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Examination of monitoring approaches for ambient air pollution: A case study for India

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ABSTRACT

India faces one of the highest disease burdens from air pollution in the world, with an estimated 100% of the population living in areas with $PM_{2.5}$ concentrations above the World Health Organization Guideline (10 μg/m^3 annual average). With development and population growth, increases in ambient air pollution are anticipated. Combined with an aging population and increasing burden of chronic diseases, ambient air pollution will remain a concern for India well into the current century. Air quality measurements make critical contributions to the identification and prioritization of sources and locations of greatest concern, benchmarking against standards and guidelines, and in the evaluation of effectiveness of actions to reduce emissions. We compare the density of India's monitoring network with that of comparator countries and find large differences. For example, given the ~200 $PM_{2.5}$ monitoring sites in operation during the 2010–2016 period, we find that India's monitor density of ~0.14 monitors/million persons (1 monitor for every 6.8 million people) is well below that of other highly populated countries such as China (1.2 monitors/million persons), the USA (3.4 monitors/million persons), Japan (0.5 monitors/million persons), Brazil (1.8) and most European countries (2–3 monitors/million persons).

To address these gaps between India and monitor densities of comparator countries will require 1600–4000 monitors (1.2–3 monitors/million persons) at an estimated capital (annual operating) cost of US $212–540 ($106–270) million. Even at these densities, only relatively basic information on common air pollutants at high temporal, but limited spatial, resolution would be available. Small-scale variability in air pollution levels within urban areas would not be well-characterized, nor would there be information on chemical constituents useful for evaluating and improving simulations and forecasts, or for characterizing source contributions. As a sufficiently dense traditional network is developed over time, the potential for an integrated monitoring framework to serve as a near-term complement to a traditional network is assessed. In this design, a smaller number of traditional monitoring sites would be linked to a single advanced surface monitoring station in each of ~11 airsheds identified as a minimal number for India. These sites would combine measurement of chemical speciation of particulate matter with measurements of aerosol scatter and aerosol optical depth to link measurements with global and regional satellite-based estimates. In turn, the advanced and traditional sites could serve as calibration nodes for low-cost sensor networks designed to complement periodic mobile monitoring campaigns and/or land use regression models, to provide high spatial and temporal resolution. Such a framework could be established at a substantially reduced cost relative to that of a traditional networks, subject to specific design and complexity considerations. The same general approach may also be applicable to the many other countries with limited or no air quality monitoring and where estimates suggest air quality is a concern.

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1. Introduction

1.1. Ambient air pollution in India

Ambient air pollution is a leading risk factor for disease burden in India. Ambient $PM_{2.5}$ is estimated as the 4th leading risk factor for mortality and accounted for ~700,000 attributable deaths in 2017, and $PM_{2.5}$ and ozone together were responsible for ~8% of total mortality in 2017 (Balakrishnan et al., 2019; Stanaway et al., 2018). The national population-weighted annual average $PM_{2.5}$ level in 2017 in India (91 μg/m^3) was more than double the World Health Organization (WHO) Interim-Target 1 (35 μg/m^3 annual average), with approximately 85% of the population living in areas above this level and 100% living in areas above the WHO Guideline of 10 μg/m^3.

Given the ongoing economic development underway in India, recent simulations (GBD-MAPS Working Group, 2018) suggest population-weighted $PM_{2.5}$ levels to increase to 85 μg/m^3 in 2030 and 106 μg/m^3 in 2050 under reference scenarios. Further, levels are still not expected to meet the WHO Interim Target 1 in 2050, even under an aspirational scenario of renewable energy, elimination of household solid fuel use, strict industrial emissions controls and high penetration of low emission vehicles. In addition, under a warmer climate and with increased emissions, ozone concentrations are also expected to increase in the next decades (Silva et al., 2017). These anticipated increases in ambient air pollution combined with a growing and aging population with an increasing burden of chronic diseases, suggests that ambient air pollution will remain a concern for India well into the current century (GBD-MAPS Working Group, 2018). While these estimates are sobering, recent dramatic progress in reducing exposures to household air pollution from the use of solid fuels (Krishna et al., 2017), as well as India's adoption of renewable energy at a pace exceeding that of its Nationally Determined Contribution (India Climate Action Tracker, 2018), and launch of the National Clean Air Programme (NCAP) (National Clean Air Programme. Ministry of Environment, 2019), provide hope that effective management of ambient air pollution will lead to substantial reductions, as have been evident recently in China and which led to dramatic improvements in air quality in Western Europe and North America (Apte and Pant, 2019).

