.4 Statistical Analyses

I employed Generalized Estimating Equations (GEEs), a multivariable modeling approach that extends the generalized linear model to accommodate clustered data, to analyze relationships between $PM_{2.5}$ exposure and social deprivation indicators. GEE models are particularly appropriate for analyzing spatial clustered data and where observations within the clusters may be correlated (Liang & Zeger, 1986). To define clusters for this analysis, I treated districts as nested within states and union territories (UTs). This definition resulted in 638 districts clustered within 34 Indian states or UTs, with the number of districts per state/UT ranging from 1 to 71. As set out below, the GEE is reported here as the starting point of my analysis rather than as the final specification: a diagnostic of its residuals led me to adopt a spatially explicit model for the results I report. I estimated a total of 10 separate GEE models, with the dependent variable comprising total $PM_{2.5}$ concentrations in the first model and $PM_{2.5}$ concentrations from each individual source category in the remaining nine models, using the same set of independent variables (i.e., six deprivation indicators from the GRDI, of which five are carried forward to the final models described below) across all GEEs. These six indicators are the primary explanatory variables of interest rather than adjustment controls, and the models include no additional covariates. Because the analysis is cross-sectional, I interpret the resulting estimates as descriptive associations between each dimension of deprivation and $PM_{2.5}$, with the six indicators mutually adjusted for one another, rather than as adjusted causal effects. As descriptive associations, they may also reflect other spatially correlated factors not included in the models, such as population density, industrial siting, and regional air quality policy. All six predictors were standardized (converted to z-scores) prior to estimation, so each coefficient reflects the association with a one standard deviation increase in that predictor, and the original measurement scale of any individual indicator does not affect the estimates.

I examined and compared three correlation structures, independent (assumes no correlation between observations within clusters), exchangeable (assumes constant correlation among observations within each cluster), and unstructured (makes no assumptions and estimates all pairwise correlations freely) to determine the most appropriate model specification for my data.

Model fit was assessed using the Quasi-Likelihood under the Independence Model Criterion (QIC; Pan, 2001), which indicated that the independent correlation structure provided the best statistical fit in all GEEs presented here.

The next step was to select the most appropriate GEE model specification. Given that my dependent variables were continuous with positive values, I compared normal (symmetric), gamma (for right-skewed positive data), and inverse Gaussian (for highly skewed positive data with variance proportional to the cube of the mean) distributions alongside two link functions, identity and logarithmic. The link function specifies the relationship between the expected value of the outcome and the linear predictor (the weighted sum of the covariates). Under the identity link, the expected PM_{2.5} concentration is modeled directly as a linear function of the predictors, so coefficients represent additive changes in concentration. Under the logarithmic link, the natural logarithm of the expected concentration is modeled as a linear function of the predictors, so that effects are multiplicative on the concentration scale; this link is well suited to strictly positive, right-skewed outcomes such as PM_{2.5} concentrations. Visual inspection of the distributions, supported by QIC comparisons, indicated that the logarithmic link was an appropriate fit for the skewed nature of the data. The inverse Gaussian distribution with a logarithmic link produced the lowest QIC values across all models and was thus selected for final estimation.

All GRDI indicators were standardized before inclusion in the GEE model. The statistical significance of each GEE coefficient was assessed using two-tailed p-values from the Wald chi-square test, and GEE estimation was performed using *IBM SPSS Statistics* (version 30.0) software.

Because the GEE groups districts administratively, by the state or union territory they belong to, it does not represent spatial dependence between neighboring districts, which may cross state boundaries. I therefore tested the GEE residuals for spatial autocorrelation. Neighbors were defined by queen contiguity, so that any two districts sharing a boundary or a vertex are treated as adjacent, and the resulting weights were row-standardized. Global Moran's I on the GEE residuals was 0.396 ($p = 0.001$), indicating that substantial spatial structure remained unmodeled. A robust-sandwich standard-error sensitivity check on this GEE further showed that only the trend in nighttime light intensity remained significant once clustering-robust variance was used in place of model-based standard errors, reinforcing my decision to move to a model that treats spatial structure directly rather than as a nuisance parameter. The three districts of the Andaman and Nicobar Islands lie outside the mainland landmass and so cannot be placed in a contiguity-based weights matrix built on shared boundaries; they were excluded at this point, giving the analytical sample of 635 districts used for the residual diagnostic and for all models reported below.

I therefore estimated multiscale geographically weighted regression (MGWR) models, which allow the association between each predictor and PM_{2.5} to vary across space and allow each predictor to vary at its own spatial scale (Fotheringham et al., 2017). Each local regression weights nearby districts more heavily than distant ones using an adaptive bisquare kernel, defined by a bandwidth expressed as a number of nearest neighbors, so that the neighborhood adjusts to district density rather than holding a fixed geographic distance. MGWR estimates a separate bandwidth for each predictor through a backfitting procedure, with bandwidths selected by minimizing the corrected Akaike Information Criterion (AICc). Because a local model fits many correlated tests across space, significance of the local coefficients was assessed against the corrected critical t-value of da Silva and Fotheringham (2016), which adjusts for this multiple testing rather than applying the conventional threshold at every district. Models were estimated in Python using the `mgwr` package (Oshan et al., 2019). As with the GEE, one model was estimated for total PM_{2.5} and one for each of the nine source categories.

Collinearity was assessed both globally and locally. Across the full sample, variance inflation factors for the six GRDI indicators ranged up to 4.85 (tolerance, its reciprocal, no lower

than 0.21) and the maximum condition index was 4.60, with the strongest pairwise correlation between built-up area and nighttime light intensity ($r = 0.78$); by conventional thresholds these do not indicate a global collinearity problem. VIF, tolerance, and the full pairwise correlation matrix for all six indicators are reported in Supplementary Table S2. Local collinearity is a distinct question in a spatially varying model, because predictors that are only moderately correlated nationally can be strongly correlated within a local neighborhood (Wheeler, 2007). Local variance inflation factors computed within each district’s kernel neighborhood showed that the Subnational Human Development Index and the Infant Mortality Rate were severely collinear locally, with a median local variance inflation factor of 66 for infant mortality. Retaining both would make their local coefficients uninterpretable, so the Subnational HDI was not carried into the final models. Removing it reduced the median local variance inflation factor for infant mortality to 3.7 and improved model fit (AICc 3579.4 with all six indicators, 3577.3 with five). The models I report therefore include five GRDI indicators: built-up area, infant mortality, child dependency, nighttime light intensity, and the trend in nighttime light intensity.

The `mgwr` implementation supports a Gaussian outcome only, so the MGWR models do not carry over the inverse Gaussian distribution and logarithmic link selected for the GEE; local coefficients are therefore additive, expressed as the change in $\text{PM}_{2.5}$ concentration in $\mu\text{g}/\text{m}^3$ associated with a one standard deviation increase in a predictor. The switch to a contiguity-based spatial structure is also what excludes the three island districts, so the modeled results describe mainland India together with the districts connected to it by shared boundaries.

3 Results

The spatial distribution of annual average $\text{PM}_{2.5}$ concentrations across Indian districts is depicted in Figure 1, where districts are classified into five quintiles of $\text{PM}_{2.5}$ exposure. This map indicates that districts in the highest quintile (top 20%) of $\text{PM}_{2.5}$ are concentrated in northern and eastern India. This spatial pattern corresponds closely to the Indo-Gangetic Plain (IGP), an agriculturally productive and densely populated region that covers about 13% of India’s land area and produces roughly half of the country’s foodgrains, feeding 40% of its population (Pal et al., 2009). Persistent air pollution in this region reflects the combined influence of high population density, intensive agricultural activity, industrial emissions, and seasonal meteorological conditions. Districts across central India generally experience moderate $\text{PM}_{2.5}$ concentrations, while districts in the lowest quintiles are located in southern and northeastern India, where population density and industrial activity are comparatively lower and atmospheric dispersion conditions are more favorable.

