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An Analysis of India's Air Feature and Environmental Injustice

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ABSTRACT

Despite the fact that India has some of the world's worst levels of air pollution, the link between air pollution and social disadvantages has not been thoroughly investigated. This study combines fine particulate matter PM2.5 concentration data from satellite observations, a global chemical transport model, and ground-based measurements with district-level socio-demographic data from the 2011 Census of India, using a distributive environmental justice paradigm. After controlling for relevant contextual factors and spatial clustering, the goal of the study is to see if annual average $PM_{2.5}$ concentrations (2010) and recent increases in average PM2.5 concentrations (2010–2016) are unequally distributed among socially disadvantaged populations and household groups. In India, more than 85% of individuals and families live in districts where $PM_{2.5}$ levels surpass international guidelines. Although $PM_{2.5}$ concentrations are much greater in more populated districts, primarily in northern India, less urbanized areas, primarily in southern and central India, have recently seen increases. According to multivariable statistical analysis, higher $PM_{2.5}$ concentrations were found in districts with higher percentages of Scheduled Castes (SCs), young children, and households with poor housing conditions and no toilets; and higher $PM_{2.5}$ increases were found in less urbanized districts with higher percentages of SCs, females, children, people with disabilities, and households with no toilets. These findings emphasize the need of considering the role of air pollution in amplifying the effects of India's social disadvantages.

Keywords- Air Feature, Explanatory Values, Environment Injustice, Variables Dependent.

I. INTRODUCTION

While outdoor air pollution is a global issue, India is thought to have some of the worst levels, particularly in terms of small particulate matter $PM_{2.5}$ pollution. According to the 2019 Global Burden of Disease report, air pollution caused 1.67 million deaths in India (17.8% of total fatalities), with ambient $PM_{2.5}$ pollution accounting for 10.4% of those deaths. According to this study, the economic losses associated with air pollution-related premature death and morbidity amounted to 1.36 percent of India's GDP, implying that the negative health consequences of air pollution may have an impact on India's long-term economic goals. Between 2011 and 2016, the World Health Organization (WHO) conducted research that looked at 100 nations and found that 14 of the top 15 cities for $PM_{2.5}$ pollution were in India. Industrial and automobile emissions, construction dust and debris, reliance on thermal power for electricity, garbage burning, and low-income and rural households' use of wood and dung for cooking and heating are the major contributors to India's particle air pollution. While switching to alternative energy sources may help, concurrent increases in affluence and intensification of poverty, and a lack of effective regulations and investment, are likely to keep air pollution at bay.

Previous studies of $PM_{2.5}$ pollution have concentrated on mapping country-level distribution patterns and relating them to global burden of disease estimates, but they have not taken into account how these patterns relate to demographic traits and socioeconomic disadvantages. In India, such research has looked at $PM_{2.5}$ pollution patterns at the state and national levels. In addition, India's air pollution has frequently been scrutinized in terms of negative health consequences or policy paths to reduce pollution. These findings appear to show that air pollution has widespread societal repercussions and hence needs to be supplemented with an examination of how air pollution's consequences may affect specific areas and demographic groups in different ways. EJ, which focuses on studying environmental risk loads borne by socially disadvantaged communities, becomes a suitable framework for further analysis of socio-spatial patterns of air pollution in India.

The goal of this study is to see if socially disadvantaged and marginalized communities are disproportionately concentrated in locations with higher levels of particle air pollution. Annual average $PM_{2.5}$ concentration data obtained from a combination of satellite observations, a global chemical transport model, and available ground-based measurements are used to measure air pollution. The 2011 Indian Census provided information on population and household characteristics. The district is our unit of analysis since it allows for finer-scale research than at the state level, and the utilization of Census data relating to district level features in India. After adjusting for important contextual factors and data clustering, we want to see if (a) average $PM_{2.5}$ concentrations in 2010 and (b) increases in average $PM_{2.5}$ concentrations from 2010 to 2016 are distributed inequitably among socially disadvantaged populations and household groups. Statistical comparisons of air quality standards set by international and national norms, bivariate linear correlations, and multivariable generalized estimating equation (GEE) models are among the statistical analyses.

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In three ways, the purpose of this article is to further study the distribution and effects of air pollution in India. First, this study aims to demonstrate the importance of incorporating environmental injustice into social and environmental policy-making by looking at associations between particulate air pollution and social inequalities in India, particularly in contexts where rising economic growth is accompanied by persistent and widening social inequities. Second, most international air pollution studies, such as WHO and IHME (Institute for Health Metrics and Evaluation) reports, focus on data relevant to the national scale. The focus in India is on state level or the most polluted cities. Thus, our district-level approach gives the study of air pollution in India a new geographical dimension. Third, while India's urban expansion is focused in major metropolises, cities below the metropolitan level are also growing in population and GDP. The ability to focus on emerging patterns of air pollution in freshly urbanizing areas is enabled by a district-level investigation. Overall, given India's increasing urbanization and significant contributions to global economic and environmental results, this article aims to address the growing need to investigate air pollution.