1.2. Role of measurements in air quality management

Effective air quality management includes three main components: 1)identification and quantification of major sources; 2)regulatory and non-regulatory approaches to reduce source contributions; and 3) measurement and monitoring of air quality to support source identification and to evaluate progress in achieving ambient air quality targets. Measurements play a central role both in identifying and prioritizing sources and locations of greatest concern, benchmarking against national or international standards and guidelines and in evaluating effectiveness of actions to reduce emissions and tracking overall progress. Traditionally, ambient air quality measurement has focused on establishing a number of fixed-location monitors situated to provide information on regional or urban background concentrations, and/or locations targeted to assess impacts of specific sources such as motor vehicles, industrial sources or power plants. These monitoring stations typically incorporate robust, high quality devices to provide a combination of real-time or integrated average measurements of common air pollutants (SO_2, CO, NOx, PM [PM_{10} and/or $PM_{2.5}$] and O_3). In many regions data are provided in near real-time via publicly accessible internet portals and incorporated into air quality (health) indices as public information tools. In addition, these measurements provide important support for air quality forecasting tools as well as spatial models describing variation within urban areas. Given the high costs of establishing each individual station (~$135,000 U.S. Dollars) as well as the historical emphasis on temporal specificity and episode surveillance, monitor density is known to poorly characterize the true spatial variability in pollutant concentrations, especially within urban areas (Brauer, 2010). This may be particularly relevant in rapidly developing economies such as India where a diverse array of numerous small sources are present. Further, given understanding of the larger magnitude of population health impacts arising from chronic exposures vs short-term variation in ambient levels (Pope et al., 2011), increasing emphasis on characterizing spatial variation in air pollution is warranted. Approaches to characterize spatial variation in pollutant levels at high (~100 m) resolution include mobile monitoring (Apte et al., 2017), land use regression models (Hoek et al., 2008), operational dispersion models (Jerrett et al., 2005), and the more recent approach of deploying networked low-cost sensors (Lewis et al., 2018). The first two approaches typically involve targeted spatial monitoring campaigns conducted at specific times to characterize spatial variation of long-term average levels (Wang et al., 2013; Gulliver et al., 2013), whereas the latter two approaches can provide information that is highly resolved both temporally (~hours) and spatially (~100 m).

Traditional ground-based monitoring networks may also be supplemented with a more limited number of locations providing information on additional pollutants or chemical speciation of particulate matter (Apte and Pant, 2019). These measurements provide critical support for more advanced tools such as chemical transport models which are combined with emissions inventories and meteorological (measurements and/or models) information to simulate the source to ambient concentration relationship. These models can be used for air quality forecasting (Kumar et al., 2018) or evaluation of control or development scenarios. Satellite remote sensing offers a powerful information source that complements ground-based observations, as discussed further below.

2. Overview of currently available ambient air quality information for India

2.1. Ground monitoring networks and data summary

We assessed the measurement density of air quality monitoring networks operated in India. The Central Pollution Control Board (CPCB) maintains the primary network across the country. In addition, the Delhi Pollution Control Committee maintains a network within the Delhi national capital territory. SAFAR (System of air quality and weather forecasting for research) is an initiative of the Ministry of Earth Sciences/India Institute for Tropical Meteorology to monitor and forecast air quality in four Indian cities, and MAPAN (Modeling Air Pollution and Networking) also operated by the Ministry of Earth Sciences/India Institute for Tropical Meteorology conducts monitoring in 11 cities. Based on measurements of PM_{10} and $PM_{2.5}$ collected as part

Table 1
$PM_{2.5}$ concentrations data in WHO Air Pollution in Cities Database (2018) (WHO, 2018).

Number of cities with measured $PM_{2.5}$ (Mean concentration, SD)	33 (84.2 ± 46.2 μg/m^3)
Number of cities with measured + converted $PM_{2.5}$ from PM_{10}	135 (53.5 ± 30.4 μg/m^3)
Number of cities with 1 station only for $PM_{2.5}$ measurements	23
Number of cities with 1/2/3 stations for PM_{10}	30/28/33
Number of cities with 4 + stations for PM_{10}	7

of the WHO Global Ambient Air Quality Database (WHO, 2018) and as used in the Global Burden of Disease 2017 and WHO (2018) exposure estimates for $PM_{2.5}$, we find that ~200 unique $PM_{2.5}$ measurement locations were operational in India in the 2010–2016 period. At the city level, the majority of urban areas measured only PM_{10} and those where $PM_{2.5}$ was measured directly had only a single $PM_{2.5}$ monitor, a density insufficient to accurately characterize spatial or temporal variability of the exposure of the population (Table 1). Further, there is uncertainty in converting PM_{10} to $PM_{2.5}$ (Shaddick et al., 2018). From a national perspective, we find that this $PM_{2.5}$ monitor density is ~0.14 monitors/million persons (1 monitor for every 6.8 million people), a level well below that of other highly populated countries such as China (1.2 monitors/million persons), the USA (3.4 monitors/million persons), Japan (0.5 monitors/million persons), Brazil (1.8) and most European countries (e.g. France, Germany, Denmark, The Netherlands: 2–3 monitors/million persons). Even when India's ~330 PM_{10} monitors are included, we find that monitor density (0.4 monitors/million persons) still lags.

Since the above data applicable to national comparisons were compiled, there has been growth in the number of monitoring stations operating in India. As of November 2018, there were 700 manual stations measuring $PM_{2.5}$, PM_{10}, NOx and SO_2 every 2–3 days and 117 (up from 74 in September 2017, and including 33 in Delhi) continuous stations measuring CO, NOx, SO_2, PM_{10} and $PM_{2.5}$. Despite this dramatic increase, monitor density (0.6 monitors/million persons) still falls behind that of most countries with networks and is well short of the targets listed by the CPCB (Central Pollution Control Board, 2003). Specifically, based on the CPCB monitoring targets (4 monitors in each settlement of 100,000 persons or less with increasing density in larger population centers), which consider the total population of the airshed and the mix of activities, we estimate a need for 4000 stations in India: 2800 in the urban areas and 1200 in the rural areas. For example, Uttar Pradesh with a population of over 200 million requires 558 stations, and Delhi with a population of over 20 million requires 77 stations (Fig. 1b). The current inadequacy of India's air quality monitoring network has been recognized previously and highlighted as a need, along with an expansion of air quality research outside of major urban areas (Pant et al., 2016, 2019).