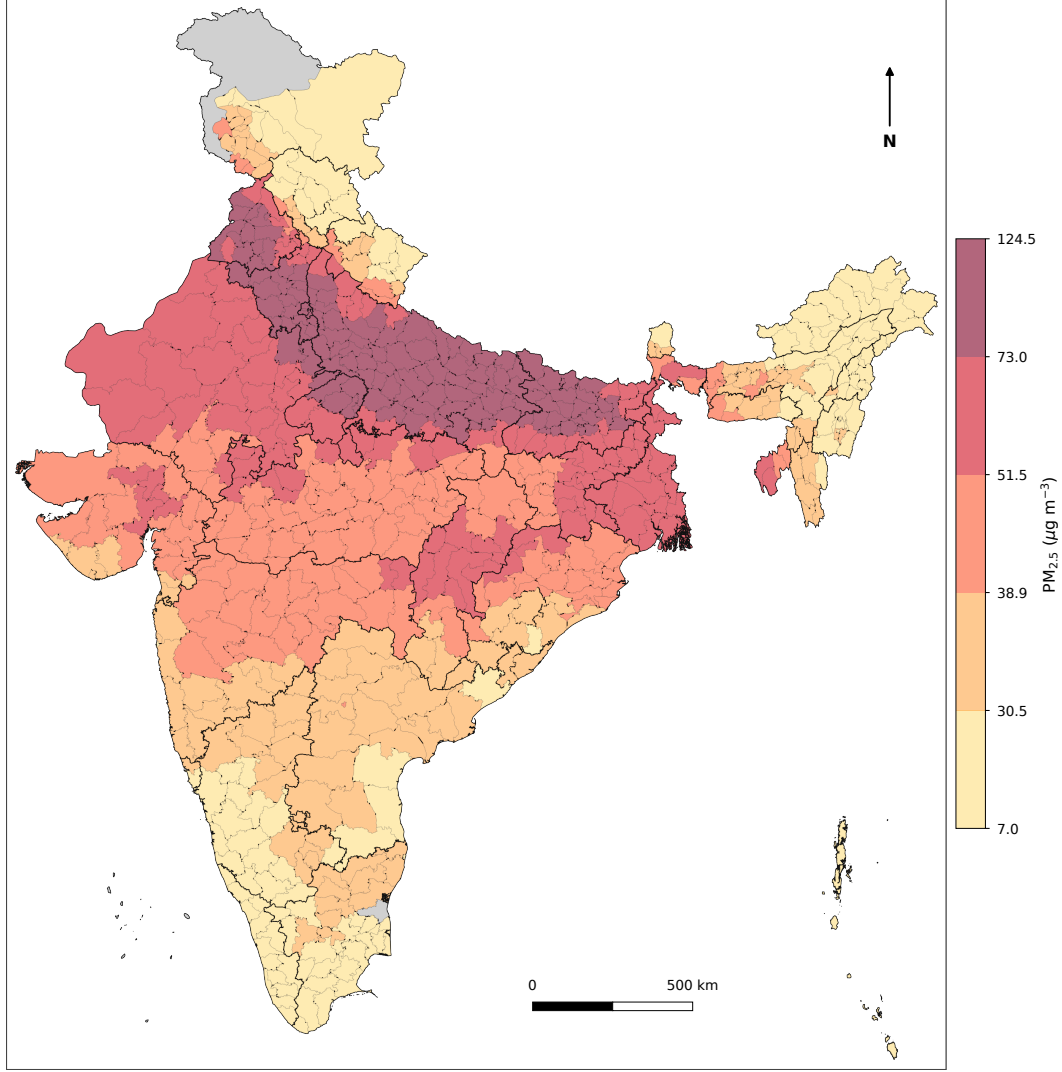


Figure 1: Spatial distribution of total PM_{2.5} concentrations ($\mu\text{g}/\text{m}^3$) across Indian districts, 2017. Concentrations are annual averages for 2017 aggregated to district means, and districts are classified into quintiles of the national distribution. Grey districts have no valid exposure estimate. $N = 638$ districts with valid estimates. PM_{2.5}, fine particulate matter with aerodynamic diameter $\leq 2.5 \mu\text{m}$.

Figure 2 illustrates the spatial distribution of source-specific PM_{2.5} concentrations across Indian districts. Contributions from anthropogenic dust, energy generation, industrial, agricultural, residential, and transport sources are most pronounced in the IGP region, closely mirroring the spatial distribution observed for total PM_{2.5} concentrations. PM_{2.5} contributions from wind erosion and biomass burning exhibit more spatially diffuse patterns, with elevated levels extending beyond the IGP into western, central, and northeastern India.