II. METHODS

Using data provided by Van Donkelaar et al., the two dependent variables for this study were estimated as $PM_{2.5}$ pollution in 2010 and the change in $PM_{2.5}$ pollution between 2010 and 2016. Explanatory factors were gathered from the 2011 Census of India and included variables that have been frequently used in previous distributive EJ studies and characteristics specific to India.

2.1. Variables Dependent

For the purposes of this study, ambient particulate matter pollution was defined as the population-weighted average mass concentration of particles having an aerodynamic diameter of less than 2.5 micrometers ($PM_{2.5}$) in a cubic meter of air, with a spatial resolution of 0.01 x 0.01 across the globe (approximately 11 x 11 km at the equator). We used surface $PM_{2.5}$ concentrations calculated by Van Donkelaar et al. using a combination of aerosol optical depth data from multiple satellite products and a global chemical transport model based on global emission inventories, which were then calibrated to ground-based $PM_{2.5}$ observations using a geographically weighted regression method (GWR). Several more studies concentrating on PM2.5 pollution in India have used this methodology and data.

Annual mean global GWR-adjusted $PM_{2.5}$ estimations for our research were downloaded as an ArcGIS-compatible NetCDF file from the Atmospheric Composition Analysis Group website. ML: Info Map/Lead Dog Consulting provided an ArcGIS shape file with a digitized map of districts demarcated for the 2011 Census of India. The 0.01 x 0.01 resolution grid containing modeled estimates of surface $PM_{2.5}$ concentrations was overlaid on the district boundaries with ArcGIS 10.6.1 software to produce our dependent variables for investigating the distributive EJ implications of $PM_{2.5}$ exposure (Environmental Systems Research Institute, Redlands, USA). On the basis of pixel values from the PM2.5 concentration grid, we used the zonal statistics function to calculate the yearly average $PM_{2.5}$ concentration for each individual district in 2010 and 2016.

Our first dependent variable was a district-level estimate of annual average surface $PM_{2.5}$ concentration in 2010, the year in which our population and housing data for the 2011 Census of India were gathered. The second variable reflected yearly average $PM_{2.5}$ concentration changes at the district level between 2010 and 2016, calculated as a ratio of the two $PM_{2.5}$ concentration values (2016/2010). Following our research focus on increases in $PM_{2.5}$ concentrations during this time period, we used statistical analysis to look at districts where this ratio was more than 1.0. We used 2016 values because they were the most recent year for which modeled estimates of surface PM2.5 concentrations were available in the 0.01 x 0.01 resolution dataset at the time of our analysis, and they were also the most temporally close to the 2011 Census of India data while still allowing us to measure observable change. Our dependent variables' measurements are given in g/m3, and summary data at the district level is shown in Table 1.

Table 1: Shows the summary statistics for the factors examined

Variables	N	Min.	Max.	Mean	SD
Dependent:					
Surface annual average $PM_{2.5}$ 2010 ($\mu g/m^3$)	640	3.60	121.70	45.03	24.38
Increase: $PM_{2.5}$ 2016 ($\mu g/m^3$) / $PM_{2.5}$ 2010 ($\mu g/m^3$)	601	1.00	1.65	1.22	0.13
Independent:					
Population density (persons per square km)	640	1	47,311	1009	3697
% Urban population	640	0.00	100.00	26.40	21.12
% Illiterate population (more than 6 years)	640	12.25	89.37	43.92	13.58
% Scheduled Caste population	640	0.00	50.17	14.86	9.13
% Scheduled Tribe population	640	0.00	98.58	17.63	26.87
% Female population	601	40.84	54.22	48.53	1.52
% Children (6 years or less)	640	5.47	23.01	13.89	2.95
% People with disabilities	640	0.76	4.51	2.15	0.57
% Households (HHs) with no assets *	640	1.00	64.90	20.38	12.93
% HHs in poor condition residence	640	13.30	87.20	50.69	14.30
% HHs with drinking water source outside premises	640	6.10	97.60	57.65	22.95
% HHs with no toilet	640	1.10	94.40	53.63	26.30

2.2. Analyses Statistical

The World Health Organization (WHO), the United States Environmental Protection Agency (USEPA), the European Union (EU), and India's National Ambient Air Quality Criteria all approved air quality standards or thresholds in 2010. (NAAQS). We next calculated the overall proportions of people and homes living in districts with ambient $PM_{2.5}$ pollution levels above these limits, and the proportions of socially disadvantaged populations and households (as a percentage of the total population in India).

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Annual average PM2.5 concentrations (2010) based on all 640 districts in India and the ratio of $PM_{2.5}$ concentrations (2016/2010) based on 601 districts that experienced an increase in $PM_{2.5}$ concentrations (i.e., the ratio of 2016/2010 $PM_{2.5}$ concentrations > 1.0) were investigated using bivariate correlation analysis.