While China has fully embraced implementation of a traditional air quality monitoring network (for example, expanding from < 100 stations in 2010 to > 1700 in 2016), we examine the potential for a different path and explore what such a framework might look like in India. We base our analysis on providing population coverage for $PM_{2.5}$, given its dominant role with respect to the burden of disease attributable to air pollution in India and the recent emphasis on PM monitoring within India. We note, however, that the challenge regarding expansion of the monitoring network capabilities in India for other common pollutants beyond particulate matter is likely to be even more daunting. For example, the recently compiled Tropospheric Ozone Assessment Report (Schultz et al., 2017) global database indicates only 7 continuous ozone monitors in India, with similar numbers for NO_2 (Larkin et al., 2017).

2.2. Composition measurements

As is typical in many countries, routine measurements of chemical composition of atmospheric constituents (e.g. particle chemical composition, speciated volatile organic compounds) beyond the common air pollutants is not undertaken in India. However, under different research programs and targeted government initiatives there have been a number of measurement campaigns conducted in major cities in India where particle chemical composition has been used to estimate source contributions (Pant et al., 2016; Guttikunda et al., 2014). One recent exception is part of the global Surface Particulate Matter Network (SPARTAN) in which IIT-Kanpur operates a site. This network collects 9-day integrated filter samples which are analyzed for $PM_{2.5}$ mass and a wide array of chemical constituents (Snider et al., 2015, 2016). Combined with continuous measurement of particle light scattering with a nephelometer, these integrated filter samples can be disaggregated to estimate daily or hourly PM levels.

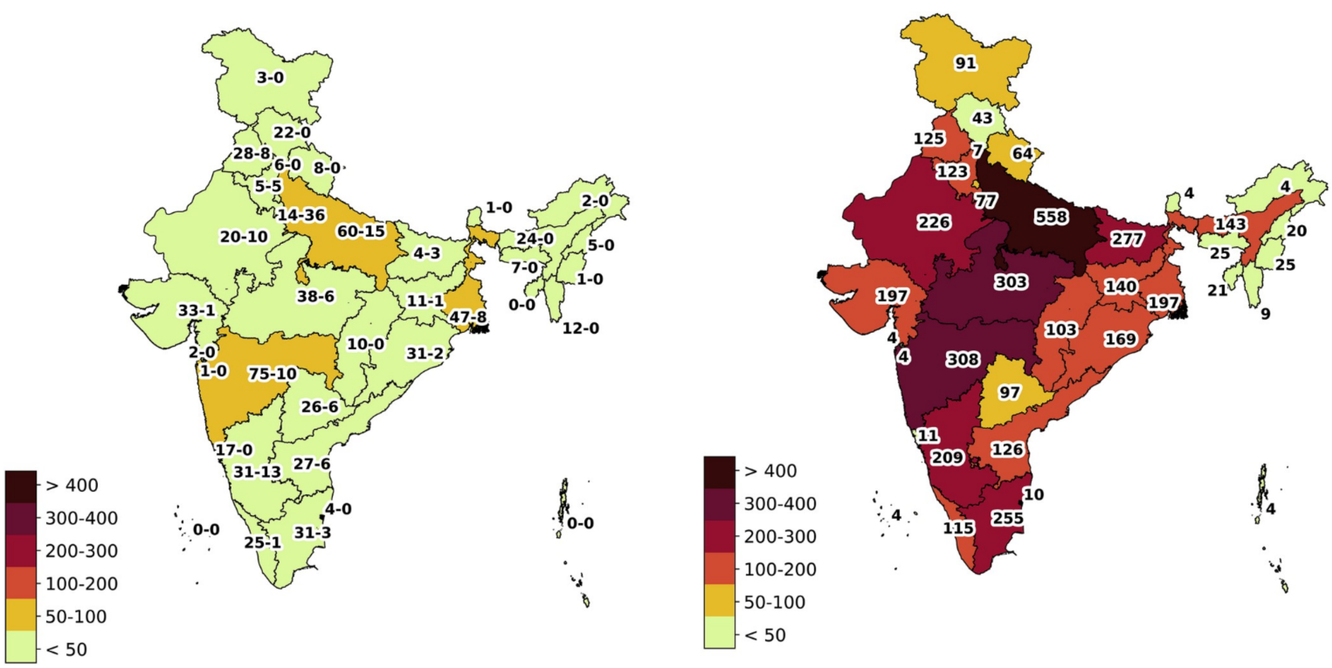

Fig. 1. Number of operating (as of November 2018) air quality monitoring stations (panel A) in India (manual - continuous), and number of recommended (PM) monitors according to low estimate from the Central Pollution Control Board (Central Pollution Control Board, 2003) (panel B).

2.3. Chemical transport models: operational models and forecasts for India

Recently several operational forecast models have become available for India. At the national level, as part of global forecasts characterizing urban/regional background levels, the Copernicus Atmosphere Monitoring Service (CAMS) (CAMS, 2018) provides ~10 × 10 km daily 4-day forecasts from an ensemble of 7 chemical transport models, with posterior adjustment with ground measurement data where available, for a number of different particulate and gaseous pollutants (CAMS, 2018).