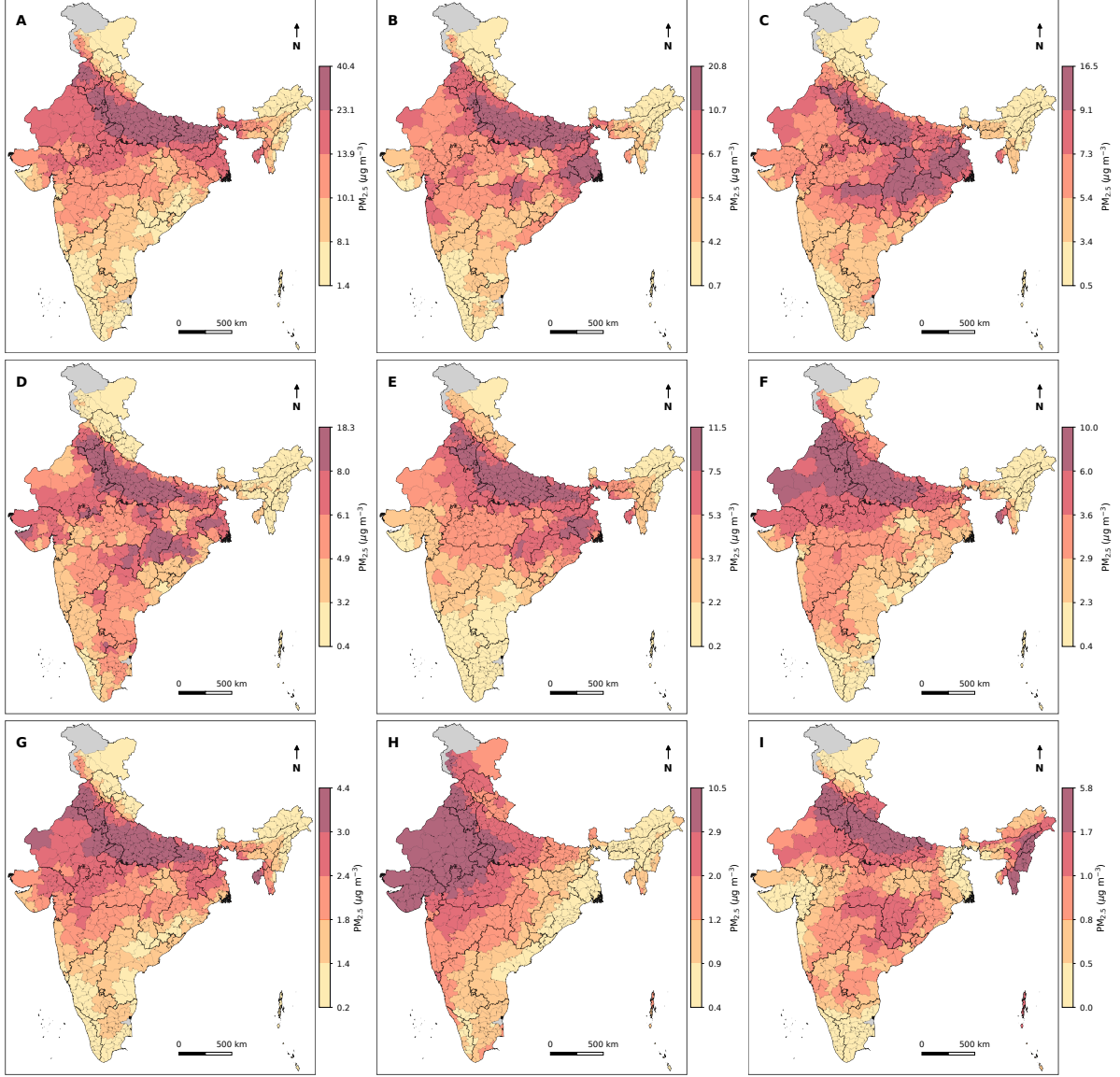


Figure 2: Spatial distribution of source-specific $\text{PM}_{2.5}$ concentrations ($\mu\text{g}/\text{m}^3$) across Indian districts, 2017. Each panel is classified into quintiles of that source's own concentration distribution (five classes), so the class breakpoints differ from panel to panel. Colors therefore indicate relative spatial variation within each source and are not directly comparable in absolute magnitude across panels; absolute source-specific concentrations are reported in Table 1. Panels are ordered by descending mean concentration: (A) residential, (B) industrial, (C) energy generation, (D) anthropogenic dust, (E) agriculture, (F) transport, (G) waste burning, (H) wind erosion, (I) biomass burning. Grey districts have no valid exposure estimate. $N = 638$ districts with valid estimates. $\text{PM}_{2.5}$, fine particulate matter with aerodynamic diameter $\leq 2.5 \mu\text{m}$.

Socioeconomic characteristics of Indian districts display pronounced spatial variation as demonstrated by the distribution of the GRDI indicators, shown in Figure 3. Districts characterized by weaker infrastructure and limited electrification, reflected in low built-up area indices and nighttime light intensity, are clustered primarily in northern and eastern India. These districts also exhibit higher demographic pressures, indicated by elevated child dependency ratios, alongside poorer health outcomes measured through infant mortality rates and lower subnational HDI values. Districts in southern and western India generally show more fa-

426 vorable socioeconomic profiles across these same indicators, with higher levels of development,
427 greater electrification and urbanization, lower dependency ratios, and reduced infant mortality.

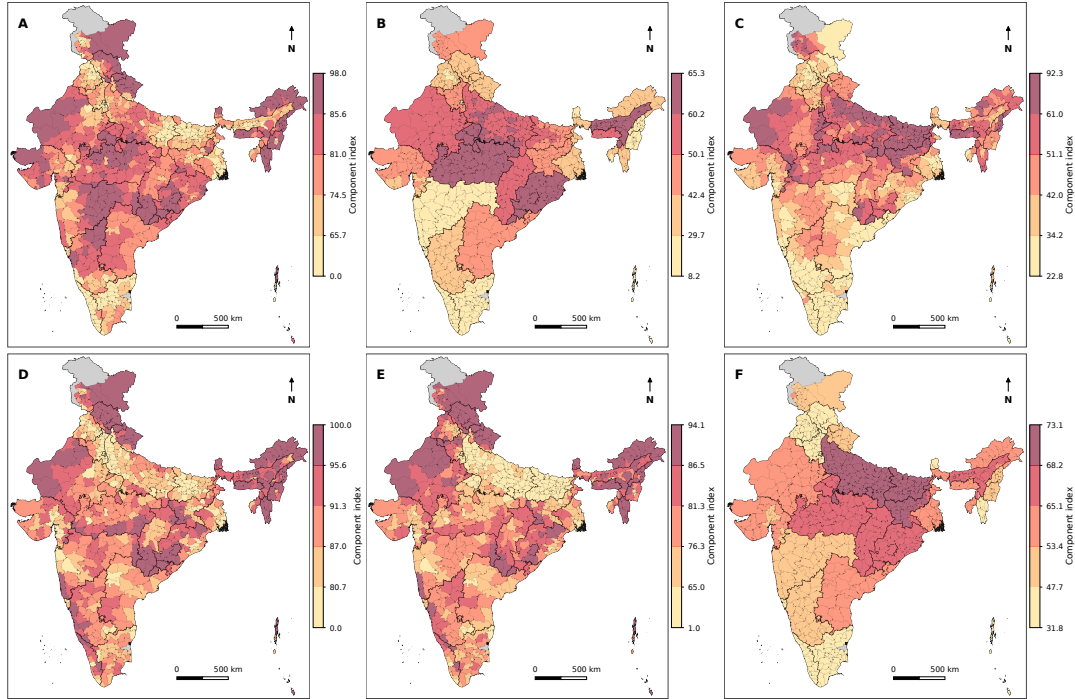


Figure 3: Spatial distribution of GRDI indicators across Indian districts. Each panel shows one of the six GRDI component indicators, which are unitless index values aggregated from approximately 1 km grid cells to district means. Higher values indicate greater deprivation for the Infant Mortality Rate and Child Dependency Ratio, and lower values indicate greater deprivation for the Built-up Area Index, Subnational HDI, Nighttime Light Intensity, and its trend. Panels are ordered as the models use them: (A) Built-up Area Index, (B) Infant Mortality Rate, (C) Child Dependency Ratio, (D) Nighttime Light Intensity, (E) Trend in Nighttime Light Intensity, (F) Subnational HDI, which was assessed and not retained as a predictor because of its local collinearity with the Infant Mortality Rate. Each panel is classified into quintiles of that indicator's own distribution, so class breakpoints differ between panels. Grey districts have no valid exposure estimate. GRDI, Global Gridded Relative Deprivation Index; HDI, Human Development Index.

428 Results from the MGWR model relating social deprivation indicators to total annual average
429 PM_{2.5} concentrations are summarized in Table 2, and the district-level local coefficients are
430 mapped in Figure 4. The central result is that these associations are not constant across the
431 country. Because MGWR estimates a coefficient for every district, each indicator is described
432 by a distribution of local values rather than by one national estimate, and for every indicator
433 that distribution spans both positive and negative values. The bandwidths selected for the five
434 indicators range from 14 to 46 nearest neighbors, so all five operate at sub-national scales rather
435 than as country-wide effects.

436 Reading the indicators individually, built-up area has a median local coefficient of -1.835
437 $\mu\text{g}/\text{m}^3$ per standard deviation and is negative in 75.3% of districts, so it is predominantly
438 but not uniformly negative, with the positive values concentrated in the west and northeast
439 (Figure 4). The trend in nighttime light intensity is the most consistently signed indicator,
440 negative in 85.4% of districts (median -1.902). Infant mortality is the most spatially divided:
441 its median is -0.892 , yet 45.5% of districts return a positive coefficient, and the map separates
442 a positive band across the northern plains from negative values in western and central India

(Figure 4). Child dependency is positive in 31.2% of districts (median -0.696). Nighttime light intensity has a median close to zero (-0.098) and is almost evenly split in sign (48.0% positive), so no national direction can be read from it. The proportion of districts at which a coefficient is significant under the corrected critical t-value ranges from 4.3% for nighttime light intensity to 40.6% for infant mortality, and the model fits the national pattern closely (R^2 0.993, AICc 3577.3).