The EJ implications of both PM2.5 (2010) concentrations and growth in $PM_{2.5}$ concentration ratio (2016/2010) were then investigated using generalized estimating equations (GEEs), a multivariable modeling technique suitable for evaluating clustered data. In addition to accounting for clustering of variables across units of analysis, GEEs loosen key assumptions of classic regression models, imposing no stringent distributional requirements for the included variables. Districts in India are divided into 35 states and union territories (UTs). As a result, our clustering criterion was based on the state or UT in which each district was located, resulting in 1 to 71 districts being assigned to each state/UT cluster.

For each of our two dependent variables, a separate GEE was calculated: the yearly average $PM_{2.5}$ concentration in 2010 (640 districts) and the ratio of $PM_{2.5}$ concentrations in 2016 and 2010 (601 districts with a ratio > 1.0). Despite the fact that the second GEE uses data from both 2010 and 2016, the explanatory variables are based on data from 2010, or the start of the period for which $PM_{2.5}$ increases are estimated. By measuring explanatory factors before the start of the time period during which change is measured, potential endogeneity among explanatory variables in a multivariable model can be decreased, and this technique has been suggested in previous econometric studies on modeling temporal change.

Three different correlation structure specifications were considered for each GEE: "independent," which assumes no dependency and all off-diagonal elements of the working correlation matrix are zero; "exchangeable," which assumes constant intra-cluster dependency and all off-diagonal elements of the correlation matrix are equal; and "unstructured," which assumes a completely general correlation matrix that is estimated without constraints. All GEEs were modeled with the three matrices, and the best appropriate specification was determined using the QIC (quasi-likelihood under the independence model criterion). We picked the 'independent' corre-lation matrix for the GEE using the average $PM_{2.5}$ concentration 2010 as the dependent variable, and the 'unstructured' corre-lation matrix for the GEE using the $PM_{2.5}$ concentration ratio 2016-2010 as the dependent variable, based on this model fit criterion.

We used logarithmic and identity link functions to evaluate the normal, gamma, and inverse Gaussian distributions with logarithmic and identity link functions to find the best-fitting models. A logarithmic link function estimates the natural logarithm of the dependent variable, whereas an identity link function implies the dependent variable can be predicted directly. For the GEE, we chose the gamma distribution with logarithmic link function, with the average $PM_{2.5}$ concentration 2010 as the dependent variable, and the normal distribution with an identity link function, with the $PM_{2.5}$ concentration ratio 2016-2010 as the dependent variable. Both of these model specs produced the lowest QIC value.

All independent variables were standardized before being used in the GEEs. We also used the variance inflation factor, tolerance, and condition index criteria to examine potential multicollinearity among these variables, and found that the GEEs are unaffected by multicollinearity. The statistical significance of each individual variable coefficient was assessed using two-tailed p-values from the Wald chi-square test.

2.3 Variables with Explanatory Values

For our distributive EJ study of $PM_{2.5}$ pollution exposure, we employed a set of socio-demographic variables from the 2011 Census of India that are available at the district level. Previous studies on distributive EJ and social vulnerability to environmental hazards in India influenced our choice of independent variables to reflect socially disadvantaged populations. Independent variables were acquired from two sources: primary census enumeration data from the 2011 Census of India and data from the House listing and Housing Census. Table 1 shows summary data for independent variables at the district level.

Illiteracy rate, caste, and tribal status were among the variables used to measure socioeconomic disadvantage, and they had previously been used in distributive EJ studies. The literacy rate defined as the percentage of the population aged seven and above who can read and write basic sentences, has long been used as a proxy for socioeconomic position and has been used to assess district development. Literacy can influence a population's ability to accept pollution as a byproduct of its own economic progress or to fight pollution due to political power. Illiteracy rates were employed as an independent variable in our research to indicate disadvantage. The percentage of the population belonging to the Scheduled Caste (SC) and Scheduled Tribe (ST) groups, as defined by the Indian Constitution, was used to represent the two primary socially marginalized groups in India. SC marginalization highlights prejudice against lower castes in India as a result of their traditional methods of subsistence and exclusion from ritual power sources. ST refers to social groupings that have retained a separate culture, often as a result of livelihoods reliant on forests or natural resources. While SCs are religiously affiliated with the Hindu, Buddhist, and Sikh faiths, STs can be affiliated with any faith. According to previous national-level study, the percentage of SCs in Indian districts that generate industrial hazardous waste is much higher than in districts that do not.