Urban Emissions provides 72-hr (hourly and daily) average ambient $PM_{2.5}$, and several other pollutant concentrations, using meteorology processed through 3D-WRF meteorological model and the GFS meteorological fields with concentrations simulated through the CAMx chemical transport modeling system, coupled to a dynamic emissions inventory. The modeling domain covers India at a spatial resolution of ~25 × 25 km (India AIr Quality Forecasts, 2019), with more detailed (~1 × 1 km) forecasts provided for Delhi (Delhi Air Quality Forecasts, 2019) and other cities in India as part of the Air Pollution Knowledge Assessment (ApnA) Program (Guttikunda et al., 2019).

The SAFAR program for air quality forecasting was initiated for Delhi during the 2010 Commonwealth Games and later expanded the forecasts to three other major cities (World Meteorological Organization, 2015). More recently, the Ministry of Earth Sciences, in collaboration with the U.S. National Centre for Atmospheric Research, also initiated air quality forecasting, including satellite data assimilation, for Delhi at very high spatial resolution. It should be noted, however, that currently India does not have a regularly updated national emissions inventory and this absence has potential implications for the quality of modeling that relies upon emission inventories.

2.4. National satellite-based estimates

Satellite-based estimates have also contributed to understanding of air quality within India. Multi-angle Imaging Spectro Radiometer (MISR) aerosol products were used to estimate $PM_{2.5}$ exposure (that is bias corrected against coincident in-situ observations) specifically for India for the period 2001–2010 (Dey et al., 2012). In this analysis nearly 51% of the Indian population was estimated to live in areas with ambient $PM_{2.5}$ exceeding WHO interim target I. Annual $PM_{2.5}$ exceeded WHO annual standard in ~70% of the Indian subcontinent's area. On 40–50% of the clear days, daily $PM_{2.5}$ exceeded the WHO interim target I in the Indo-Gangetic Plain and Mumbai. PM_{10} exposure (estimated using Modern-Era Retrospective analysis for Research and Applications [MERRA] reanalysis and Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observation [CALIPSO] aerosol products (Pande et al., 2018)), exceeded the WHO Interim Target I in ~70% of the districts in India. Under the NCAP, the CPCB has initiated work to implement retrospective and prospective satellite-derived concentration estimation across the country (National Clean Air Programme. Ministry of Environment, 2019). This effort will help prioritize expansion of the existing ground based monitoring network.

3. Beyond traditional ground monitoring

3.1. Low-cost sensors

Low cost monitors have attracted substantial attention in recent years with their potential to meet citizen needs for “what is my air quality, right here, right now?”. Such networks also have the potential, when linked in a network, for individual monitors to borrow information from others in the network to provide high-quality and highly resolved spatiotemporal air quality information with self-calibration, and integrated network training to improve accuracy. Such sensors have the potential to provide, at comparatively low cost, continuous measurements of air quality everywhere throughout an urban area. To date there has been relatively low realization of this potential, given issues with sensor accuracy and precision (Zheng et al., 2018), maintenance and calibration as well as a realization of personnel costs for network data management and maintenance (Lewis et al., 2018). Low-cost sensors have also been utilized by citizen groups when government measurement data have been unavailable, or considered unreliable (for example due to lack of representativeness of specific hot spots). While there are benefits of such initiatives in increasing citizen awareness and empowerment, there are also concerns that responding to citizen queries based upon inaccurate or faulty sensors can detract limited government air quality personnel from a focus on air quality management.

Especially when deployed as part of a local network of tens or hundreds of sensors, low cost sensors can be used to understand changes in pollutant concentrations over small spatial areas and short time periods. However, it is important to consider the larger context of any such data. A short spike (seconds to minutes) in levels measured by a single sensor may indicate a malfunctioning sensor or a temporary increase in localized air pollution, where the latter has little relevance for air quality management unless it affects a large population or occurs regularly. In addition, as many low-cost sensors have been developed by start-ups, there are concerns regarding their longer term availability and sustainable supply. In response, a number of local and national air quality management agencies have initiated testing and evaluation programs for specific sensors as well as guidance regarding their deployment in networks (Zheng et al., 2018; AQ-SPEC, 2019; US, 2019; Air Quality Map, 2187; Zheng et al., 2019).

As sensor quality and networking algorithms improve, low cost monitors can play an important role in supplementing traditional air quality monitoring networks and in contributing to data with improved spatial resolution. To date, sensor data have not been integrated with government air quality monitoring stations in India or elsewhere. While the low cost of sensor units is appealing and may provide opportunities for improved understanding of spatial and temporal patterns in air quality, the cost of QA/QC for low cost monitors may be larger than for traditional monitors due to data quality issues with low cost monitors. Operational costs of such networks with respect to sensor replacement, calibration and maintenance, and the expected personnel requirements for data management and interpretation must be balanced against the lower capital costs of monitor purchase and deployment. However, there is potential for these approaches to improve our understanding of air quality, particularly where a government site serves as a high-quality data node to help calibrate a larger network of low-cost sensors. As government data products improve and increasingly meet citizen goals for accessible air quality information, the need for citizen-based sensor networks may decline.

