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18-Year Ambient $PM_{2.5}$ Exposure and Night Light Trends in Indian Cities: Vulnerability Assessment

Rupali Pal[1], Sourangsu Chowdhury[2], Sagnik Dey[2*], Anu Rani Sharma[3]

[1] *TERI University, New Delhi 110070, India*
[2] *Centre for Atmospheric Sciences, Indian Institute of Technology Delhi, New Delhi 110016, India*
[3] *Department of Natural Resources, TERI School of Advanced Studies, New Delhi 110070, India*

ABSTRACT

Exposure to ambient fine particulate matter ($PM_{2.5}$) is identified as one of the leading risk factors for morbidity and mortality in India. Here we estimate ambient $PM_{2.5}$ exposure and its 18-year (1998–2015) trend in 109 Indian cities using satellite data and further classify them into six vulnerable classes (from index 1 for low vulnerability to index 6 for extreme vulnerability). $PM_{2.5}$ exposure has shown a rapid increase in Delhi and the cities in Uttar Pradesh, Bihar, Jharkhand, West Bengal, Punjab, Haryana, Rajasthan, Madhya Pradesh, Chhattisgarh and Odisha. Amongst the cities with a population of more than 0.5 million (as per the 2011 census), Thiruvananthapuram is the least vulnerable and Aligarh is the most vulnerable city based on 18-year statistics. Only 27 cities are identified as 'low' to 'moderately' vulnerable to ambient air pollution. The median incremental rate of the annual $PM_{2.5}$ exposure has increased by 57.9% (from 0.9 to 1.15 $\mu g\ m^{-3}$ per year) with the night-light counts (a proxy for urbanization rate) increasing from < 20th percentile to > 80th percentile. 51 out of the 60 Indian cities chosen for the 'smart city' mission are highly vulnerable to $PM_{2.5}$ exposure (vulnerability index > 2) and thereby face challenges to achieve the core objective of the mission (i.e., a sustainable environment). Our results will facilitate prioritizing a clean-air action plan for the cities based on their vulnerability rankings to achieve the maximum health benefit for the exposed population.

Keywords: $PM_{2.5}$; Remote sensing; Indian city; Night light; Health-risk; Vulnerability.

INTRODUCTION

Chronic exposure to ambient fine particulate matter ($PM_{2.5}$) leads to morbidity and mortality and reduces life expectancy (WHO, 2005). In the Global Burden of Disease (GBD) and several other studies (Anenberg *et al.*, 2010; van Donkelaar *et al.*, 2010; Brauer *et al.*, 2012; Cohen *et al.*, 2017), air pollution has already been identified as one of the leading risk factors for morbidity and mortality. Numerous studies (e.g., Pope *et al.*, 2002; Lipsett *et al.*, 2011; Xing *et al.*, 2016) around the world have documented the causal relation between various health endpoints (viz., respiratory, cardiovascular and pregnancy outcomes) and ambient $PM_{2.5}$ exposure.

In all the global studies, the Indian subcontinent has been identified as one of the major pollution hotspots. Aerosol optical depth shows large space-time variability in the Indian subcontinent (Dey and Di Girolamo, 2010) influenced by emission characteristics, meteorology and topography. AOD has been found to increase in parts of the subcontinent mainly during the dry season in the last decade (Dey and Di Girolamo, 2011; Krishna Moorthy *et al.*, 2013). Satellite-retrieved AOD data are used to infer $PM_{2.5}$ concentrations (Dey *et al.*, 2012) to examine the ambient $PM_{2.5}$ exposure in the entire country. It has been observed that 51% of the country's population is exposed to the World Health Organization (WHO) interim target (IT) 1 of 35 $\mu g\ m^{-3}$, while another 13% and 18% of the population are exposed to the ranges 25–35 $\mu g\ m^{-3}$ and 15–25 $\mu g\ m^{-3}$. Five hotspots have been identified where annual $PM_{2.5}$ have increased over the last decade by > 10–15 $\mu g\ m^{-3}$. In three of these five hotspots, the major sources are industrial, vehicular and household emissions, while household emission is the dominant source in the remaining two. The high-resolution ambient $PM_{2.5}$ exposure data have been further utilized to estimate the premature mortality burden in India at the district level (equivalent to 'county' in the western world) (Chowdhury and Dey, 2016). Based on the exposure data, it has been estimated that 44,900 (5,900–173,300) premature deaths can be avoided annually by meeting the Indian annual $PM_{2.5}$ standard (40 $\mu g\ m^{-3}$).

The population distribution in India is changing rapidly because of the migration from rural areas to cities to avail

*Corresponding author.
E-mail address: sagnik@cas.iitd.ac.in

oneself of better social and economic opportunities (Jaysawal and Saha, 2014). According to Census 2011, ~31% of India's current population lives in urban areas and contributes 63% to the gross domestic product (GDP) of India. By 2030, the urban areas in India are expected to house 40% of the country's population and contribute 75% of India's GDP. This would change population-weighted $PM_{2.5}$ exposure, even if the $PM_{2.5}$ concentration remains unchanged. Moreover, a higher population density in the cities demands specific exposure estimates for better policy. In India, 46 cities (according to the 2011 census) have a population greater than 1 million, and 94 cities have a population greater than 0.5 million. $PM_{2.5}$ measurement in India following international protocol in a systematic manner was started by the Central Pollution Control Board (CPCB) in 2008–2009, and as of today, 61 sites across 37 cities have continuous $PM_{2.5}$ data freely accessible from the CPCB network (www.cpcb.gov.in/CAAQM/mapPage/frmindiamap.aspx). CPCB has been extending the network over the years and will continue to do so in future. The government of India has launched an air quality index (AQI) for the effective communication of the air quality status to the public using six broad categories (good, satisfactory, moderately polluted, poor, very poor and severe) and colors (green, light green, yellow, orange, red and dark red for the six classes from 'good' to 'severe,' respectively). AQI is calculated based on data of eight pollutants: $PM_{2.5}$ and PM_{10}, CO, NO_2, SO_2, CO, O_3, NH_3 and Pb. AQI is calculated only if data are available for a minimum of three pollutants, one of which should be either PM_{10} or $PM_{2.5}$. Every month, a bulletin is released by CPCB (accessible from their website [www.cpcb.nic.in]) on AQI of various Indian cities along with an advisory on possible health impacts. For example, 'good' AQI is considered to have a minimal impact, and 'satisfactory' AQI may cause breathing discomfort to sensitive people. People with lung and heart disease, children and older adults may face breathing problems if AQI degrades to 'moderate', while 'poor' AQI may cause breathing discomfort to any person with prolonged exposure. Prolonged exposure to 'very poor' AQI may cause respiratory illness, and 'severe' AQI may have respiratory effects even on healthy people. Periodic bulletins on AQI have sensitized the Indian population to air pollution. However, most of the calculations rely on PM_{10} rather than $PM_{2.5}$ due to limited $PM_{2.5}$ data across the country. Even in cities such as Delhi, where multiple $PM_{2.5}$ monitoring sites are operational, $PM_{2.5}$ data prior to 2011 are not available.