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To investigate the exposure of demographically and physiologically sensitive groups to $PM_{2.5}$ pollution, the percentages of the district population who are female, aged six years or less, and have a handicap were added. Despite the fact that gender has received less attention in the distributive EJ literature, the occurrence of a masculine sex ratio in northern India makes gender a useful component of social exposure to pollution in this region. Children's exposure to risks has also been understudied in India, although it has been a major emphasis of EJ studies in the United States. Because of their larger breathing rate to body size ratio and the fact that their lungs are still developing, children are thought to be more sensitive to air pollution than adults. In the United States, EJ studies have indicated that communities with a higher population of children have significantly higher levels of industrial hazard exposure. As an additional explanatory variable, the proportion of the population with disabilities was used. Although the relationship between disability and air pollution exposure has yet to be studied in India, recent studies in the United States have found that people with disabilities live in neighborhoods where they are exposed to significantly more pollution sources than people without disabilities. Our research aims to see if these tendencies may be found in India as well.

In addition to the aforementioned factors from the Primary Census Enumeration, we used four indicators of socioeconomic disadvantage from the 2011 House listing and Housing Census. These were the percentages of households without any assets, such as a television, computer, laptop, phone, mobile phone, or scooter/car; living in a house that was not in "good" condition (either "dilapidated" or "livable"); having no drinking water source within their premises (either "near premises" or "away from the house"); and having no toilet or latrine facility within their premises. These variables have previously been used to represent social and economic disadvantage in previous research on environmental hazards in India, and they are likely to be linked to increased intensity of air pollution exposure (due to poor housing quality and amenities) and a reduced ability to cope with air pollution (due to lower economic status).

It is based on the population of census and statutory towns. Census towns have a population of at least 5000 people, a population density of at least 400 persons per square kilometer, and at least 75% of the major male employees are employed in non-agricultural occupations. Municipalities, corporations, cantonment boards, and notified area committees are in charge of statutory towns. Previous research has found that pollution-producing activities in India are frequently located in low-density or sparsely populated areas adjacent to densely populated urban centers, in order to take advantage of the higher availability of vacant land that is still accessible and close to large urban areas. Overall, our selection of independent factors represents the social and economic traits that are most important for understanding the inequities associated with particle air pollution exposure.

III. FINDINGS

The district level distribution of population density is first displayed in Figure 1 to offer a geographic context for comparing and interpreting the spatial patterns of our air pollution-related dependent variables. Districts in India are divided into five quintiles depending on the number of people per square kilometer on this map. The Indo-Gangetic Plain, a multi-state region spanning northwest to eastern India, is home to the districts with the greatest population density numbers (IGP). Because of the Ganges and Yamuna rivers, the IGP is India's largest agricultural belt and one of the world's most densely inhabited Int. J. Environ. Res. Public Health 2021, 18, x 7 of 16 regions. In addition, the IGP contains 12 of the 14 Indian cities that are among the world's top 20 most polluted in terms of $PM_{2.5}$ levels.

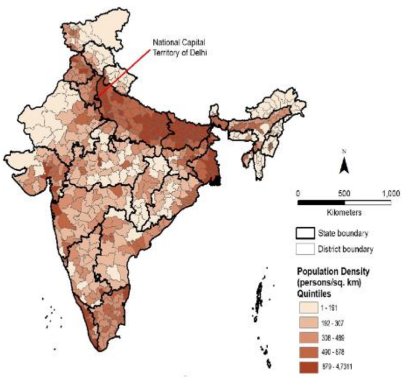

Figure 1: Distribution of 2011 population density by district and district in India

On the other hand, southern India, northeast India, and northern India have a disproportionately high number of districts in the lowest quintile (bottom 20%) of $PM_{2.5}$ concentration. The bordering states of Uttar Pradesh (three districts) and Haryana have a larger population (one district). When Delhi's districts are removed, eight of the top 10 districts are in Uttar Pradesh, with two in Haryana, highlighting the IGP's high levels of air pollution once again. On the other hand, southern India, northeast India, and northern India have a disproportionately high number of districts in the lowest quintile (bottom 20%) of $PM_{2.5}$ concentration. The discrepancies in air pollution levels between the landlocked IGP and southern India have been explained by higher population density, the prevalence of coal mines, brick kilns, and power plants, and meteorological conditions. Lower levels of particle pollution can be connected to lower levels of industrialization in the northeast and northern India.

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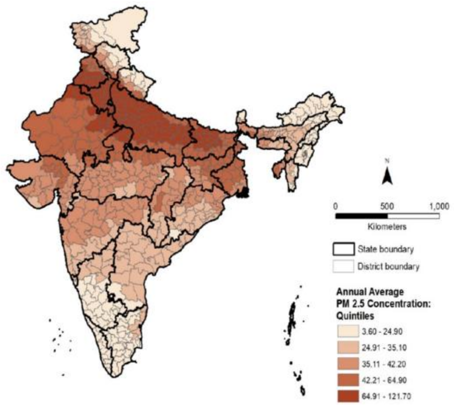

Figure 2: Surface annual average $PM_{2.5}$ concentrations (µg/m3) in India by district in 2010.