3.2. Mobile monitoring

Mobile monitoring is an approach in which relatively high quality instrumentation is deployed in a vehicle to map air quality throughout urban areas. Depending upon instrumentation, this method may be general or targeted towards specific sources or pollutant components. A recent example suggests the potential for automated data processing and a highly scalable approach to map air quality at high spatial resolution throughout major urban areas using research grade instrumentation (Apte et al., 2017; Messier et al., 2018), while other more modest examples designed to characterize spatial variability have been described in the literature (Fanning et al., 2009; Minet et al., 2018; Tessum et al., 2018), including mobile monitoring campaigns linked to automated data processing and citizen science initiatives (Wagstaff, 2018; Lim et al., 2019). While monitors can be deployed on dedicated vehicles, increased efficiency may be obtained by locating monitors on commercial (e.g. Uber, taxis, delivery vehicles) or public fleets (buses, police vehicles, etc.).

3.3. Land use regression models

Land use regression modeling has revolutionized understanding of air pollution variability within urban areas and become increasingly the norm for epidemiologic investigations of long-term exposure to air pollution (Hoek et al., 2008). In this approach, targeted measurements are collected over defined periods at a relatively high number (~50–100) of locations within an urban area. These measurements are used in combination with geospatial data describing air pollution sources (e.g. road or traffic density, land use, source proximity) in a simple regression model. As the geospatial data are typically available throughout urban areas at high resolution (10–100 m) resulting models prediction provide highly resolved spatial estimates of annual or seasonal air pollutant concentrations. A recent example developed for Delhi shows the potential applications for India, although the lack of comprehensive geospatial data remains a limitation (Saraswat et al., 2013).

3.4. Satellite remote sensing

Satellite remote sensing offers a powerful information source about $PM_{2.5}$ concentrations (Wang and Christopher, 2003; Engel-Cox et al., 2004). Attributes of satellite remote sensing include spatially and temporally consistent observations worldwide spanning from 1998 to the present. The technique builds upon satellite retrievals of aerosol optical depth (AOD), a measure of light extinction in the atmospheric column, that are publicly available from a variety of instruments (e.g. SeaWiFS, MODIS, MISR, VIIRS) and algorithms (e.g. Dark Target (Levy et al., 2007), Deep Blue (Hsu et al., 2013), MISR (Martonchik et al., 1998), and MAIAC (Lyapustin et al., 2011)). These area-averaged observations with resolution as fine as 1 km offer valuable information about $PM_{2.5}$ exposure. These observations have been applied to infer ground-level $PM_{2.5}$ concentrations across regions with both high monitor density (e.g. North America (Kloog et al., 2011; van Donkelaar et al., 2015), Europe (de Hoogh et al., 2016), and China (Ma et al., 2014) and regions with low monitor density (e.g. India (Dey et al., 2012), and worldwide (van Donkelaar et al., 2010)).

The technique involves relating satellite AOD with ground-level $PM_{2.5}$. In regions with very high monitor density such as the United States and China, statistical techniques alone have been successful (Kloog et al., 2011; Ma et al., 2014). In regions of low monitor density, a chemical transport model is first used to calculate the time- and space-varying relationship of satellite AOD with $PM_{2.5}$ (van Donkelaar et al., 2010). This initial geophysical estimate can be subsequently statistically fused with ground-based monitors to refine the estimate (Shaddick et al., 2017, 2018; van Donkelaar et al., 2016).

A key source of uncertainty is the relationship of columnar AOD at satellite overpass time for cloud-free conditions at ambient relative humidity, with ground-level 24-hr $PM_{2.5}$ concentrations at controlled relative humidity. Collocated ground-based measurements of both AOD and $PM_{2.5}$ offer a powerful information source to evaluate and enhance satellite-based estimates of $PM_{2.5}$ by measuring this key source of uncertainty (Snider et al., 2015). If well designed, such a network could also contribute to measurements of $PM_{2.5}$ for regulatory monitoring, to $PM_{2.5}$ composition for bottom-up and top-down source attribution, and as reference monitors for low-cost networks, all of which are described further below in section 4.2.

4. Options for India

4.1. Traditional ground monitoring network expansion

Table 2 provides rough estimates of the number of monitoring stations required by India and the estimated capital and annual operating costs to meet levels of monitor density currently achieved in a range of comparator countries with large populations or similar population densities. Currently India has a similar monitor density (0.2–0.6 monitors/million persons) to that of the relatively low $PM_{2.5}$ exposure setting of Japan, but lags well behind all of the comparator countries. Meeting a similar monitor density to that of China would require a substantial investment, with an estimated total annual cost (assuming annual operating costs plus 10-year amortized capital costs) of approximately $127 Million. This sum is approximately equivalent to 0.15% of the annual (2017–18) Ministry of Road Transport and Highways central sector project budget (Union Budget, 2019), 0.2% of the estimated (2015) annual labour productivity or 0.02% of the estimated annual welfare losses attributable to ambient $PM_{2.5}$ in India (The World Bank., 2016).

Fig. 1 indicates the State level distribution of both manual and continuous monitors within India (panel a) as of November 2018, and the required distribution based upon the CPCB low (4000 monitors) estimate (panel b) (see also Table 2). Note that a traditional monitoring network meeting any of the comparator coverage densities would only provide relatively basic information on common air pollutants at high temporal, but limited spatial, resolution. Small-scale variability in air pollution levels within urban areas would not be well-characterized nor would there be information on chemical constituents useful for evaluating and improving simulations and forecasts or characterizing source contributions. Thus, while undeniably useful for air quality management, such a traditional ground-monitor based network would be

Table 2
Estimated monitoring network requirements and costs for India based on CPCB guidelines (Central Pollution Control Board, 2003) and comparator countries.