In India, a few studies have analyzed limited in situ $PM_{2.5}$ data available from CPCB or other sources. For example, Sahu and Kota (2017) noticed that $PM_{2.5}$ exceeded the national ambient air quality standard during 85% of the days in Delhi for the period 2011–2014. Matawle *et al.* (2015) characterized $PM_{2.5}$ source profiles in Raipur. $PM_{2.5}$ distribution and composition were studied in Agra by Pipal *et al.* (2014) and Pachauri *et al.* (2013). Similarly, Pipalatkar *et al.* (2014) have studied $PM_{2.5}$ source apportionment in Nagpur for the period Sep. 2009 till Feb. 2010. There are several other studies in the literature examining $PM_{2.5}$ distributions, sources and compositions across India. All of these studies are limited mostly to a season or, at best, to a few years. Moreover, so far, $PM_{2.5}$ data exists only for a few cities. Therefore, the long-term temporal pattern of $PM_{2.5}$ in the Indian cities cannot be examined due to such a short period.

Here, we generate 18-year (1998–2015) $PM_{2.5}$ statistics for 109 cities (Table 1) in India (94 of them have a population of > 0.5 million, and the other 15 are major cities in their respective states) to examine the changing pattern of the ambient $PM_{2.5}$ exposure. The locations of these cities in India are shown in Supplementary Fig. 1. The cities are classified into 6 vulnerable classes based on the annual mean exposure, its trend over an 18-year period, exposed population and the baseline mortality of major diseases that can be attributed to chronic exposure to air pollution. The trends in annual $PM_{2.5}$ exposure are interpreted in view of the urbanization rates in these cities using night-light data.

METHODOLOGY

In the present analysis, we consider 94 cities with a population exceeding 0.5 million, 8 other major cities with a population in the range 0.35–0.5 million and 7 capital cities with a population < 0.35 million: Gangtok, Itanagar, Panjim, Shillong, Shimla, Kohima and Aizawl. The state of Maharashtra has the highest number of cities (19) in our list (Table 1), followed by Uttar Pradesh (16), Tamil Nadu (9), Andhra Pradesh, Karnataka and Gujarat (6 each) and Madhya Pradesh, Rajasthan and West Bengal (5 each). Other states have 1–3 cities in this population range. The cities in India are classified administratively as 'X', 'Y' and 'Z' category as per the recommendations of the Sixth Central Pay Commission (www.ccis.nic.in) based on the living standards. Currently, Delhi, the greater Mumbai area, Hyderabad, Kolkata, Chennai and Bangalore are categorized as the highest class, 'X', followed by 68 cities in the 'Y' category and the remainder in the 'Z' category (see Table 1). The Ministry of Urban Development, Government of India, chooses 60 of these 109 cities for the 'smart city' mission. The core objective of this national mission is to promote cities that provide its citizen with a high quality of life and a clean and sustainable environment by employing adequate infrastructure and smart solutions. The goal of the vulnerability analysis here is to provide the status of the air quality in these cities, as air quality is an integral part of a sustainable environment.

Generation of City-level Ambient $PM_{2.5}$ Statistics

Due to the lack of presence of adequate in situ $PM_{2.5}$ data in India, we utilize satellite aerosol products. Over the last two decades, passive sensors have been routinely retrieving columnar AOD globally from sun-synchronous orbits. AOD data are matched to in situ $PM_{2.5}$ using the GEOS-Chem model using geographically weighted regression that represents aerosol columnar optical properties and vertical distribution (van Donkelaar *et al.*, 2006). $PM_{2.5}$ estimated from three different passive sensors are combined to generate a consistent global $PM_{2.5}$ database at a 0.01° × 0.01° resolution. The methodology of development of the

Table 1. Statistics of annual $PM_{2.5}$ exposure level, trend, exposed population, number of monitoring sites in the Indian cities and the state they belong to. The vulnerability class of these cities are ranked as 'low' (1), 'moderate' (2), 'high' (3), 'very high' (4), 'severe' (5) and 'extreme' (6). The cities falling in 'X' category are marked by **, those in 'Y' category by * and the remaining are classified in 'Z' category. The cities in 'bold' font are chosen for the 'smart city' mission of the Ministry of Urban Development, Government of India. Number of existing continuous $PM_{2.5}$ monitoring sites with open access data from CPCB website (http://www.cpcb.gov.in/CAAQM/mapPage/frmindiamap.aspx) is mentioned. Note that $PM_{2.5}$ measurement using traditional filter-based technique, individual efforts and through other state and central agency (e.g., SAFAR) are also ongoing, but those data are not accessible freely.