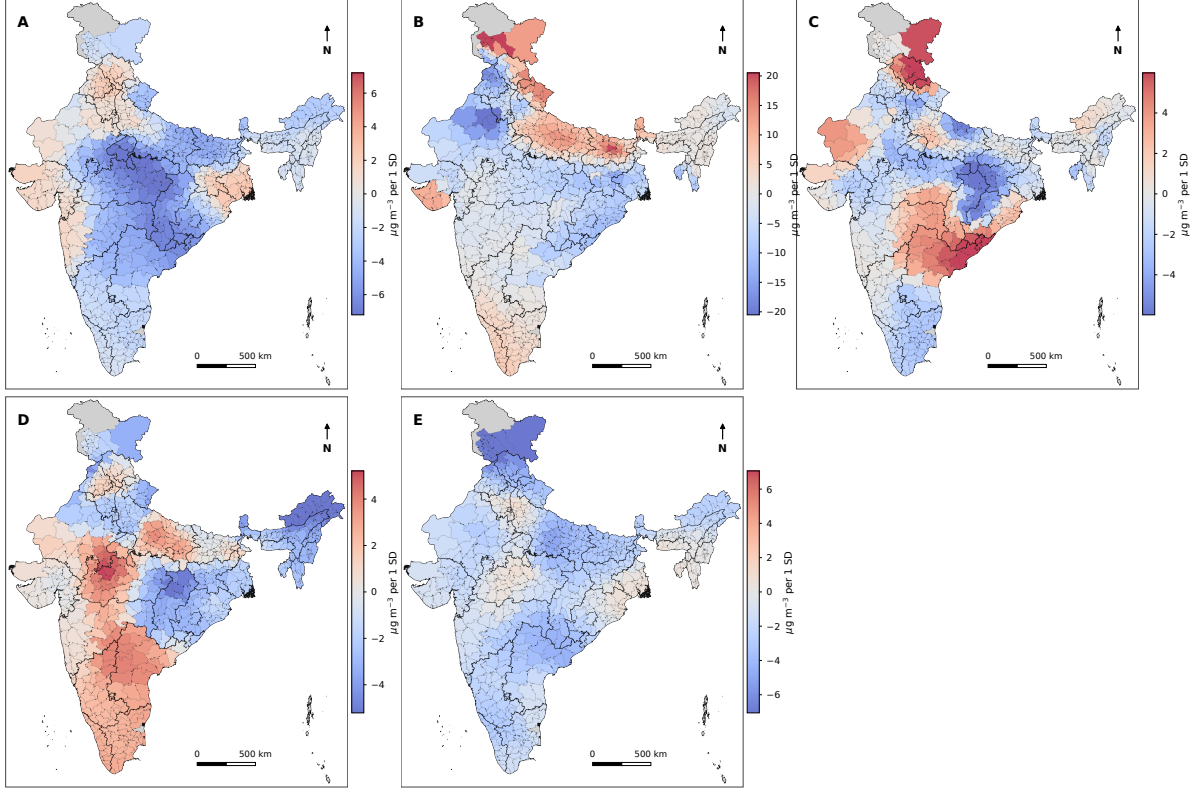


Figure 4: Local MGWR coefficients for total $PM_{2.5}$ across Indian districts, 2017. Panels show (A) Built-up Area Index, (B) Infant Mortality Rate, (C) Child Dependency Ratio, (D) Nighttime Light Intensity, and (E) the Trend in Nighttime Light Intensity. Each district is shaded by its own estimated local coefficient, in $\mu g/m^3$ of $PM_{2.5}$ per one standard deviation increase in the indicator, with the diverging scale centered at zero so that blue indicates a negative and red a positive local association. Each panel's scale is symmetric about zero and trimmed at the 98th percentile of the absolute coefficient, so that a few extreme districts do not flatten the rest of the map; scales differ between panels, so shading is comparable within a panel but not across panels. Grey districts lie outside the modelled sample. $N = 635$ districts. $PM_{2.5}$, fine particulate matter with aerodynamic diameter $\leq 2.5 \mu m$; MGWR, multiscale geographically weighted regression.

Source-specific results are summarized in Table 3, where each column reports a separate MGWR model with one source category's $PM_{2.5}$ concentration as the outcome (anthropogenic dust, energy generation, wind erosion, industrial, waste burning, biomass burning, residential, agriculture, and transport). The same spatial variability seen for total $PM_{2.5}$ is present for every source: no indicator holds a single direction in all districts in any of the nine models. The magnitude of the median coefficients also tracks the mean concentration of the source, so the largest values appear for residential $PM_{2.5}$ (built-up area -0.661 , nighttime light trend -0.820) and the smallest for biomass burning and wind erosion, the two categories with the lowest mean concentrations (Table 1).

The proportion of districts at which an association is significant differs more between indicators than between sources. Built-up area is the most frequently significant indicator overall, exceeding 20% of districts in seven of the nine models, and is significant in every district in the industrial model, where its bandwidth of 634 nearest neighbors means the association is estimated as effectively constant across the country rather than varying locally. Infant mortality is significant in 17.3% to 35.9% of districts depending on source, with the highest proportions for waste burning, residential, and transport $\text{PM}_{2.5}$. Nighttime light intensity is significant in fewer than 16% of districts in every model except energy generation, where it reaches 23.1%, and in under 3% for wind erosion, industrial, and transport $\text{PM}_{2.5}$, so it distinguishes little between districts once the other four indicators are included. The nighttime light trend is the exception among the development indicators, reaching 43.1% of districts for energy generation and 33.9% for residential $\text{PM}_{2.5}$.

A median coefficient close to zero, as for child dependency in the waste burning and biomass burning models, summarizes local values of opposing sign rather than an absence of association, which is why the percentage of districts significant is reported alongside it. The four bandwidths that approach the full sample, listed in the note to Table 3, describe associations that are effectively national rather than local, and should not be interpreted as spatially varying. Built-up area and nighttime light intensity are the most strongly correlated pair of indicators nationally ($r = 0.78$) and are locally collinear across much of the country at the smaller bandwidths, so their local coefficients are best read together rather than as independent measures of development.

4 Discussion

4.1 Main Findings

This study examined how multidimensional social deprivation is associated with both total and source-specific $\text{PM}_{2.5}$ exposure across Indian districts using high-resolution sociodemographic and satellite data, based on multiscale geographically weighted regression models adopted after diagnostics of an initial GEE revealed substantial unmodeled spatial structure. By linking district-level $\text{PM}_{2.5}$ concentrations to indicators from the GRDI, I present a national-scale assessment of how social inequalities are spatially associated with patterns of air pollution exposure in India. Because the analysis is cross-sectional and based on a single year (2017), these results identify statistical associations and spatial overlap between social deprivation and $\text{PM}_{2.5}$ exposure rather than causal or mechanistic relationships.

The central empirical fact is spatial heterogeneity rather than a uniform national gradient: no indicator holds a single direction nationally, and the same variability holds within every emission source category. The following two subsections examine, in turn, how the deprivation indicators relate to total $\text{PM}_{2.5}$ and how that relationship varies by emission source.

4.2 Social Deprivation and Total $\text{PM}_{2.5}$ Exposure

The clearest and most consistent association is for the trend in nighttime light intensity. Its local coefficients are negative in 85.4% of districts, so districts where nighttime lights have grown more slowly, which the GRDI reads as greater deprivation, tend to record higher total $\text{PM}_{2.5}$ than their neighbors. To the extent that a single deprivation gradient survives the move to a spatially varying model, this is it: limited recent socioeconomic change and elevated exposure co-occur across most of the country. The infant mortality rate is used here as a deprivation indicator rather than as a modeled health outcome; it is separately documented in the epidemiological literature as associated with $\text{PM}_{2.5}$ exposure, with prior evidence from India linking exposure to increased neonatal and infant mortality (deSouza et al., 2022), which makes the regional structure of the infant mortality association directly relevant to where those risks concentrate.

Infant mortality is the most regionally divided indicator. Its local coefficients form a band of positive values across the northern plains, so in the part of the country where concentrations are highest, districts with worse infant survival also record higher PM_{2.5}; across much of western and central India the association reverses. Its national median therefore summarizes two regional regimes rather than one gradient, and the same reading applies, at smaller magnitude, to child dependency (positive in 31.2% of districts). These are descriptive statements about where health disadvantage and exposure coincide; the cross-sectional design does not identify why the alignment holds in one region and not another.