Comparator ($PM_{2.5}$ monitors/ million persons)	# monitors required for India	Estimated Cost (Capital) million USD	Estimated Cost (Capital) Rs Crore	Estimated Cost/year operating million USD	Estimated Cost/year operating Rs Crore
CPCB low (3.0)[a]	4000	540	4000	270	2000
CPCB high (6.6)[b]	8600	1161	8600	581	4300
Japan (0.6)	785	106	785	53	392.5
China (1.2)	1571	212	1571	106	785.5
USA (3.5)	4582	619	4582	309	2291
Korea (1.4)[c]	1833	247	1833	124	916.5
Netherlands (2.8)[c]	3665	495	3665	247	1832.5
Israel (3.2)[c]	4189	566	4189	283	2094.5

[a] CPCB low estimate assumes ~ 4 monitors per 100,000 population (for urban areas) which is the minimum monitor density in the CPCB document and is comparable to monitor density in the USA and several high income countries with similar population density.

[b] CPCB high estimate includes higher monitor density in larger cities, following guidance in the CPCB document; achieving this high estimate would require India to be the most densely monitored country in the world.

[c] Countries with similar population density to India. Costs are rough estimates based upon reports of the estimated capital cost of approximately 135,000 USD (equal to ~ Rs 1 crore) as reported for a station commissioned in Gurgaon in 2017, plus 50% annual costs of operation and maintenance and personnel fee (Pant et al., 2019). Estimates based on UK figures from 2003 (Money, 2006) (without adjusting for inflation or efficiencies in technology) suggest ~25% lower capital costs and ~5% lower operating costs.

unlikely to fully meet citizen interest regarding "air quality, right here, right now" compared with a framework including high spatial resolution information, and would need to be complemented by additional monitoring to support source attribution.

4.2. Integrated framework

While enhancing the ground monitoring network within India is undoubtedly necessary for advanced air quality management, especially in the context of an increasing (and urbanizing) population, there are opportunities to accelerate the availability and quality of information regarding air pollution. Advancement in satellite-based assessment of air quality as well as increasing understanding of the importance of high resolution spatial variability within urban areas suggests the potential for a hybrid approach as illustrated in Fig. 2. Aspects of this framework, such as national satellite-based estimates (Chowdhury et al., 2019), development of advanced air quality monitoring sites, and support for dense sensor networks (Zheng et al., 2018, 2019) have already been identified in India's NCAP. (National Clean Air Programme. Ministry of Environment, 2019) Further, the feasibility of implementing such a framework is supported by the existence at present of many of the framework components. Enhancements to existing infrastructure such as use of current monitoring programs for speciation measurements may also be an efficient approach to consider. Taken together, the integrated framework option we describe may be considered more of a scheme for integrating various currently diffuse and separate monitoring efforts rather than an entirely new system. As such we describe this framework as a complement to existing efforts, including the operation and enhancement of the traditional ground monitoring network, to maximize the acquisition of useful information for air quality management.

In this framework there is direct linkage of tools spanning global to local scales. At the global to national scale, satellite-based estimates are combined with chemical transport model simulations to estimate surface concentrations, as described above. Such estimates are now readily available for ~ annual average concentrations of $PM_{2.5}$ at ~10 × 10 km resolution (with some information available at ~ 1 × 1 km resolution), with examples of estimates for NO_2 at ~ 10 × 10 km resolution. A number of examples also exist where satellite-based NO_2 estimates have been used as inputs to land use regression models. The (~10 × 10 km resolution) satellite-based estimates are combined with land use information to provide coverage at continental (Novotny et al., 2011; Vienneau, 2013; Knibbs et al., 2014) or even global (Larkin et al., 2017) scales at sub-kilometer resolution. Satellite-based estimates for ground-level ozone are less feasible in part due to the high impact of stratospheric ozone on satellite observations. Satellite-based approaches are not a replacement for ground monitoring, but rather the two can be integrated for improved spatial and temporal coverage. Future use of near real time data streams from geostationary satellites focused on India (vs the current polar-orbiting satellites which provide snapshots 1–2 times per day) could provide further information to enhance public communications, forecasts and source analysis.

Advanced surface monitoring stations combining measurement of chemical speciation of particulate matter along with measurements of aerosol optical depth via a sun photometer could improve the accuracy of satellite-based estimates from both global and regional perspectives. Such advanced measurement nodes could also serve as important evaluation data for chemical transport model simulations and provide necessary inputs for receptor modeling source apportionment. The latter two approaches provide information on source contributions which could be further developed for forecasting and evaluation of air quality management options and initiatives. One such monitoring station began in Kanpur in 2013 to cost effectively collect 9-day integrated filter samples that are analyzed for $PM_{2.5}$ mass and a wide array of chemical constituents (Snider et al., 2015, 2016). Combined with continuous measurement of particle light scattering with a nephelometer, these measurements offer the critical measurements needed to evaluate and enhance satellite-based $PM_{2.5}$ estimates.