	State	City	Annual $PM_{2.5}$ exposure (in µg m^{-3})	Total change (in µg m^{-3})	Population (2011)	Monitoring sites	Vulnerability
1	Jammu and Kashmir	**Srinagar***	32.3	13.9	1192792	0	4
		Jammu*	37.5	19.4	503690	0	4
2	Himachal Pradesh	**Shimla**	32.2	6.5	169578	0	1
3	Punjab	**Amritsar***	53.4	25.0	1132761	1	4
		Jalandhar*	54.1	22.9	862196	0	3
		Ludhiana*	57.7	22.9	1613878	1	4
4	Chandigarh	**Chandigarh***	58.1	19.5	960787	0	3
5	Uttarakhand	**Dehradun***	46.9	15.5	578420	0	3
6	Haryana	**Faridabad***	97.3	19.4	1404653	1	4
		Gurgaon*	85.8	21.0	876824	1	4
7	Delhi	**New Delhi****	97.4	32.6	11034555	20	5
8	Rajasthan	**Jaipur***	52.4	24.3	3046163	1	5
		Ajmer	42.6	23.7	542580	1	4
		Bikaner*	39.8	19.6	647804	0	4
		Jodhpur*	41.0	21.3	1033918	1	4
		Kota*	44.9	22.2	1001694	1	4
9	Uttar Pradesh	**Agra***	91.6	29.6	1585704	1	6
		Aligarh*	103.8	31.9	872575	0	6
		Allahabad*	59.3	31.5	1117094	0	5
		Bareilly*	87.1	24.0	898167	0	5
		Firozabad	95.1	28.4	603797	0	5
		Ghaziabad*	101.0	24.5	1636068	1	6
		Loni	101.2	30.8	512296	0	6
		Meerut*	98.0	30.4	1309023	0	6
		Moradabad*	86.1	24.8	889810	1	5
		Varanasi*	60.8	33.3	1201815	1	5
		Gorakhpur*	70.0	35.9	671048	0	5
		Jhansi	53.7	23.2	507293	0	5
		Kanpur*	77.4	31.3	2765348	1	6
		Lucknow*	77.0	32.4	2817105	1	6
		Noida*	103.4	32.4	642381	1	6
		Saharanpur	71.3	26.1	703345	0	5
10	Bihar	Gaya	55.9	21.7	463454	1	6
		Muzaffarpur	69.5	32.0	351838	1	6
		Patna*	65.9	31.9	1683200	1	6
11	Sikkim	**Gangtok**	23.1	34.9	98658	0	3
12	Arunachal Pradesh	Itanagar	20.8	11.6	59490	0	2
13	Nagaland	**Kohima**	16.5	10.1	267988	0	2
14	Mizoram	**Aizawl**	21.8	17.6	293416	0	3
15	Tripura	**Agartala**	49.2	25.4	400004	0	4
16	Meghalaya	Shillong	24.3	13.3	143229	0	3
17	Assam	**Guwahati***	32.9	25.4	963429	0	5
18	West Bengal	Asansol*	44.4	28.9	564491	0	4
		Durgapur	41.6	27.9	566937	1	4
		Howrah	36.8	32.1	1072161	1	4
		Kolkata**	34.8	26.5	4496694	2	4
		Siliguri	46.0	28.8	509709	0	4

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Table 1. *(continued).*

	State	City	Annual $PM_{2.5}$ exposure (in µg m^{-3})	Total change (in µg m^{-3})	Population (2011)	Monitoring sites	Vulnerability
19	Jharkhand	Dhanbad*	45.1	27.5	1161561	0	5
		Jamshedpur*	43.3	23.2	631364	0	4
		Ranchi*	40.0	19.3	1073440	0	4
20	Odisha	**Bhubaneswar***	29.7	24.0	837737	0	4
		Cuttack*	30.6	23.4	606007	0	4
		Rourkela	35.4	21.5	552970	0	4
21	Chhattisgarh	Bhilai*	52.9	26.0	625697	0	4
		Raipur*	49.1	27.3	1010087	0	5
22	Madhya Pradesh	**Bhopal***	37.2	23.0	1798218	0	5
		Ujjain	37.3	20.9	515215	0	4
		Gwalior*	65.4	24.9	1053505	0	5
		Jabalpur*	38.7	17.9	1054336	0	4
		Indore*	34.6	18.8	1960631	0	5
23	Gujarat	**Ahmedabad***	37.0	20.9	5557940	1	4
		Bhavnagar*	32.7	20.7	593768	0	3
		Jamnagar*	30.2	26.2	529308	0	3
		Rajkot*	32.0	23.8	1286995	0	3
		Surat*	31.3	19.4	4467797	0	3
		Vadodara*	34.7	20.7	1666703	0	3
24	Maharashtra	Amravati*	34.9	22.7	646801	0	2
		Aurangabad*	34.4	20.2	1171330	1	3
		Bhiwandi*	35.9	20.0	711329	0	2
		Kalyan- Dombivali**	34.5	21.7	1246381	0	3
		Kolhapur*	28.5	18.8	549283	0	2
		Malegaon	31.3	17.6	471006	0	2
		Mira Bhayandar	37.3	19.4	814655	0	2
		Mumbai**	37.6	19.0	12442373	1	4
		Nanded	32.1	22.9	550564	0	3
		Nashik*	31.8	18.7	1486973	1	2
		Navi Mumbai**	39.6	19.8	1119477	1	3
		Pimpri-Chinchwad	39.4	20.4	1729359	0	3
		Pune*	38.5	19.7	3124458	1	3
		Sangli-Miraj Kupwad	26.4	17.4	502697	0	2
		Solapur*	28.8	19.7	951118	1	2
		Ulhasnagar	32.5	18.9	506937	0	2
		Vasai-virar**	36.7	20.0	1221233	0	3
		Thane	37.6	19.8	1818872	1	3
		Nagpur*	38.3	22.2	2405665	1	3
25	Andhra Pradesh	Vijayawada*	28.7	17.8	1034358	2	3
		Vishakhapatnam*	27.8	17.1	2035922	2	3
		Guntur*	28.2	19.1	743354	0	3
		Nellore	22.1	12.1	600869	0	2
		Hyderabad**	25.7	18.0	6731790	7	4
		Warangal*	25.6	20.7	811844	0	3
26	Karnataka	**Belgaum***	23.1	13.5	488292	0	2
		Bengaluru**	22.5	9.1	8443675	5	4
		Gulbarga	30.2	27.6	532031	0	3
		Hubli-Dharwad*	22.2	16.7	943857	0	3
		Mangalore*	17.2	10.7	499486	0	2
		Mysore*	19.4	7.4	887446	0	1
27	Goa	**Panjim**	23.7	15.2	40017	0	1
28	Kerala	**Kochi***	16.1	11.0	601574	0	1
		Thiruvananthapuram*	15.0	9.4	957730	1	1
29	Tamil Nadu	Ambattur	24.2	12.6	478134	0	1