Figure 3 depicts the average $PM_{2.5}$ concentration ratio distribution at the district level 2016–2010. In comparison to Figure 2, the geography of recent changes in $PM_{2.5}$ pollution differs significantly from the overall pattern of $PM_{2.5}$ pollution in 2010, indicating a more dispersed spatial pattern. The distribution of PM2.5 growth at the district level does not show a clear spatial correlation with the population density distribution illustrated in Figure 1. Although there are numerous districts in the IGP that are in the highest quintile of $PM_{2.5}$ concentration ratio 2016–2010, additional districts in this quintile are in southern, central, and northern India. Figure 3 shows significant increases in $PM_{2.5}$ pollution in several southern districts, particularly along a belt that includes large cities like Bengaluru and Hyderabad, both key information technology hubs. Increased urbanisation could also be linked to rising air pollution along India's northern border. Increases in central India coincide geographically with a coal-mining area and concomitant industrial activities. Because of lower levels, districts where $PM_{2.5}$ concentrations have decreased since 2010 are mostly in Rajasthan in the northwest, Mizoram and Manipur in the northeast, and Kerala in the south. This is a common misunderstanding.

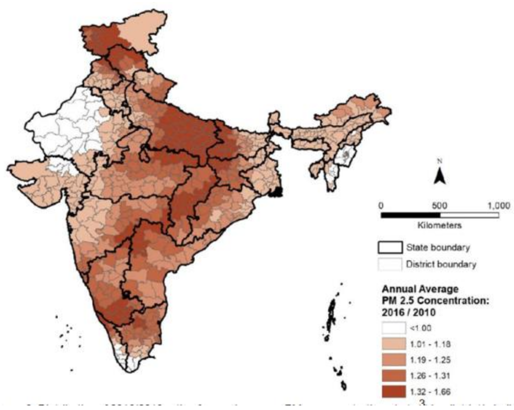

Figure 3: Annual average $PM_{2.5}$ concentrations (µg/m3) by district in India from 2016 to 2010.

Table 2: Shows the percentages of people and households in India whose annual average $PM_{2.5}$ concentrations above WHO, USEPA, EU, and Indian guidelines in 2010.

Variables	WHO: >10 µg/m^3	USEPA: >12 µg/m^3	EU: >25 µg/m^3	India: >40 µg/m^3
Districts (640 total)	632	627	510	291
Total population	99.96%	99.92%	87.04%	55.59%
Urban population	99.96%	99.92%	82.74%	51.60%
Illiterate population	99.96%	99.92%	90.28%	60.08%
Scheduled Caste population	99.99%	99.99%	88.63%	61.98%
Scheduled Tribe population	99.62%	99.39%	89.98%	32.95%
Female population	99.96%	99.92%	86.62%	54.82%
Children (6 years or less)	99.96%	99.92%	89.68%	60.47%
People with disabilities	99.95%	99.91%	88.39%	54.48%
Total households (HHs)	99.97%	99.92%	84.99%	51.28%
% HHs with no assets	99.97%	99.92%	91.58%	49.92%
% HHs in poor condition residence	99.97%	99.93%	88.80%	57.26%
% HHs with drinking water sourceoutside premises	99.96%	99.92%	85.08%	48.01%
% HHs with no toilet	99.99%	99.96%	88.89%	55.67%

When the EU regulations (25 µg/m3) are applied, these figures increase to roughly 13% of the population and 15% of households. At least 85 percent of the people and households associated with the socially disadvantaged categories we studied lived in districts where $PM_{2.5}$ pollution exceeded all of these international standards. However, districts with average $PM_{2.5}$ concentrations exceeding the higher national threshold (40 µg/m3) used in India continue to house approximately 56% of the people and 51% of the homes. In these areas, the percentages of illiterates, SCs, and children outnumber the general population (55.6%), while the percentages of poor-quality housing and households without toilets outnumber the overall percentage of households (51.3 percent). In districts where India's $PM_{2.5}$ requirements are surpassed, however, the percentages of STs, women, and individuals with disabilities, and households without assets and homes with a drinking water source outside their premises, are lower than the total population and household percentages.

We used bivariate linear correlations to examine the statistical effects of our explanatory variables on 2010 $PM_{2.5}$ concentrations and 2016/2010 $PM_{2.5}$ concentration ratios. Table 3 shows the Pearson product-moment correlation coefficients associated with each pair of variables. According to a study published in 2010, $PM_{2.5}$ concentrations are strongly and positively related to population density, percentages of the urban population, illiterates, SCs, and children, and families with poor housing conditions and no toilets. The percentages of the female and ST population, and homes with no assets and no outside drinking water source, all indicate a substantial negative link with $PM_{2.5}$ pollution. The percentages of SCs, children, and households without toilets are significantly and positively associated with the $PM_{2.5}$ concentration ratio 2016–2010 in districts with an increase, while the percentages of STs and households with no assets are negatively associated; these results align with PM2.5 pollution correlations. Despite their significant negative relationships with PM2.5 pollution levels, population density, female percentage, proportion of households in poor condition housing, and proportion of households with outside

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drinking water sources have no significant correlation with $PM_{2.5}$ rise. Although the percentage of people with impairments has a non-significant relationship with $PM_{2.5}$ pollution, it is strongly and positively linked to a rise in $PM_{2.5}$ levels.