Ideally, within such a framework one advanced monitoring station would be located in each distinct airshed within India. Airsheds are commonly defined by geographic/topographic and meteorological regions as well as sources. We estimated airsheds for India from a

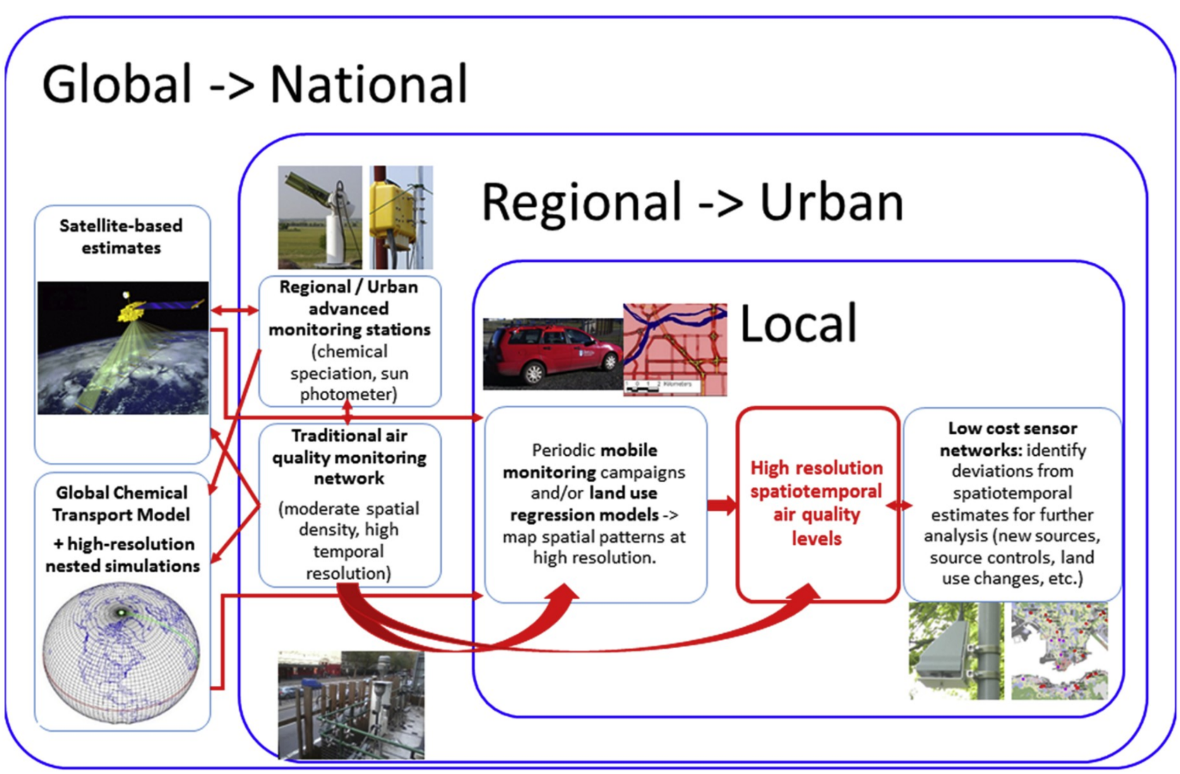

Fig. 2. Schematic of an integrated global to local framework for air quality monitoring.

combination of major cities (those with populations above 3 million inhabitants), sensitivity simulations and satellite-based $PM_{2.5}$ estimates (GBD-MAPS Working Group, 2018; Weagle et al., 2018). The sensitivity simulations perturbed major $PM_{2.5}$ sources in India and identified coherent regions with similar $PM_{2.5}$ characteristics, which were then used to define airsheds. Within these source-based airsheds, we further delineated city-level airsheds around the major cities. With this approach as a conservative estimate for initial prioritization we identified 11 airsheds in India (Fig. 3).

This number is similar to the proposal in the National Clean Air Program (National Clean Air Programme. Ministry of Environment, 2019) to establish a 10-city Super Network, with advanced monitors. As an additional estimate, the ApnA program is developing forecasts and source contribution estimates for 50 distinct airsheds encompassing additional major cities (Guttikunda et al., 2019). Under the National Clean Air Programme (National Clean Air Programme. Ministry of Environment, 2019), 102 non-attainment cities in India have been identified and requested to develop air quality management plans. As such, additional airsheds with distinct air quality management plans may be required to meet these longer term objectives.

These advanced monitoring sites would also serve as nodes that are linked to traditional air quality monitoring stations within each airshed, thus providing additional information on spatial variability in pollutant concentrations at high temporal resolution and also linking the network directly to satellite-based estimates. Monitor density can thus be based on satellite-based estimates of variability in concentrations with higher density in areas of greater variability and weighted towards areas with higher population density. This approach also facilitates regional to urban scale modeling and forecasting with a goal of providing temporally resolved accurate estimates of concentrations of common pollutants at fine resolution within the entire region.

Within urban areas, where spatial variability is likely to be higher, enhanced spatial resolution on the order of ~100 m can be informed by periodic mobile monitoring campaigns and/or land use regression or dispersion models. When combined with temporal patterns from traditional ambient monitors within the airshed, high resolution spatiotemporal estimates can be produced in near real time. While low cost sensor networks at present are unlikely to directly replace such estimates, their deployment can be informed by the spatiotemporal air quality patterns and, once calibrated to the traditional air quality monitoring stations, can be used to identify deviations from the spatiotemporal estimates, for example impacts from new sources, and use changes. Regular linkage of sensor networks to traditional air quality monitoring stations or advanced monitoring nodes can facilitate network calibration and even allow for integration of sensor networks using different instrumentation. In turn, the sensor networks can inform improvements in the spatiotemporal estimates and suggest when mobile monitoring campaigns or modeling exercises should be repeated. While this approach meets the ultimate objective for citizens of air quality information wherever they are at whatever time, from the air quality management perspective in order to provide dynamic estimates of population exposure (Nyhan et al., 2016, 2018; Tang et al., 2018) such high resolution data also requires information on population mobility, for example from Census information, cell phone records, transportation surveys or transit cards. Simulation analyses for Delhi (Saraswat et al., 2016) suggests rather small variation in exposure once mobility is considered although this may differ by metropolitan area and age group.