Table 1. *(continued).*

State	City	Annual $PM_{2.5}$ exposure (in μg m^{-3})	Total change (in μg m^{-3})	Population (2011)	Monitoring sites	Vulnerability
	Chennai**	24.5	12.8	4646732	3	3
	Coimbatore*	20.1	12.5	1601438	0	1
	Erode	21.9	19.8	498129	0	2
	Madurai*	20.3	12.6	1561129	0	1
	Salem*	22.2	14.9	831038	0	2
	Tiruchirappalli*	23.8	14.2	916674	0	2
	Tiruppur*	19.8	13.3	877778	0	1
	Tirunelveli	17.9	8.9	473637	0	1

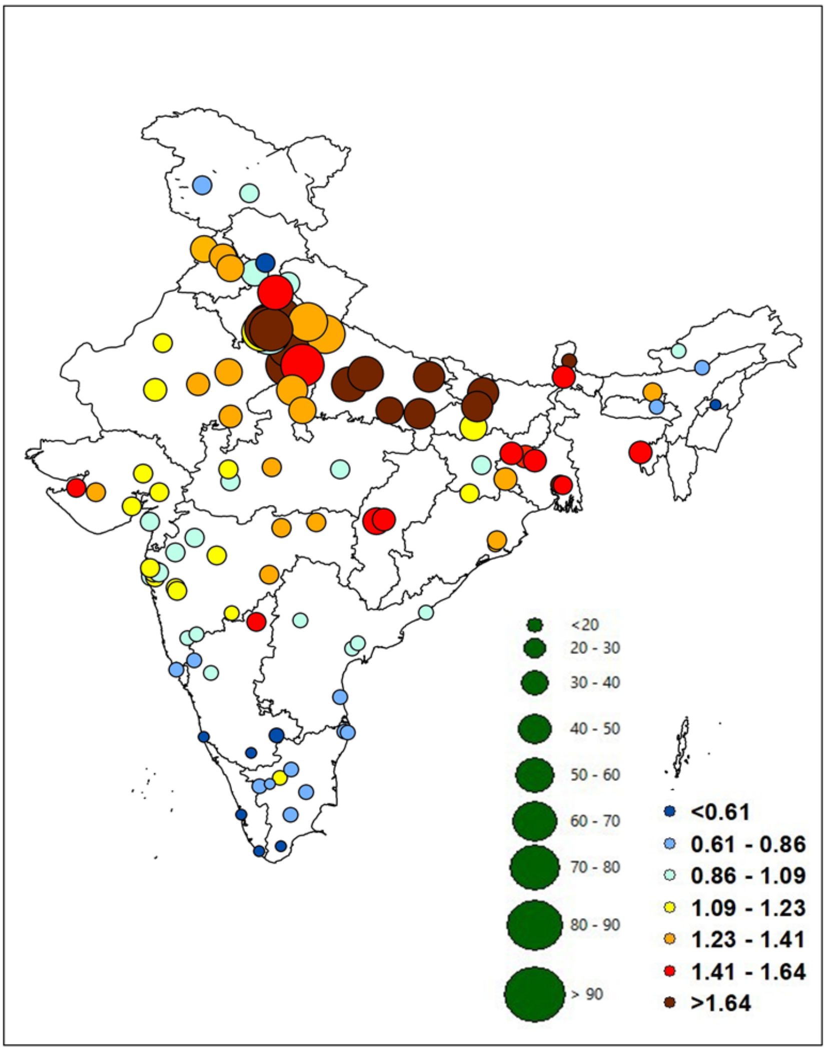

Fig. 1. 18-year mean annual $PM_{2.5}$ exposure (in μg m^{-3}) for the period 1998–2015 in the 109 Indian cities shown by the size of the circles, while the colors indicate the annual rate of change of $PM_{2.5}$ exposure (in μg m^{-3} per year).

$PM_{2.5}$ product is described in detail in a different study (van Donkelaar *et al.*, 2016). In brief, information from chemical transport model simulations, ground-based monitors and satellite (MODIS, MISR and SeaWiFS)-retrieved AOD satellite-derived $PM_{2.5}$ data are integrated using a geographically weighted regression technique. The resultant $PM_{2.5}$ product is highly consistent (R^2 = 0.81) with direct in situ measurements. Over India, the satellite-derived $PM_{2.5}$ data shows a bias of ±10 μg m^{-3} on an annual scale.

$PM_{2.5}$ data is converted from ASCII files to raster using the GIS Software (ArcGIS 10.1). The shape files are created for each of the 109 cities. The gridded satellite-derived $PM_{2.5}$ data are merged with the shape files, and

$PM_{2.5}$ concentrations in all 0.01° × 0.01° grids within the city boundary are extracted and averaged to estimate the $PM_{2.5}$ concentration representative of that particular city. Similarly, mean annual $PM_{2.5}$ statistics for all 109 cities are extracted. The temporal trends of annual $PM_{2.5}$ are derived using linear regression.