The Built-up Area Index illustrates most clearly why the global and local views differ. Estimated globally, built-up area is positively associated with PM_{2.5}; estimated locally, its coefficient is negative in 75.3% of districts. The two are not contradictory: the global association reflects covariation between regions, whereas the local coefficients compare each district with its neighbors, and within most neighborhoods the more built-up districts do not record higher total PM_{2.5}. This is consistent with the regional character of total PM_{2.5} in India, which is shaped by atmospheric transport across administrative boundaries and by seasonal stagnation as much as by any district’s own emitting activity (David et al., 2019; Zhou et al., 2024), and it cautions against reading a national coefficient for urbanization as evidence that urban districts are systematically more exposed. The index documentation itself notes that the assumed inverse relationship between built-up area and deprivation is context-dependent and may break down where rapid unplanned urbanization concentrates deprived populations within built-up areas (CIESIN, 2022), a further reason to treat this indicator’s coefficient as an exposure pattern rather than a statement about advantage. Nighttime light intensity, finally, carries little local information once the other indicators are included: its median is close to zero, its sign is nearly evenly split across districts, and it is significant in only 4.3% of them. Given its strong correlation with built-up area both nationally ($r = 0.78$) and within local neighborhoods, I do not interpret its local coefficients independently of built-up area.

4.3 How the Deprivation Gradient Varies by Emission Source

The spatial variability documented for total PM_{2.5} persists when concentrations are disaggregated by emission source: in none of the nine source models does any indicator hold a single direction across all districts. Within that variability, the strongest deprivation-aligned associations appear for residential PM_{2.5}. Built-up area and the trend in nighttime lights have their largest negative median coefficients in the residential model (-0.661 and $-0.820 \mu\text{g}/\text{m}^3$ per standard deviation), so residential concentrations are highest, relative to neighboring districts, where districts are less built-up and where recent development has been slower. This is consistent with continued dependence on solid biofuels for cooking and heating among less developed districts, which remains a dominant source of PM_{2.5} emissions in India (David et al., 2019). Infant mortality is significant in roughly a third of districts for the waste burning, residential, and transport models, so the sources most closely tied to everyday combustion are also the ones for which health disadvantage aligns most often with exposure; emissions from power and industrial sectors have likewise been shown to impose greater burdens on socially disadvantaged groups, and open waste burning contributes substantially to particulate pollution in many under-developed regions (Kopas et al., 2020; Rentschler & Leonova, 2023).

Two source models depart from the local pattern. In the industrial model, built-up area is estimated as effectively constant across the country and negative everywhere, so less built-up districts record higher industrial-attributed PM_{2.5} conditional on the other indicators, which is consistent with evidence that industrial activity is often disproportionately sited away from advantaged areas (Kopas et al., 2020), although my cross-sectional design cannot establish siting as the mechanism. In the energy generation model, the trend in nighttime lights is the most frequently significant association of any in Table 3 (43.1% of districts) and is predominantly positive, the opposite of its direction for most other sources; I report this as an observed pattern

without asserting a mechanism. More generally, because the local coefficients vary from region to region, which dimension of deprivation aligns with which source is itself a regional question, and the medians in Table 3 should be read together with the percentage of districts at which each association is significant.

4.4 Regional Contrasts Across the Indo-Gangetic Plain, Central, and Southern India

My results reveal a pronounced north–south gradient in exposure to $\text{PM}_{2.5}$, mirroring observed patterns in which the IGP registers the nation’s highest $\text{PM}_{2.5}$ levels (WHO, 2016). High $\text{PM}_{2.5}$ levels in the IGP are driven by the combined effects of population density, intensive agricultural practices such as crop residue burning, industrial and vehicular emissions, and seasonal meteorological conditions that limit dispersion, particularly winter inversions. This aligns with evidence that extreme pollution in the IGP stems from dense local emissions (e.g. crop burning, industries, transport) compounded by winter stagnation and strong temperature inversions that trap pollutants (Zhou et al., 2024). A similar dynamic is documented in Delhi during 2021 lockdown periods, where a 120–587% surge in crop residue burning over Haryana and Punjab measurably raised $\text{PM}_{2.5}$ concentrations in the capital through long-range transport even as local emissions were suppressed (Saharan et al., 2022). In contrast, central India’s elevated $\text{PM}_{2.5}$ concentrations align more closely with industrial and energy production zones, a pattern supported by findings that pollution from coal-fired power plants disproportionately affects marginalized communities in poorer, coal-dependent central and eastern states (Kopas et al., 2020). Meanwhile, southern and northeastern regions generally experience lower $\text{PM}_{2.5}$ due to less intensive urbanization, fewer industrial activities, and more favorable atmospheric dispersion. For example, far fewer stagnation events occur in peninsular southern India than in the IGP, resulting in better ventilation of pollutants (Zhou et al., 2024). The local coefficients give this contrast statistical expression: the band of positive infant mortality coefficients in Figure 4 lies across the northern plains, so it is precisely in the most polluted region of the country that health disadvantage and exposure align.

Regional differences are also evident within individual source categories. Residential $\text{PM}_{2.5}$ contributions are particularly elevated in central and eastern states characterized by limited adoption of clean cooking fuels; nationally, 57% of the rural population depends solely on solid fuels such as firewood, crop residues, and dung cakes (Statesman News Service, 2021). Recent findings by Dhamija (2023) indicate that Chhattisgarh records the lowest share of households using Liquefied Petroleum Gas (LPG) as their primary cooking fuel, at 30.6%, and that in Odisha 67.7% of households continued to rely on solid fuels, with eleven states in total falling below 50% LPG use. Conversely, states such as Telangana report among the highest shares of households using LPG (Dhamija, 2023). These regional differences point to the importance of adapting air quality mitigation strategies to local emission sources and environmental conditions.

4.5 Comparison With Previous Studies

These results are broadly consistent with earlier national-scale work while differing in the measures used and in what they resolve. Chakraborty and Basu (2021) reported higher concentrations in districts with larger Scheduled Caste populations, more young children, and more households without toilets, drawing on census measures of disadvantage; I find a comparable gradient using gridded indicators that are produced independently of the decennial census, and extend it by showing that the gradient is not uniform across emission sources. deSouza et al. (2023) found that associations differed across social groups and between urban and rural clusters; my spatially varying estimates make that heterogeneity explicit at the district scale, since every indicator I examine changes direction somewhere in the country. Sarkar et al. (2026) reported that exposure disparities widened in urban India between 2015–2016 and

2019–2021 even as average concentrations declined; my cross-sectional design cannot speak to change over time, but the divergence I find between the global and local associations for built-up area indicates that no single national statement about urban and rural districts describes exposure equally well in every region. My source-specific findings also parallel evidence from other national settings that exposure disparities are structured by emission sector rather than distributed uniformly (Tessum et al., 2021; Knobel et al., 2023), and within India they extend the single-sector evidence on coal-fired power generation reported by Kopas et al. (2020) across nine source categories.

4.6 Policy Implications for Equitable Air Quality Management

Because the associations between deprivation and concentrations differ by source and by region, measures targeted at particular sources will not distribute their benefits evenly, and the same source measure will have different equity implications in different parts of the country. The residential category shows the strongest deprivation-aligned associations in my results, so reductions in household and commercial combustion would be expected to deliver their largest gains in less built-up districts and in districts where recent development has been slower, although my cross-sectional estimates describe where concentrations are currently higher rather than how the benefits of any specific intervention would in fact be distributed. Beyond this, assessments of the National Clean Air Programme have found that transport and road dust dominate city action points while domestic cooking and heating receive minimal attention (Ganguly et al., 2020), and that most cities remain well above national standards, with progress better assessed at the regional airshed scale (Guttikunda et al., 2024). Evidence from other settings indicates that geographically targeted reductions in a small share of emissions can substantially reduce exposure inequality (Wang et al., 2022). Taken together, these point to the choice of which sources are addressed in which places, rather than the overall stringency of measures alone, as central to whether air quality gains reach the most deprived districts.