For the integrated framework, we estimate an approximate capital cost per airshed of $0.7 Million with annual operating costs of $0.4 Million USD. This assumes each airshed would include a minimum of 4 traditional air quality monitoring stations (at a capital cost of $135,000/station with annual operating costs equal to 50% of capital costs), a low cost sensor network with 200 nodes (assuming a cost of $100/sensor), and a single advanced station similar to those in the SPARTAN network (at a capital cost of $50,000 with $10,000 annual operating costs) that is co-located with a traditional air quality monitoring station. We note that the $135,000 estimated cost of the traditional air quality monitoring station assumes measurement of multiple pollutants and is the same estimated cost described above for a traditional measurement network, based on a site recently commissioned in India. Measurement of a single pollutant would lower the costs of both a traditional monitoring network and the integrated framework described here. Further, a mobile monitoring campaign (at an estimated cost of $25,000 for a basic campaign not including instrument purchase) could be conducted every 5 years for detailed information on spatial patterns at high resolution. These costs are estimates and may be higher or lower depending on specific design considerations and

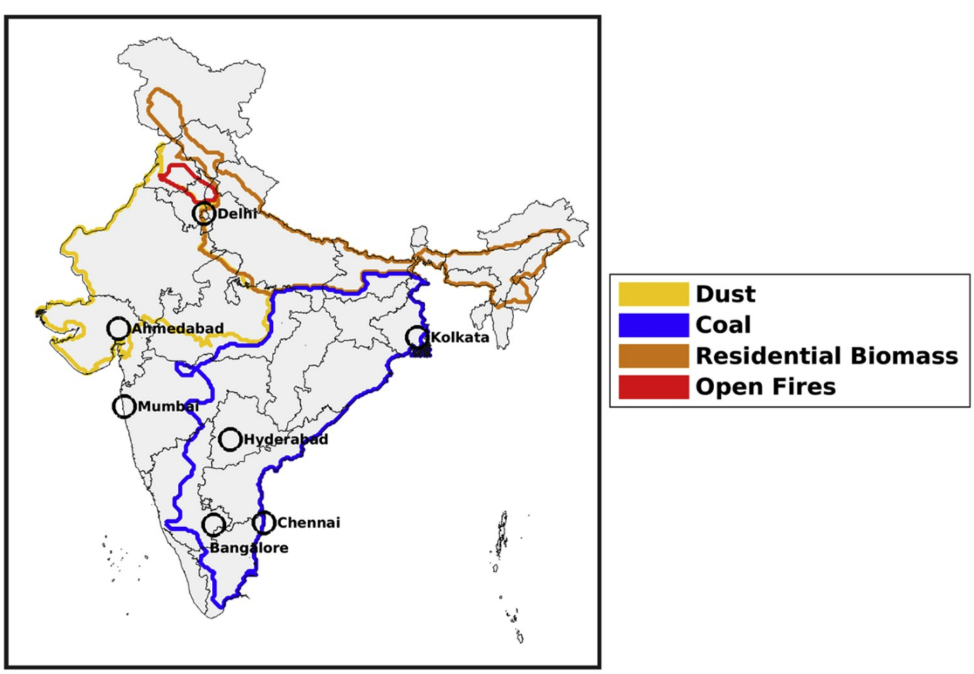

Fig. 3. Possible airsheds within India defined by dominant source contributions and major cities.

operating approaches, such as sensor calibration and maintenance, the extent of automated vs manual data processing and specific instrumentation options, among others. Depending on the number of airsheds (10–50) ultimately determined for India, total costs would range from $7.5–37.5 Million plus annual operating costs of $3.7–18.6 Million. These costs range from < 10% of the cost of a traditional network meeting the CPCB low target (4000 monitors) and < 20% of the costs of a network with density equal to that of China's network (e.g. 1571 monitors in India).

As a cost-effective approach to provide more detailed air quality information at national to local scales in a manner whereby local data can be linked to global satellite-based estimates and a global network, the integrated airshed framework could help fill current information gaps and provide a foundation for more efficient routine network expansion over time. While it is acknowledged that merging information from such different data sources in an operational framework may be challenging, integration of ground measurements, chemical transport model simulations and satellite retrievals has been common for several years for global estimates (Shaddick et al., 2018; van Donkelaar et al., 2016) and in national or regional wildfire smoke air quality forecasts (Yao and Henderson, 2014; FireSmoke.ca, 2019). Multiple examples also exist of continental (de Hoogh et al., 2016; Knibbs et al., 2014; Hystad et al., 2011b) or global (Larkin et al., 2017) land use regression estimates combining both global and high resolution local data to provide static long-term average air quality (e.g. NO_2) estimates at approximately 100 m resolution.

New traditional monitoring stations can be prioritized for areas of high variability and high uncertainty, as indicated by the integrated framework. As additional traditional ground monitoring stations are commissioned they can be integrated into this framework to enhance spatial and temporal coverage. The same general approach may also be applicable to the many other countries in the world with limited or no air quality monitoring and where estimates suggest air quality may be a concern (Shaddick et al., 2018).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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