Vulnerability Analysis

The premature mortality and morbidity burden from chronic and acute ambient $PM_{2.5}$ exposure is directly proportional to the exposed population, $PM_{2.5}$ concentration and baseline mortality. Also, in cities where $PM_{2.5}$ concentration has been increasing over time, it poses a threat of higher exposure, as the population is bound to increase in the coming years. Epidemiological studies have shown a strong causal connection between ambient $PM_{2.5}$ exposure, and chronic obstructive pulmonary disease (COPD) and cardiovascular (stroke and ischemic heart disease, IHD) diseases (Pope *et al.*, 2002, Pope *et al.*, 2011). Therefore, we consider four parameters—the annual mean $PM_{2.5}$, temporal trend, exposed population and baseline mortality of COPD, stroke and IHD—for the vulnerability assessment. The population data is taken from Census of India 2011, conducted by the Office of the Registrar General and Census Commissioner under the Ministry of Home Affairs, Government of India. Baseline mortality data for the cities are estimated using the nonlinear baseline mortality-GDP functions discussed in our earlier work (Chowdhury and Dey, 2016). In the absence of GDP data for the cities, we consider the GDP data of the states to which these cities belong.

We develop a multi-parametric vulnerability ranking based on the four key parameters (viz., annual exposure, trend in exposure, exposed population and baseline mortality of COPD, IHD and stroke) that govern the premature mortality burden from chronic ambient $PM_{2.5}$ exposure. For each city, a score in the range from 0 (no risk) to 1 (highest risk) is assigned to each of these parameters depending on the range of values across all the cities. We consider the counterfactual concentration to be 2.4 µg m^{-3}, following a GBD 2015 study (Cohen *et al.*, 2017), below which no risk exists due to chronic exposure and hence results in a score of 0. A score of 1 is assigned to Aligarh for the largest mean (over the 18-year) annual $PM_{2.5}$ concentration (101.4 µg m^{-3}) from the counterfactual value. All the cities are assigned a score proportionately within the range 2.4–101.4 µg m^{-3} based on the 18-year mean annual $PM_{2.5}$ concentration (summarized in Table 1). Similarly, for the trend in $PM_{2.5}$ exposure, a score is given to each city in proportion to the observed trend relative to the entire range (i.e., from maximum to minimum). For example, Gorakhpur is given a score of 1 for the largest trend in annual $PM_{2.5}$ (1.99 µg m^{-3} per year), and Shimla is given a score of 0 for the smallest trend (0.36 µg m^{-3} per year). The remaining cities are scored in between. Any population, however small it is, is vulnerable to chronic exposure to ambient $PM_{2.5}$ above the counterfactual concentration. Hence, no city gets a score of 0 for the parameter 'exposed population'. Mumbai is ranked 1 for the highest exposed population (12.4 million). The scores of the other cities are adjusted relative to the minimum and maximum value. Panjim, capital of Goa, scores the lowest (0.003) for the lowest exposed population (40,017). Using the same method, cities are given individual scores separately for baseline mortality (relative to the zero baseline mortality value) values for COPD, stroke and IHD.

Night-Light Data

We use night light data measured by the Defense Meteorological Satellite Program-Operational Line Scanner (DMSP-OLS) to infer the urbanization rates in these cities during this period. Anthropogenic activities in a city expand due to an increase in human settlement, which is associated with artificial lighting during nighttime due to infrastructural development. DMSP-OLS has been monitoring night light since the early 1970s, but the more recent digital data are analyzed to produce a consistent and stable cloud-free nightlight database (Elvidge *et al.*, 2001). The DMSP-OLS visible band was originally designed to detect moonlit clouds, but the photomultiplier tube intensifies the signal by a million-fold, allowing detection of lights present during nighttime at the earth's surface. The night-light data are available at 30 arc seconds (~1 km at equator) in units of 6-bit digital numbers ranging from 0 to 63. The bright pixels represent fully developed urban areas with outdoor illumination, while less brightly lit pixels represent less dense built-up areas (Small and Elvidge, 2013; Zhou *et al.*, 2015).

The night light data for the period 1998–2015 is analyzed. To ensure anthropogenic activities at full scale, we estimate the frequency of the brightest pixels within each city's limits for each year and generate temporal data of the night-light for 109 Indian cities. In all the cities, night light frequency is found to increase at varying rates. The rate of change in population weighted ambient $PM_{2.5}$ exposure is analyzed in view of the rate of change in night light (a proxy of the urbanization rate) to examine the relation between them.

RESULTS

The annual mean $PM_{2.5}$ concentration and its rate of change per year in the 109 Indian cities are shown in Fig. 1. The size of the circles represents the 18-year annual mean exposure, and the color represents the rate of change in mean $PM_{2.5}$ per year. Across the cities, the annual mean $PM_{2.5}$ shows a wide range of variation with the lowest (15.0 µg m^{-3}) exposure in Thiruvananthapuram (the capital of southern state Kerala) and the highest (103.8 µg m^{-3}) exposure in Aligarh. In addition to the cities in the Delhi National Capital Region (NCR)—New Delhi, Noida, Ghaziabad, Meerut, Faridabad and Gurgaon—the 18-year annual mean $PM_{2.5}$ exposure exceeds twice the Indian standard in Aligarh, Firozabad, Agra, Bareilly and Moradabad. Concentrations in the range 60–80 µg m^{-3} are observed in Kanpur, Lucknow, Saharanpur, Gorakhpur, Muzaffarpur, Patna, Gwalior, Varanasi and Allahabad. All these cities are situated in the Indo-Gangetic Plain (IGP). The annual exposure exceeds the Indian standard (40 µg m^{-3}) in 20 more Indian cities, also spread throughout IGP. Outside IGP, an annual $PM_{2.5}$