4.7 Strengths, Limitations, and Future Research

This study has several strengths. It analyzes source-apportioned $\text{PM}_{2.5}$ alongside total concentrations, so the association with deprivation can be examined for each major emission source rather than only in aggregate. It links these estimates to gridded deprivation indicators produced at approximately 1 km resolution and independently of the decennial census, which avoids the temporal mismatch that arises when recent pollution estimates are paired with older census measures. It covers all districts of India rather than a subset or a sample of survey clusters, so the associations describe the national distribution of exposure. It treats deprivation as multidimensional, entering the component indicators separately rather than relying on a single socioeconomic measure or a composite score, which is what allows a particular dimension of disadvantage to be linked to a particular source. And by allowing every association to vary across districts, it reports where a relationship holds rather than assuming one national coefficient describes the whole country. Finally, because the source categories correspond to sectors that air quality policy already targets, the results speak directly to the distributional consequences of source-specific intervention.

While my study provides valuable insights on social inequities in the distribution of air pollution in India, several limitations should be considered for future research. First, this analysis is based on $\text{PM}_{2.5}$ concentration data from a single year (2017), which restricts the ability to examine temporal changes or trends in social deprivation–pollution relationships; future analyses should include data from multiple years to identify temporal trends and variability in air pollution levels and their sources. Second, the GRDI indicators used in this study, while internationally robust, do not include locally relevant factors such as gender disparities and household access to clean fuels, which are central to the Indian context; continued reliance on solid biomass

fuels for household energy use in low-income regions contributes to elevated ambient PM_{2.5} concentrations, particularly from residential and biomass-burning sources (David et al., 2019), and this prevalence of solid-fuel use remains a key contributor to PM_{2.5} exposure not directly captured by the GRDI's indicators. Third, the analysis is ecological: associations are estimated between district-level averages, so they characterize places rather than individuals and cannot be assumed to hold for people living within those districts. Fourth, the PM_{2.5} estimates are modeled surfaces derived from satellite retrievals and chemical transport modeling calibrated to ground measurements, so they carry uncertainty that may vary across space, particularly where ground monitoring is sparse; higher-resolution daily products now available for India offer one route to testing how sensitive these associations are to the exposure surface used (Mandal et al., 2024). Fifth, the models include five deprivation indicators and no further covariates, so the estimates may partly reflect omitted regional factors such as land use, meteorology, and population density, and do not speak directly to the sixth GRDI indicator, subnational HDI, excluded for the local collinearity described in Subsection 2.4. Sixth, the analysis uses district boundaries as defined by the 2011 Census of India and therefore does not reflect district reorganizations that have occurred since.

A further set of limitations follows from the MGWR specification itself. The MGWR describes spatial variation but does not explain it: the local coefficients show where the associations differ, without identifying the local factors responsible for those differences. Residual spatial autocorrelation, though substantially reduced relative to the initial GEE (Subsection 2.4), remains statistically significant, so some spatial structure in the outcome is still unmodeled; the available MGWR implementation also supports Gaussian outcomes only, so the skewed-outcome family used in the GEE does not carry over; and nighttime light intensity is locally collinear with built-up area across much of the country, which limits how far its local coefficients can be read on their own. Spatially explicit models for non-Gaussian outcomes, spatial lag and spatial error specifications, and Bayesian spatial (e.g., conditional autoregressive) models remain useful extensions for testing how far these results depend on the modeling choices made here. Because the source-specific outcomes are derived from total PM_{2.5}, they represent absolute source-attributed concentrations rather than relative source shares, and their associations partly reflect the total-PM_{2.5} gradient. A supplementary sensitivity analysis refitting the same models with each source's fractional share of total PM_{2.5} in place of its absolute concentration shows reduced residual spatial autocorrelation for eight of the nine sources and generally weaker, more localized associations with the GRDI indicators (Supplementary Table S1), consistent with part of the source-specific patterning in Table 3 reflecting the shared total gradient. My indicators and PM_{2.5} estimates are aggregated to district means from approximately 1 km gridded data, so the analysis characterizes between-district variation and may mask within-district differences across urban, rural, industrial, and informal settlement areas, and does not fully capture finer-scale environmental inequality within districts. Finally, as described in Subsection 2.4, the modeled sample excludes the island districts, which lie outside the mainland contiguity structure the spatial weights require. Combining such approaches with more locally derived social indicators could provide additional insights into geographically specific mechanisms shaping patterns of air pollution exposure across India (Luo et al., 2017).

5 Conclusion

By linking district-level estimates of total and source-specific PM_{2.5} exposure with high-resolution, multidimensional measures of social deprivation, this study advances empirical research on air pollution disparities in India. I find that the association between social deprivation and PM_{2.5} exposure is real but regionally structured rather than uniform. Districts where nighttime lights have grown more slowly tend to record higher concentrations than their neighbors across most of the country, and districts with higher infant mortality record higher concentrations across

the northern plains, where national exposure is highest. No indicator holds a single direction in every district, as the built-up area reversal illustrates (Subsection 4.2), and the alignment between a dimension of deprivation and an emission source differs from region to region, with the strongest deprivation-aligned associations found for residential $\text{PM}_{2.5}$. These inequalities are most pronounced in the IGP region and parts of central India, where multiple drivers including agriculture, industry, and population density combine with unfavorable meteorology to produce extreme levels of exposure. In contrast, districts in southern and northeastern India, which on average exhibit relatively lower levels of social deprivation and more favorable air dispersion conditions, generally indicate lower concentrations of $\text{PM}_{2.5}$. To my knowledge this is the first national-scale analysis in India to relate several dimensions of gridded deprivation, measured independently of the decennial census, to source-apportioned $\text{PM}_{2.5}$ across all major emission categories, and it is that combination which allows the source dependence of the deprivation gradient to be observed at all.

My findings suggest that fine particulate air pollution is not only an environmental and public health issue, but also a reflection of social inequalities. Districts already burdened by overlapping social disadvantages face the highest exposure, highlighting the need for mitigation strategies that consider both environmental and social vulnerabilities. National programs such as the National Clean Air Programme (NCAP), launched in 2019 to reduce $\text{PM}_{2.5}$ concentrations through city-level action plans, are important steps forward, but uniform targets will be insufficient to address these spatial and social disparities. Region-specific interventions that respond to dominant local emission sources and development contexts are therefore warranted to help ensure more equitable outcomes. In terms of future research, extending this work with multiple years of data on both pollution and sociodemographic characteristics would help determine whether social inequalities in air pollution exposure are widening or narrowing. Incorporating locally relevant measures of social deprivation would also provide a more comprehensive understanding of vulnerability in the Indian context. The spatially varying associations documented here already provide evidence for geographically targeted policies, and extending them with spatially explicit models for non-Gaussian outcomes would test how far they depend on the modeling choices made in this study, in support of policies that seek to reduce both air pollution and the social inequalities associated with differential exposure across districts. Set against environmental justice research in India, which has largely related total pollution to categorical measures of social identity, these results indicate that the distribution of exposure is better understood as source-dependent and regionally differentiated, so equitable air quality policy will turn on which sources are reduced as much as on where reductions are made.

Table 1: Variable definitions and summary statistics: dependent variables.