Table 3: Shows the bivariate linear relationships between average $PM_{2.5}$ concentration (2010) and $PM_{2.5}$ concentration ratio (2016/2010) and district characteristics.

Variables	$PM_{2.5}$: 2010		$PM_{2.5}$: 2016/2010	
	Pearson's *r*	*p*-Value	Pearson's *r*	*p*-Value
Population density	0.251	<0.01	−0.078	0.057
% Urban population	0.103	<0.01	−0.169	<0.01
% Illiterate population	0.190	<0.01	0.155	<0.01
% Scheduled Caste population	0.407	<0.01	0.323	<0.01
% Scheduled Tribe population	−0.399	<0.01	−0.295	<0.01
% Female population	−0.473	<0.01	0.071	0.083
% Children (6 years or less)	0.255	<0.01	0.095	<0.05
% People with disabilities	−0.072	0.068	0.179	<0.01
% HHs with no assets	−0.257	<0.01	−0.214	<0.01
% HHs in poor condition residence	0.227	<0.01	0.024	0.556
% HHs with drinking water source outside premises	−0.336	<0.01	0.029	0.481
% HHs with no toilet	0.081	<0.05	0.347	<0.01
N (districts)	640		601	

Table 4 and 5. Table 4 describe the results of our multivariable GEE models. After controlling for clustering and other relevant factors, Table 4 shows that average $PM_{2.5}$ concentrations (2010) are significantly higher in densely populated districts with higher percentages of urban, SC, and children, and higher proportions of households living in poor condition and without toilets. The only variables that show a statistically negative relationship with $PM_{2.5}$ concentration are female population percentages and residences with an outdoor drinking water source.

Table 4: shows the Generalized Estimating Equation (GEE) for estimating average $PM_{2.5}$ levels in 2010 (N = 640).

Variables	Standardized Beta	Standard Error	Lower 95% CI	Upper 95% CI	Wald chi-square	*p*-Value
Population density	0.052	0.017	0.019	0.085	9.644	<0.01
% Urban population	0.066	0.039	−0.010	0.142	2.908	<0.05
% Illiterate population	−0.063	0.046	−0.154	0.028	1.865	0.172
% Scheduled Caste population	0.169	0.035	0.099	0.238	22.648	<0.01
% Scheduled Tribe population	−0.059	0.038	−0.132	0.015	2.468	0.116
% Female population	−0.129	0.040	−0.208	−0.050	10.197	<0.01
% Children (6 years or less)	0.232	0.053	0.128	0.337	18.974	<0.01
% People with disabilities	−0.025	0.030	−0.085	0.034	0.696	0.404
% HHs with no assets	−0.047	0.043	−0.132	0.037	1.198	0.274
% HHs in poor condition residence	0.091	0.038	0.016	0.165	5.735	<0.05
% HHs with drinking water source outside premises	−0.143	0.044	−0.228	−0.058	10.812	<0.01
% HHs with no toilet	0.112	0.043	0.028	0.196	6.889	<0.01
Intercept	3.722	0.045	3.633	3.810	6833.022	<0.01
Scale	0.103					
Model fit (QIC)	213.831					

Note: The GEE algorithm is based on a gamma distribution with a log link function and an independent correlation matrix.

Table 5: GEE for estimating the $PM_{2.5}$ concentration ratio between 2016 and 2010 (N = 601).

Variables	Std. Beta	Std. Error	Lower 95% CI	Upper 95% CI	Wald chi-square	*p*-Value
Population density	0.001	0.005	−0.008	0.011	0.087	0.768
% Urban population	−0.023	0.007	−0.037	−0.010	11.121	<0.01
% Illiterate population	−0.040	0.014	−0.067	−0.014	8.800	<0.01
% Scheduled Caste population	0.023	0.010	0.003	0.043	5.105	<0.05
% Scheduled Tribe population	0.014	0.009	−0.003	0.031	2.780	0.095
% Female population	0.016	0.008	0.000	0.033	3.865	<0.05
% Children (6 years or less)	0.063	0.011	0.041	0.086	31.137	<0.01
% People with disabilities	0.028	0.007	0.014	0.042	15.509	<0.01
% HHs with no assets	−0.071	0.013	−0.096	−0.046	29.919	<0.01
% HHs in poor condition residence	−0.035	0.012	−0.058	−0.011	8.248	<0.01
% HHs with drinking water source outside premises	−0.010	0.012	−0.034	0.014	0.675	0.411
% HHs with no toilet	0.075	0.012	0.051	0.098	38.350	<0.01
Intercept	1.228	0.010	1.207	1.248	13,920.182	<0.01
Scale	0.011					
Model fit (QIC)	88.625					

Note: GEE is based on a normal distribution with an unstructured correlation matrix and an identity link function.