exposure close to the Indian standard (in the range 30–40 µg m^{-3}) is observed in the Mumbai industrial corridor (Mumbai, Navi Mumbai, Thane, Vasai-Virar), Pimpri-Chinchwad and Pune, Nagpur, Jabalpur, Bikaner, Bhopal, Ujjain and industrial towns (Howrah, Rourkela and Ahmedabad). The exposure is relatively lower in cities in southern India, northeastern India and the hilly regions in northern India. The annual $PM_{2.5}$ exposure has changed at a rate varying in the range from < 0.6 to 1.6 µg m^{-3} per year. In 29 cities, the annual $PM_{2.5}$ exposure has increased by more than WHO IT-2 in the last 18 years, and it has increased by more than WHO IT-3 in another 60 cities. The lowest increase (by 6.5 µg m^{-3}) is observed in Shimla. Similar to the annual $PM_{2.5}$ exposure pattern, the rates of increase in $PM_{2.5}$ exposure in the southern Indian cities are lower compared to the rates in the northern and eastern Indian cities. It is noteworthy that the $PM_{2.5}$ exposure has been increasing at a rapid rate in relatively smaller ('Y' and 'Z' category) cities in the states of Uttar Pradesh, Bihar, West Bengal, Punjab, Madhya Pradesh, Chhattisgarh and Gujarat. Amongst the 'X' category cities, a large increase in the annual $PM_{2.5}$ exposure is observed in Delhi, Mumbai, Kolkata and Hyderabad. Bangalore and Chennai have maintained relatively better air quality ($PM_{2.5}$ has increased only by 6.5 and 12.8 µg m^{-3}, respectively) despite their remarkable growth over the years.

Fig. 2 depicts the time series of the annual $PM_{2.5}$ exposure averaged over the 'X', 'Y' and 'Z' category cities. The top and bottom ends of each box represent the 75th and 25th percentiles, and the top and bottom ends of the solid lines in each box represent the 95th and 5th percentiles. It is to be noted that the 'Y' category cities have a higher annual $PM_{2.5}$ exposure compared to the other two categories of cities in India. The annual $PM_{2.5}$ exposure statistics in 'X' category cities (which are megacities) is weighed down (relative to the 'Y' category cities) by low annual exposure in the southern Indian cities (Hyderabad, Bangalore and Chennai). It is evident that the annual $PM_{2.5}$ exposure has been increasing steadily over all the cities in the last 18 years. In the 'X' category cities, the annual mean (± 1 σ) $PM_{2.5}$ exposure rises from 25.1 ± 8.2 µg m^{-3} in 1998 to 43.1 ± 11.7 µg m^{-3} in 2015, implying a 71.4% increase. The corresponding changes in 'Y' and 'Z' category cities are from 37.7 ± 22.3 µg m^{-3} to 54.4 ± 24.2 µg m^{-3} (a 54.2% increase) and from 30.5 ± 19.4 µg m^{-3} to 49.8 ± 23.8 µg m^{-3} (a 63.4% increase), respectively. To summarize, the annual $PM_{2.5}$ exposure has increased by 1.6 ± 0.08-fold in the last two decades in the Indian cities.

Are the observed rates of changes in the annual $PM_{2.5}$ exposure related to the rise in emission due to urbanization in these cities? To answer this question, we analyze the trends in night-light data. Rapid urbanization would definitely have increased the emission from various anthropogenic activities. The trends in $PM_{2.5}$ exposure and night-light counts should have been perfectly correlated without any transport of pollution to or from the city. However, variability in $PM_{2.5}$ concentration is also influenced by meteorology. Therefore, we extract statistics of trends in the annual $PM_{2.5}$ exposure and the sum of night-light digital counts within each city's limits for the 3 categories of cities (Fig. 3). It can be seen that for 'X' category cities, the trend of the total night-light intensity count is exponentially related to increase in the trend of annual $PM_{2.5}$ exposure. This clearly shows the influence of rapid urbanization in these megacities on the increasing pollution. The 'Y' category cities throw a surprise by showing a bell-shaped curve. This implies that the annual $PM_{2.5}$ exposure increases in some cities with an increase in the night-light count, while the exposure has increased in other cities without much change in the night light count. Night-light intensity would increase over time in a city where infrastructure development took place. If the night-light does not increase to a great extent over time, one plausible explanation of the increasing pollution level is the rise in emission from sources (such as the transport

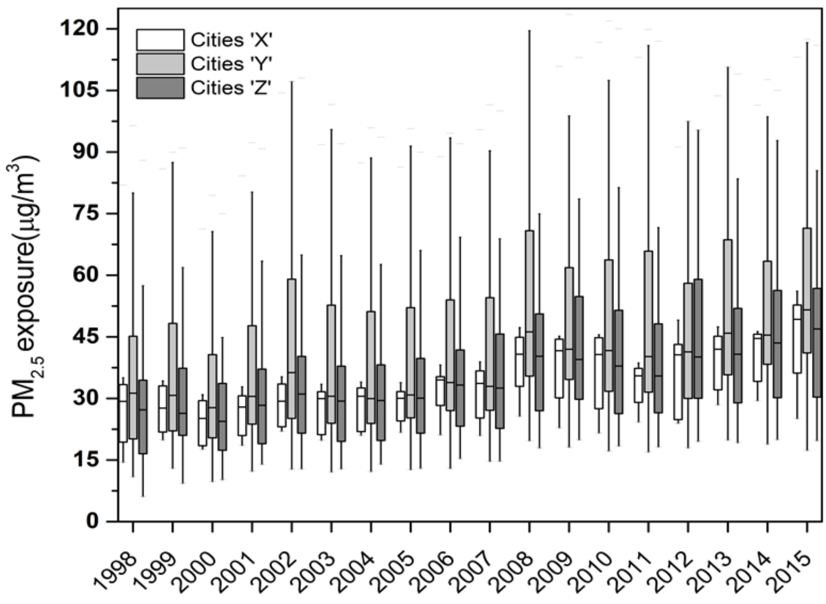

Fig. 2. Box plots of annual $PM_{2.5}$ exposure for 'X', 'Y' and 'Z' categories of cities in India.