Variable	Definition and Measurement	Min.	Max.	Mean	Std. Dev.
Total PM _{2.5} concentration	Annual average PM _{2.5} concentrations (2017) from satellite-derived AOD and GEOS-Chem modeling, validated with ground observations ($\mu\text{g}/\text{m}^3$)	6.99	124.53	51.42	25.27
Anthropogenic Dust	Annual average PM _{2.5} concentrations (2017) from anthropogenic fugitive and industrial dust sources, including construction activities, roads, mining, and material handling ($\mu\text{g}/\text{m}^3$).	0.42	18.32	5.96	3.01
Wind Erosion	Annual average PM _{2.5} concentrations (2017) from natural wind-blown dust emissions from exposed soils and arid surfaces ($\mu\text{g}/\text{m}^3$).	0.47	10.48	1.89	1.24
Waste Burning	Annual average PM _{2.5} concentrations (2017) from solid waste disposal and open waste burning, including landfill fires and waste incineration ($\mu\text{g}/\text{m}^3$).	0.27	4.39	2.20	0.89
Residential	Annual average PM _{2.5} concentrations (2017) from commercial and residential cooking, lighting, and heating, including combustion of solid biofuels, coal, and other fuels ($\mu\text{g}/\text{m}^3$).	1.43	40.35	15.41	9.42
Transport	Annual average PM _{2.5} concentrations (2017) from transport excluding aviation, including on-road vehicles, non-road transport, and shipping ($\mu\text{g}/\text{m}^3$).	0.44	10.00	3.94	2.16
Energy Generation	Annual average PM _{2.5} concentrations (2017) from electricity and heat production, fuel transformation, and fossil fuel combustion in power plants ($\mu\text{g}/\text{m}^3$).	0.51	16.55	6.51	3.16
Industrial	Annual average PM _{2.5} concentrations (2017) from industrial combustion and non-combustion processes, including cement production, metal processing, manufacturing, and solvent and product use ($\mu\text{g}/\text{m}^3$).	0.71	20.83	7.45	4.23
Biomass Burning	Annual average PM _{2.5} concentrations (2017) from open biomass burning, including forest fires and agricultural waste burning such as crop residue burning ($\mu\text{g}/\text{m}^3$).	0.02	5.83	1.19	0.86
Agriculture	Annual average PM _{2.5} concentrations (2017) from agricultural activities excluding agricultural waste burning, including fertilizer application, soil management, and manure management ($\mu\text{g}/\text{m}^3$).	0.63	11.52	4.90	2.71

Note: PM_{2.5}, fine particulate matter with aerodynamic diameter $\leq 2.5 \mu\text{m}$. PM_{2.5} variables are annual average concentrations for 2017 in $\mu\text{g}/\text{m}^3$, reported as absolute source-attributed concentrations rather than shares of the total. Summary statistics are computed on the analytical sample of 635 districts. The independent variables are reported in the continuation of this table.

Table 1: (continued) Variable definitions and summary statistics: independent variables.

Variable	Definition and Measurement	Min.	Max.	Mean	Std. Dev.
Built-up Area Index	Degree of urbanization based on built-up areas; lower values indicate rural isolation (0–100 scale). <i>Lower value = Higher deprivation</i>	0.03	97.97	74.01	15.41
Infant Mortality Rate	Infant deaths (<1 year old) per 1,000 live births; indicator of population health (deaths per 1,000 births). <i>Higher value = Higher deprivation</i>	8.24	65.34	45.09	15.06
Subnational Human Development Index	Composite index measuring health, education, and living standards, natively defined on a 0–1 scale and expressed here on a 0–100 scale. <i>Lower value = Higher deprivation</i>	31.75	73.14	57.70	10.35
Child Dependency Ratio	Ratio of children aged 0–14 to adults aged 15–64; indicates economic dependency (Ratio). <i>Higher value = Higher deprivation</i>	22.78	92.35	48.15	13.89
Nighttime Light Intensity	Proxy for economic activity and infrastructure access using Visible Infrared Imaging Radiometer Suite satellite data (0–100 scale). <i>Lower value = Higher deprivation</i>	0.00	99.97	85.56	16.27
Trend in Nighttime Light Intensity	Estimated annual change in nighttime light intensity. <i>Lower value = Higher deprivation</i>	0.96	94.14	74.58	15.33

Note: GRDI, Global Gridded Relative Deprivation Index; HDI, Human Development Index. GRDI indicators are unitless index values aggregated to district means. Summary statistics are computed on the analytical sample of 635 districts. The Subnational Human Development Index is reported here for completeness but is not among the predictors in the models reported in this paper; it was assessed and not retained because of its local collinearity with the Infant Mortality Rate, as described in Subsection 2.4.

Table 2: MGWR for total PM_{2.5} concentration (2017): distribution of local coefficients across districts.

Variables	Bandwidth (neighbors)	Median local beta	2.5th–97.5th percentile	Districts significant (%)	Districts positive (%)
Built-up Area Index	41	−1.835	−6.880 to 2.175	34.3	24.7
Infant Mortality Rate	14	−0.892	−13.763 to 15.021	40.6	45.5
Child Dependency Ratio	24	−0.696	−5.419 to 5.598	14.2	31.2
Nighttime Light Intensity	37	−0.098	−5.095 to 3.980	4.3	48.0
Trend in Nighttime Light Intensity	46	−1.902	−7.045 to 0.607	24.3	14.6
Intercept	13	52.226	23.846 to 101.409	100.0	100.0

Note: N = 635 districts. PM_{2.5}, fine particulate matter with aerodynamic diameter ≤ 2.5 μm ; GRDI, Global Gridded Relative Deprivation Index; MGWR, multiscale geographically weighted regression. MGWR estimates a separate coefficient for every district, so this table summarizes the distribution of those local coefficients rather than reporting a single national estimate. The 2.5th–97.5th percentile range describes the spread of local coefficients across districts and is not a confidence interval. Coefficients are additive: the change in PM_{2.5} in $\mu\text{g}/\text{m}^3$ associated with a one standard deviation increase in the predictor, with the five GRDI indicators standardized (z-scored) and entered jointly. Bandwidths are adaptive and expressed as the number of nearest-neighbor districts, selected per predictor by minimizing AICc; smaller bandwidths indicate an association operating at a more local scale. Significance is assessed against the corrected critical t-value of [da Silva and Fotheringham \(2016\)](#). The Subnational Human Development Index is not included, having been dropped for local collinearity with the Infant Mortality Rate (Subsection 2.4). Model AICc 3577.3, R^2 0.993, residual Moran’s I 0.089 ($p = 0.001$).

Table 3: MGWR for source-specific PM_{2.5} concentrations: median local coefficient and percentage of districts significant.

Variables	Dust	Energy	Wind Erosion	Industrial	Waste Burning	Biomass Burning	Residential	Agriculture	Transport
Built-up Area Index	-0.184 (20.3)	-0.146 (21.9)	-0.046 (8.7)	-0.306 (100.0)	-0.109 (37.0)	-0.005 (5.4)	-0.661 (29.6)	-0.190 (36.4)	-0.149 (23.3)
Infant Mortality Rate	-0.058 (17.3)	-0.102 (24.3)	0.014 (17.3)	-0.050 (27.9)	0.011 (35.9)	-0.045 (17.8)	-0.176 (35.0)	0.039 (32.0)	-0.045 (34.3)
Child Dependency Ratio	-0.291 (12.9)	0.041 (19.5)	-0.018 (7.7)	-0.218 (22.5)	-0.003 (11.5)	-0.000 (10.4)	-0.066 (14.6)	0.031 (19.2)	-0.059 (11.8)
Nighttime Light Intensity	-0.034 (5.8)	-0.371 (23.1)	0.040 (2.7)	0.143 (2.8)	-0.034 (8.8)	-0.032 (12.8)	-0.015 (1.1)	-0.038 (15.4)	0.009 (0.9)
Trend in Nighttime Light Intensity	-0.099 (13.9)	0.077 (43.1)	-0.018 (8.8)	-0.490 (25.4)	-0.008 (8.5)	0.011 (8.0)	-0.820 (33.9)	-0.041 (9.1)	-0.128 (10.6)
Intercept	6.207 (100.0)	7.240 (100.0)	1.518 (100.0)	7.397 (100.0)	2.325 (100.0)	0.959 (93.1)	13.247 (100.0)	5.314 (100.0)	3.434 (100.0)

Note: $N = 635$ districts. PM_{2.5}, fine particulate matter with aerodynamic diameter $\leq 2.5 \mu\text{m}$; GRDI, Global Gridded Relative Deprivation Index; MGWR, multiscale geographically weighted regression. Each cell reports the median local coefficient across districts, with the percentage of districts at which that coefficient is significant in parentheses. Column headings abbreviate the source categories: Dust denotes anthropogenic dust and Energy denotes energy generation; all other headings match the category names used in the text. Each column reports a separate MGWR model with that source's PM_{2.5} concentration as the outcome, so total and source-specific concentrations were analyzed separately rather than jointly. Coefficients are additive, in $\mu\text{g}/\text{m}^3$ per one standard deviation increase in the predictor, with the five GRDI indicators standardized (z-scored) and entered jointly in every model. Significance is assessed against the corrected critical t-value of [da Silva and Fotheringham \(2016\)](#). Because a median summarizes coefficients that vary across districts, a median close to zero can still conceal opposing local associations, and the percentage significant should be read alongside it. Bandwidths are selected separately for each predictor in each model; most fall between 13 and 50 nearest neighbors, but four are large enough that the association is effectively constant across the country rather than local, namely built-up area in the industrial model (634), the nighttime light trend in the energy generation (223), agriculture (74), and waste burning (59) models. The Subnational Human Development Index is not included, having been dropped for local collinearity with the Infant Mortality Rate (Subsection 2.4).