Table 5 shows that districts with larger percentages of SCs, females, children, and individuals with disabilities, and houses without toilets, had considerably higher $PM_{2.5}$ concentration ratios 2016/2010. Increases in $PM_{2.5}$ pollution are also linked to lower percentages of urban and illiterate people, households with no assets, and those living in dilapidated housing.

IV. DISCUSSION

Our early statistical study highlighted a variety of international and national requirements for $PM_{2.5}$ pollution, and districts in India where these standards were surpassed (Table 2). More than 85 percent of India's population and households live in districts with higher outdoor $PM_{2.5}$ concentrations in 2010 than suggested by international norms. These districts also host at least 85% of the people and families linked to each of our socially disadvantaged groups. With the exception of the ST population, districts whose $PM_{2.5}$ pollution exceeds India's national air quality limits comprise around 56 percent and 51 percent of the individuals in our socially disadvantaged population and household groups, respectively. The existence of ST communities in less industrialized areas of the northeastern and northern India, as found in prior studies, implies that they are also concentrated in areas with lower particulate air pollution.

After controlling for spatial clustering, population density, and other contextual characteristics, we wanted to see if $PM_{2.5}$ pollution and recent increases were considerably higher in districts with higher proportions of socially disadvantaged groups. Our multivariable GEE analysis found that urbanized districts with larger numbers of SCs, young children, houses in poor condition, and households without toilets had higher $PM_{2.5}$ concentrations. In less urbanized districts with larger percentages of SCs, females, children, and individuals with disabilities, and households without toilets, we found considerably higher $PM_{2.5}$ concentration increases.

Our findings show that various disadvantaged and vulnerable population groups face significantly higher air pollution risk loads. SCs and young children (0–6 years) are disproportionately located in districts with higher exposure to $PM_{2.5}$ pollution, and those with the greatest increases in $PM_{2.5}$ pollution, according to both bivariate and multivariable statistical analyses. These findings highlight the critical importance of addressing and reducing $PM_{2.5}$ emissions because SCs, as a socially marginalized group, frequently lack access to protective resources or cannot afford risk mitigation, and children are physically more vulnerable to the harmful effects of such emissions. The female percentage was lower in districts with higher $PM_{2.5}$ concentrations but higher in areas where $PM_{2.5}$ levels increased. The negative relationship between $PM_{2.5}$

pollution and the male population can be explained by $PM_{2.5}$ increases in southern states and medium-sized cities with relatively higher female proportions, while the positive relationship can be explained by $PM_{2.5}$ increases in medium-sized cities with relatively higher female proportions. These findings could also point to a male-dominated urban migration pattern in India, with the most polluted locations also providing more job prospects for migrant men. The proportion of women exposed to $PM_{2.5}$ pollution has increased as a secondary tier of urban settlements begins to demonstrate the effects of economic and industrial development.

Unlike the SC population, STs are disproportionately underrepresented in the most polluted areas, according to our bivariate analysis, and our multivariable models indicate no significant association. Their lower proportions in IGP districts and other places with higher $PM_{2.5}$ pollution and recent increases can explain this conclusion. It could also be due to a lack of commercial or industrial development in districts with larger ST proportions, which could lead to lower $PM_{2.5}$ levels in these locations. According to our multivariable analysis, the percentage of people with impairments is significantly greater in districts with the highest $PM_{2.5}$ increases, but not significantly associated with $PM_{2.5}$ exposure. This conclusion may represent a pattern similar to that of women, in which people with disabilities are not found in highly metropolitan regions because they may not be able to find industrial employment, but as air pollution rises in medium-sized cities, they, too, are exposed to greater levels of pollution. In our bivariate study, we discovered that the illiterate population was overrepresented in areas with the greatest $PM_{2.5}$ concentrations and increases. However, after adjusting for other socioeconomic variables in our multivariable models, the illiteracy rate showed a non-significant link with $PM_{2.5}$ exposure and a significantly negative relationship with $PM_{2.5}$ rise. The latter could be linked to considerable rises in $PM_{2.5}$ levels in certain southern Indian districts with higher literacy rates.

Inequalities in the distribution and rise of $PM_{2.5}$ pollution are also revealed by our data, which is linked to housing quality. Both bivariate and multivariable analyses show that districts with a higher percentage of households without toilets had considerably higher $PM_{2.5}$ exposure and increases. This could be partly explained by their relatively larger numbers in the IGP and central India states. In bivariate and multivariable studies of $PM_{2.5}$ exposure, similar positive relationships were found for the percentage of households living in poor conditions. On the other hand, the negative coefficient for this variable in the multivariable model for $PM_{2.5}$ rise could be linked to lower proportions of households in poor condition houses in districts in south India that have recently experienced $PM_{2.5}$ increases. In our multi-variable study, the percentage of households without assets was not substantially connected to $PM_{2.5}$ levels and was adversely related to $PM_{2.5}$ rises. This is not surprising given the lower proportions of this category in the IGP and southern India, where $PM_{2.5}$ exposure and growth were significantly higher. The statistical results for the fraction of homes having drinking water outside their premises, which was found to be adversely and non-significantly related to $PM_{2.5}$ concentration and rise, were influenced by similar location patterns. Overall, these data indicate that, while asset ownership and access to drinking water have increased in urban India, housing building quality and access to toilets remain issues, particularly in areas with higher levels of air pollution and recent increases.