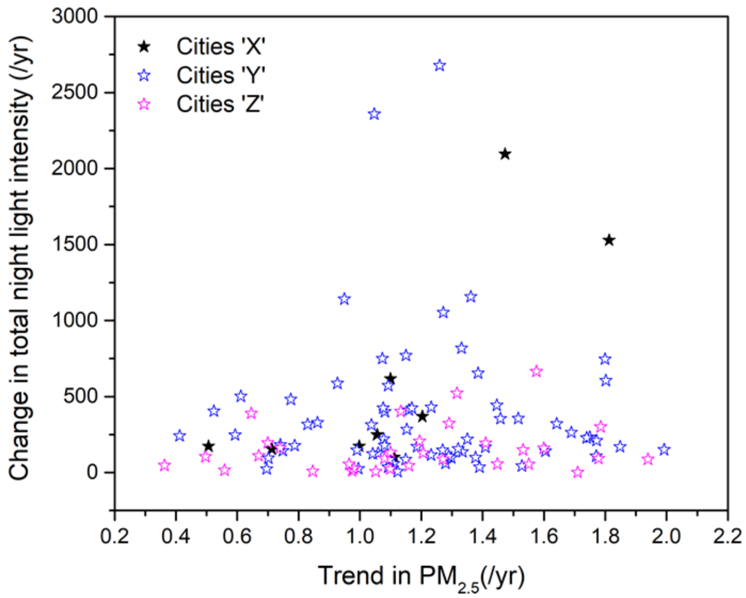

Fig. 3. Relation between night light digital count trend (used as a proxy for urbanization rate) and the trend in annual $PM_{2.5}$ exposure for 109 Indian cities divided into 3 categories - 'X', 'Y' and 'Z'. Each star represents a city.

sector, trash burning and unorganized industries) that are not directly related to lighting at night. This contrasting pattern may also be attributable to the changing role of meteorology, which influences the transport of pollutants from outside the city. In the 'Z' category of cities, $PM_{2.5}$ exposure has increased without much change in the night light. City-specific emission inventories need to be developed and their trends analyzed to ascertain the exact cause for the contrasting behavior in $PM_{2.5}$ exposure trends in these cities. Overall analysis reveals that the incremental median rate of annual $PM_{2.5}$ exposure increases from 0.9 to 1.15 µg m^{-3} per year with the night-light count increasing from the < 20^{th} percentile to the > 80^{th} percentile.

Next, we assess the vulnerability of these cities due to the changing pattern of air pollution, and epidemiological and demographic transitions in the period 1998–2015 (see Table 1 for the statistics of each city). The cities are grouped into six vulnerable classes based on the final score as discussed earlier (Fig. 4). Vulnerability to air pollution is 'low' (index 1) in 10 cities, of which only one (Shimla) is located in the hilly terrain in northern India and the rest of which are in southern India. 17 cities are classified as 'moderately' vulnerable (index 2). These cities are distributed in peninsular India—high altitude cities in northern and northeastern India and in the coastal regions. 27 cities identified as 'highly' vulnerable (index 3) are located in the states of Gujarat, Maharashtra, Karnataka, Andhra Pradesh, Uttarakhand, Punjab and northeastern India. The cities in the greater Mumbai metropolitan area also fall in this category. The highest number (28) of cities have a vulnerability index of 4 and include four 'X' category cities: Mumbai, Bangalore, Hyderabad and Kolkata. 16 and 11 cities have a vulnerability index of 5 ('severely' vulnerable) and 6 ('extremely' vulnerable) respectively. We note that Delhi, although touted as one of the most polluted cities in the world, does not belong to the highest vulnerability class (index 6) because of a much lower baseline for mortality (perhaps due to better healthcare access). Instead, cities in the states of Uttar Pradesh and Bihar with annual $PM_{2.5}$ exposures lower than that of megacity Delhi are categorized as extremely vulnerable (index 6) due to a combination of factors, such as wide $PM_{2.5}$ exposure, a high increasing trend in annual $PM_{2.5}$ exposure, high population density and most important, high baseline mortality for all diseases.

90 cities were chosen by the Ministry of Urban Development, Govt. of India, for the 'smart city' mission, with a focus on sustainable and inclusive development in these cities. In our study, we extracted statistics for 60 of the 90 cities (the remaining cities have a population smaller than our threshold and hence are not considered in this analysis) and found that the vulnerability index for air pollution exposure and trend is 3 and above ('high', 'severe' and 'extreme') in 51 of them. Only 9 cities (Shimla in Himachal Pradesh, Nashik in Maharashtra, Kohima in Nagaland, Panjim in Goa, Kochi and Thiruvananthapuram in Kerala, and Coimbatore, Madurai, Tirunelveli and Salem in Tamil Nadu) have ambient air somewhat suitable for a sustainable environment. It must be noted that the annual mean exposure in these cities is still higher than the WHO guideline. In the remaining 51 cities, it would be a challenge to achieve a sustainable environment since the $PM_{2.5}$ exposure has been increasing over the years, a trend that is expected to continue with further development under the 'smart city' mission.

DISCUSSION AND CONCLUSIONS

The goal of this work is to generate $PM_{2.5}$ statistics for the Indian cities and understand their vulnerability to ambient $PM_{2.5}$ exposure. The impact of chronic exposure to $PM_{2.5}$ on human health depends not only on the $PM_{2.5}$ concentration but also on the population distribution and