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Supplementary Material

Who Breathes Worse?

Socio-economic Deprivation and PM_{2.5} in India

Simran Koul

Bren School of Environmental Science & Management, University of California, Santa Barbara, USA

Email: skoul@bren.ucsb.edu

October 13, 2026

Supplementary Table S1: Source-share sensitivity analysis

Section 2.2 of the main text notes that the source-specific outcomes are absolute, source-attributed PM_{2.5} concentrations, mechanically related to total PM_{2.5} because each is obtained by multiplying a source’s fractional contribution by the district’s total concentration. To assess how much of the source-specific associations reported in Table 3 reflect this shared total rather than source-specific patterning, the same five-predictor multiscale geographically weighted regression (MGWR) specification was refit with each source’s fractional share of total PM_{2.5} (in percent) as the outcome in place of its absolute concentration, for all nine source categories ($N = 635$).

Table S1 reports the median local coefficient and percentage of districts significant for each predictor in each share model, in the same format as Table 3. Residual spatial autocorrelation is markedly reduced relative to the concentration models: Moran’s I on the model residuals is not statistically significant for eight of the nine share models (Moran’s I between -0.002 and 0.041 , p between 0.05 and 0.49), and only anthropogenic dust remains significant (Moran’s $I = 0.083$, $p = 0.001$). The share models also show weaker and more localized associations with the GRDI indicators than the concentration models: for most source–predictor pairs the percentage of districts significant falls below 15%, consistent with a meaningful part of the concentration-model associations reflecting the shared total-PM_{2.5} gradient rather than a pattern specific to that source. The clearest exception is the residential share model, where the trend in nighttime light intensity remains significant in 100% of districts (median -0.82 percentage points per standard deviation), indicating that slower recent development is associated with a higher residential *share* of PM_{2.5}, not only with higher residential concentrations that track the total.

Supplementary Table S2: Global collinearity diagnostics

Subsection 2.4 of the main text reports that global variance inflation factors (VIF) for the six GRDI indicators ranged up to 4.85 and the maximum condition index was 4.60, with the strongest pairwise correlation between built-up area and nighttime light intensity ($r = 0.78$). Table S2 reports the complete diagnostic underlying that statement: VIF and tolerance (the reciprocal of VIF) for each of the six indicators, and the full 6×6 pairwise correlation matrix, computed on the same mainland analytical sample ($N = 635$).

Table 1: MGWR for source-specific shares of total PM_{2.5} concentration: median local coefficient and percentage of districts significant.

Variables	Dust	Energy	Wind Erosion	Industrial	Waste Burning	Biomass Burning	Residential	Agriculture	Transport
Built-up Area Index	0.013 (0.9)	0.067 (9.6)	0.020 (11.8)	-0.264 (9.6)	0.005 (10.1)	0.033 (0.0)	-0.088 (11.7)	0.058 (10.6)	-0.001 (14.6)
Infant Mortality Rate	0.085 (3.1)	0.053 (22.0)	-0.024 (11.8)	-0.132 (23.0)	-0.012 (14.3)	-0.041 (18.9)	-0.114 (30.2)	0.098 (23.6)	-0.000 (21.3)
Child Dependency Ratio	-0.487 (7.6)	0.160 (27.7)	0.007 (4.4)	-0.349 (20.6)	0.017 (6.8)	-0.001 (6.9)	0.131 (18.1)	0.074 (13.1)	0.024 (5.4)
Nighttime Light Intensity	0.011 (0.0)	-0.324 (22.4)	0.033 (4.3)	0.301 (7.6)	-0.010 (7.6)	0.044 (6.1)	0.214 (4.3)	-0.042 (5.0)	0.111 (10.6)
Trend in Nighttime Light Intensity	0.189 (3.6)	0.370 (57.5)	0.077 (5.0)	-0.452 (100.0)	0.043 (0.0)	0.001 (0.0)	-0.820 (100.0)	0.079 (0.0)	0.047 (30.4)
Intercept	11.573 (100.0)	13.890 (100.0)	3.062 (100.0)	13.765 (100.0)	4.416 (100.0)	1.905 (94.2)	28.566 (100.0)	9.776 (100.0)	7.607 (100.0)
Residual Moran's I	0.083*	0.026	0.006	-0.002	0.032	0.020	0.028	-0.001	0.041

Note: PM_{2.5}, fine particulate matter with aerodynamic diameter $\leq 2.5 \mu\text{m}$; GRDI, Global Gridded Relative Deprivation Index; MGWR, multiscale geographically weighted regression. $N = 635$ districts (mainland sample, as in Table 3). Each cell reports the median local coefficient across districts, with the percentage of districts at which that coefficient is significant in parentheses. The outcome in each model is that source's fractional share of total PM_{2.5} (in percent), not its absolute concentration; coefficients are therefore in percentage points of share per one standard deviation increase in the predictor and are not directly comparable in magnitude to Table 3. Column headings abbreviate the source categories as in Table 3. Residual Moran's I is computed on each model's residuals using the same queen-contiguity spatial weights as the concentration models; * denotes $p < 0.05$ (999 permutations). See the limitation stated in Subsection 4.7 of the main text.

Table 2: Global variance inflation factor (VIF) and tolerance for the six GRDI indicators.

Indicator	VIF	Tolerance (1/VIF)
Built-up Area Index	3.02	0.331
Infant Mortality Rate	3.22	0.311
Subnational HDI	4.81	0.208
Child Dependency Ratio	1.76	0.568
Nighttime Light Intensity	2.97	0.337
Trend in Nighttime Light Intensity	2.52	0.397

Table 3: Pairwise Pearson correlation matrix for the six GRDI indicators (N = 635 districts).

	Built-up Area	Infant Mortality	Subnational HDI	Child Dependency	Nighttime Light	Nighttime Light Trend
Built-up Area Index	1.000	0.285	0.253	0.246	0.776	0.524
Infant Mortality Rate	0.285	1.000	0.805	0.503	0.131	-0.116
Subnational HDI	0.253	0.805	1.000	0.640	0.129	-0.341
Child Dependency Ratio	0.246	0.503	0.640	1.000	0.210	-0.195
Nighttime Light Intensity	0.776	0.131	0.129	0.210	1.000	0.572
Trend in Nighttime Light Intensity	0.524	-0.116	-0.341	-0.195	0.572	1.000

Note: GRDI, Global Gridded Relative Deprivation Index; VIF, variance inflation factor. N = 635 districts (mainland sample). Values are Pearson correlation coefficients among the six raw (unstandardized) GRDI indicators; standardizing indicators before estimation, as done in the models reported in the main text, does not change these correlations. VIF and the correlation matrix reported here (maximum VIF 4.81) closely reproduce the values stated in Subsection 2.4 (maximum VIF 4.85, condition index 4.60); the small difference reflects minor implementation differences in how the diagnostic was computed and does not change the conclusion that global collinearity is not a concern.