V. CONCLUSION

At the district level in India, our distributive EJ analysis uncovers geographically and socially diverse patterns of ambient $PM_{2.5}$ pollution exposure, and recent increases in $PM_{2.5}$ pollution. Even after controlling for clustering and contextual characteristics, districts with larger percentages of SCs, children, and houses without toilets have significantly higher levels of surface $PM_{2.5}$ and recent $PM_{2.5}$ increases. Aside from these three indicators of social disadvantage or vulnerability, districts with higher $PM_{2.5}$ pollution have a significantly higher proportion of households in poor condition residences and a significantly higher proportion of people with disabilities. While $PM_{2.5}$ exposure is much higher in more urbanized districts, primarily in the IGP region, it has recently increased in less urbanized areas, primarily in southern and central India. These disparities in spatial patterns could indicate an increase in air pollution in medium and small Indian cities, which could be caused by migration and regional population shifts, and industry migrating to less urbanized areas to take advantage of lower pollution levels. This pattern of increase also shows that, in addition to SCs and children, women and people with disabilities are increasingly exposed to air pollution, broadening the profile of vulnerable populations in India. While our research is a good start, further research and data are needed to understand how factors like population growth, rural-urban migration trends, and changing economic and industrial development patterns have led to increases in $PM_{2.5}$ pollution and their disproportionate societal repercussions.

As air pollution becomes a more visible issue in urban India, citizen pressure is projected to push government and business interests to priorities laws and practices that protect environmental quality. These could include more stringent pollution regulation by the Central and State Pollution Control Boards, a shift to less polluting modes of transportation, and increased investment in "green" technologies, renewable energy, and industrial effluent treatment. However, there may be a propensity to create "pollution havens," worsening pollution exposure for socially disadvantaged sections

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while allowing more advantaged parts to relocate to less polluted enclaves. In addition, India's unwavering focus on economic growth has led to the relaxation of environmental regulations in an effort to attract foreign investment. As a result, there is a larger global framework in which the economic incentive to pollute is strong enough for firms and governments to ignore the social costs. Local activists' and national environmental organizations' work becomes much more difficult in this context, especially when the wealthy and middle classes have the ability to relocate away from polluted areas. There is still a lot of work to be done to match EJ's goals with profit pressures.

This study has shown the link between rising particulate air pollution and rising environmental inequalities in India, underlining the necessity to investigate the social repercussions of poor environmental quality further. Future research should look into how other types of pollution, such as water and soil pollution, reveal comparable inequalities. Furthermore, the ways in which different types of pollution interact with one another and with socioeconomic disadvantages should be investigated further. While the severity of particulate pollution signals the urgent need to limit polluting activities, it should also be seen as the leading edge of a bigger goal to address India's environmental injustices through enhancing environmental quality.

REFERENCES

[1] S.K.; Goel, (2014).Nature of air pollution, emission sources, and management in the Indian cities. *Atmos. Environ.* *95*, 501–510.
[2] M.S. Sharma Socioeconomic Disparities and Air Pollution Exposure: A Global Review. *Curr. Environ. Health Rep.* 2015, *2*, 440–450.
[3] Chowdhury, S.; Dey, S. (2018). Cause-specific premature death from ambient PM2.5 exposure in India: Estimate adjusted for baseline mortality. *Environ. Int*, *91*, 283–290.
[4] Press Information Bureau. Delhi and adjoining States asked to submit action plans to control air pollution in Delhi [Internet]. 2016. Available from: http://pib.nic.in/newsite/PrintRelease.aspx?relid=155679
[5] A.M. Shikawat. (2016). Global Estimates of Fine Particulate Matter using a Combined Geophysical-Statistical Method with Information from Satellites, Models, and Monitors. *Environ. Sci. Technol.* 2016, *50*, 3762–3772.
[6] Kumar P, Gulia S, Harrison RM, Khare M. The influence of odd–even car trial on fine and coarse particles in Delhi. Environ Pollut [Internet]. 2017 Jun; 225:20–30.
[7] *The Global Burden of Disease: Generating Evidence, Guiding Policy*; IHME: Seattle, WA, USA, 2018
[8] Collins, (2012). Geographic and social disparities in exposure to air neurotoxicants at U.S. public schools. *Environ. Res.* 2018, *161*, 580–587.
[9] Chakraborty, J. (2018). Proximity to extremely hazardous substances for people with disabilities: A case study in Houston, Texas. *Disabil. Health J.*
[10] Smokey Bot [Internet]. [cited 2017 Jul 1]. Available from: http://airairair.org/