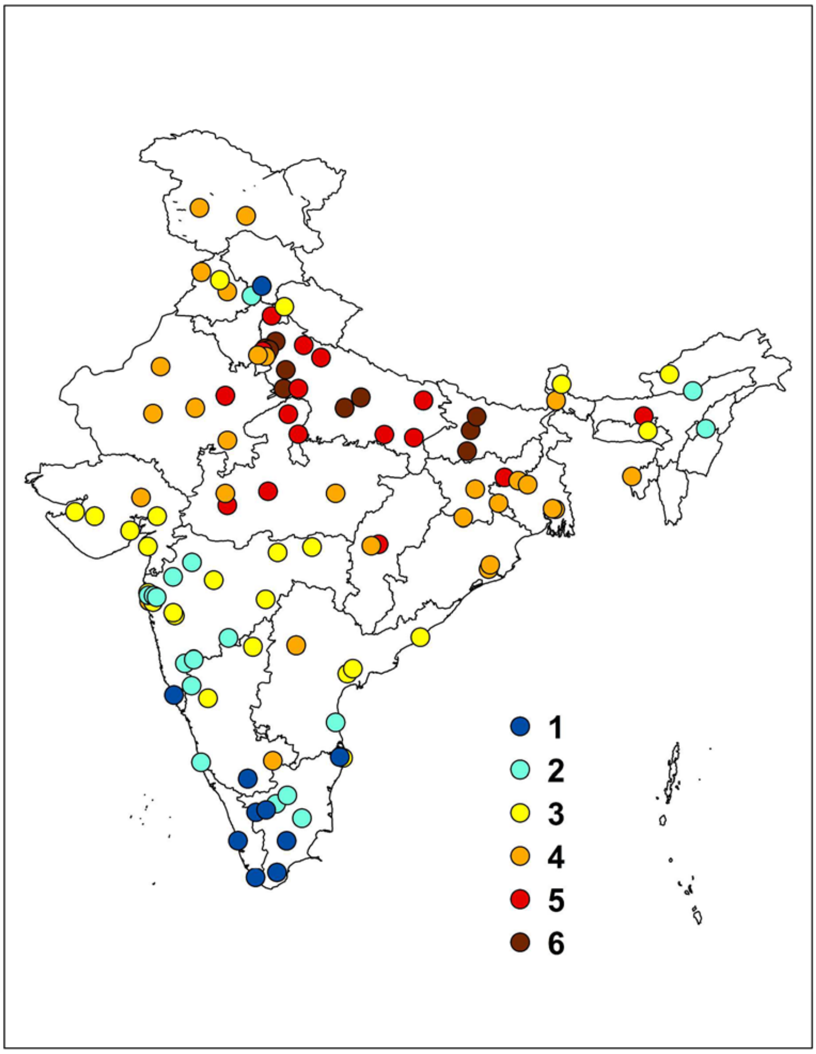

Fig. 4. Vulnerability index for the 109 Indian cities due to ambient $PM_{2.5}$ exposure. Index '1' indicates the least vulnerable cities while index '6' indicates the most vulnerable cities. The statistics are given in Table 1.

baseline mortality rates. Moreover, if the $PM_{2.5}$ concentration has been increasing over the years, the burden is expected to continue rising with the predicted increase in population, making the cities more vulnerable. Therefore, our vulnerability index for the Indian cities accounts for the population-weighted annual $PM_{2.5}$ exposure and its trend over almost two decades, the population distribution and the baseline mortality of COPD, IHD and stroke. Exposure data at a very high resolution (0.01° × 0.01°) has helped in generating improved exposure statistics, as the population distributions within the cities are highly variable.

In India, the focus of air pollution discussions often remains limited within Delhi NCR. So far, mitigation attempts have only been made in the national capital, Delhi, to stall the rising level of air pollution. First, the operation of the mass transit system was switched from diesel and petrol to CNG in the period 2001–2002. The annual $PM_{2.5}$ exposure dropped by 16.3%, but eventually it started rising again rapidly. In 2016, vehicle rationing was introduced for a short period of time (15 days) as an emergency measure to reduce the pollution. Though the attempt was commendable, it failed to mitigate pollution on a larger scale due to the meteorological impact and various other factors (Chowdhury *et al.*, 2017). After the great smog episode from late October till early November in 2016, during which $PM_{2.5}$ concentration shot beyond 600 µg m^{-3} (10 times the Indian daily standard and 24 times the WHO daily standard) in the national capital territory of Delhi, the honorable Supreme Court of India formed a graded action plan for air pollution mitigation. Several measures, such as stopping garbage burning, mechanizing the sweeping of roads, discouraging the public from using private vehicles by increasing parking fees, intensifying public transport, stopping the usage of diesel generators, minimizing biomass burning and restricting the use of old diesel vehicles, were initiated.

Our results show that the vulnerability due to ambient $PM_{2.5}$ exposure is 'very high', 'severe', or 'extreme' in many cities that are smaller than Delhi and other 'X' category cities in India. In these cities, the rate of pollution increase is much higher than in Delhi. Therefore, the current inaction will potentially create Delhi like situations in these cities in the near future. In many of these cities, not a single in situ $PM_{2.5}$-monitoring site (Table 1 displays the existing monitoring network) is in operation. In cities that possess a single monitoring site, the method of deployment is still critical, as the exposure varies drastically within a city. The analysis of night-light trends reveals an interesting fact about the changing behaviors of emission patterns in these cities. Rather than assigning an absolute rank, we group the cities into six vulnerable classes to allow policymakers to prioritize cities that need city-specific clean air action plans. Unless the cities achieve clean air, the true essence of the 'smart city' mission will remain unfulfilled.

The major conclusions of this work are as follows:

1. Contrary to the perception that the air pollution problem is limited to the Delhi National Capital Region, our analysis shows that vulnerability due to ambient-$PM_{2.5}$ exposure is equally high or even higher in cities located in the states of Uttar Pradesh, Bihar, Jharkhand, West Bengal, Punjab, Haryana, Rajasthan, Madhya Pradesh, Chhattisgarh and Odisha.
2. Amongst the 60 cities selected for the Indian government's 'smart city mission', only 9 cities (Shimla, Nashik, Kohima, Panjim, Kochi, Thiruvananthapuram, Coimbatore, Madurai, Tirunelveli and Salem) are identified as possessing 'low' to 'moderate' vulnerability to ambient air pollution. Therefore, achieving a sustainable environment, thus fulfilling one of the core objectives of the national mission, poses a big challenge to the remaining 51 cities.
3. Rapid urbanization in Indian cities in the last two decades has definitely increased the level of air pollution.

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SUPPLEMENTARY MATERIAL

Supplementary data associated with this article can be found in the online version at http://www.aaqr.org.

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