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No one knows which city has the highest concentration of fine particulate matter

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HIGHLIGHTS

- The location of the city with the highest PM2.5 concentration is unknown.
- Most countries have no PM2.5 monitoring.
- The global mean population distance to PM2.5 monitor is 220 km.
- A harmonized PM2.5 monitoring network covering multiple spatial scales is needed.

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ABSTRACT

Exposure to ambient fine particulate matter ($PM_{2.5}$) is the leading global environmental risk factor for mortality and disease burden, with associated annual global welfare costs of trillions of dollars. Examined within is the ability of current data to answer a basic question about $PM_{2.5}$, namely the location of the city with the highest $PM_{2.5}$ concentration. The ability to answer this basic question serves as an indicator of scientific progress to assess global human exposure to air pollution and as an important component of efforts to reduce its impacts. Despite the importance of $PM_{2.5}$, we find that insufficient monitoring data exist to answer this basic question about the spatial pattern of $PM_{2.5}$ at the global scale. Only 24 of 234 countries have more than 3 monitors per million inhabitants, while density is an order of magnitude lower in the vast majority of the world's countries, with 141 having no regular $PM_{2.5}$ monitoring at all. The global mean population distance to nearest $PM_{2.5}$ monitor is 220 km, too large for exposure assessment. Efforts to fill in monitoring gaps with estimates from satellite remote sensing, chemical transport modeling, and statistical models have biases at individual monitor locations that can exceed 50 $\mu g\, m^{-3}$. Progress in advancing knowledge about the global distribution of $PM_{2.5}$ will require a harmonized network that integrates different types of monitoring equipment (regulatory networks, low-cost monitors, satellite remote sensing, and research-grade instrumentation) with atmospheric and statistical models. Realization of such an integrated framework will facilitate accurate identification of the location of the city with the highest $PM_{2.5}$ concentration and play a key role in tracking the progress of efforts to reduce the global impacts of air pollution.

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Introduction

Exposure to ambient fine particulate matter ($PM_{2.5}$) is a major global health concern (Landrigan et al., 2018). Exposure to $PM_{2.5}$ is a leading global mortality risk factor, with an estimated three (Stanaway et al., 2018) to nine (Burnett et al., 2018) million attributable deaths in ca. 2017. Annual global welfare costs associated with premature deaths attributable to $PM_{2.5}$ are projected to rise from US$3 trillion in 2015 to US$18–25 trillion in 2060 (OECD, 2016). The United Nations Sustainable Development Goals include targets to reduce annual mean $PM_{2.5}$ concentrations as part of Goal 3, on healthy lives, and Goal 11 on sustainable cities. Combustion sources of fine particulate matter also affect climate (IPCC, 2013). Knowledge about the global distribution of $PM_{2.5}$ has improved dramatically over the last decade (West et al., 2016). Networks of ground-based monitors are growing across the world; for example monitor density in China has dramatically increased in the last several years and the U.S. State Department is increasingly deploying monitors at its embassies and consulates. Initiatives such as OpenAQ (openaq.org) have increased data availability. These advances have made important contributions to improving awareness of air quality locally and globally. Nonetheless, despite the broad implications of $PM_{2.5}$, and recent growth in $PM_{2.5}$ monitoring, we find that insufficient monitoring exists for air quality management in most regions of the world.

Insufficient ground-based monitoring

Ground-based monitors have been at the forefront of $PM_{2.5}$ exposure and epidemiological research (Hoek et al., 2013). We analyze measurement data collected by the World Health Organization (WHO, 2018) and as used in the Global Burden of Disease and WHO exposure estimates for $PM_{2.5}$. We focus on these annual data since they are the most extensive. We aggregate these data by country, and combine with population data to assess monitor density. Country population totals are from the 2015 revision of the World Population Prospectus, United Nations Population Division (United Nations, 2017). Where within-country population distribution is needed, population estimates are based on the Gridded Population of the World (GPW v4) database (CEISIN, 2017).

Fig. 1 shows the number of $PM_{2.5}$ monitors per million inhabitants by country. Only 24 of 234 countries, comprising less than 9% of the world's population, have more than 3 monitors per million inhabitants. Monitor density is an order of magnitude lower in the vast majority of the world's countries. Sixty percent of countries, accounting for 1.3 billion people (18% of the global population), have no $PM_{2.5}$ monitoring at all. Monitor density is particularly low in Africa, with an average monitor density of 0.03 per million inhabitants, far too low for air quality management for these 1.2 billion people. The public media often present discussion of the most polluted cities in the world (e.g. Scott, 2017). But the low monitor density implies that many cities do not have ground-based measurements. To put this in perspective, for the 1,700 cities with at least 300,000 inhabitants globally, there are only about 5,500 $PM_{2.5}$ monitors, with more than half of these in China or the United States (United Nations, 2016). Many cities with high $PM_{2.5}$ may be unmonitored and thus lack essential information to manage their air quality.

Alternative $PM_{2.5}$ information sources

Given the paucity of ground-based $PM_{2.5}$ monitoring in many countries, other exposure assessment methods warrant consideration. Global atmospheric models (informed by emission inventories, meteorological data sets, and equations that represent atmospheric processes) are widely used for exposure assessment (Anenberg et al., 2010; Brauer et al., 2016; Lelieveld et al., 2015; OECD, 2016; Shindell et al., 2012). But such modeled exposure estimates are impaired by coarse spatial resolution and uncertainty that is difficult to quantify, in large part due to ambiguity about emission sources and intensity for many of the same countries where $PM_{2.5}$ monitor density is low. In 2010 the first global observational estimate of long-term $PM_{2.5}$ concentrations was derived from satellite observations interpreted with a chemical transport model (van Donkelaar et al., 2010). Current methods to estimate concentrations throughout the world include a combination of satellite remote sensing data, chemical transport models, and ground-based monitors, with promising accuracy (Shaddick et al., 2018a, 2018b; van Donkelaar et al., 2016). We examine current global estimates of annual $PM_{2.5}$ concentrations as used in the most recent Global Burden of Disease Assessment (Shaddick et al., 2018b), and their relation with population-distance to $PM_{2.5}$ monitor.

The background greyscale in Fig. 2 shows these global $PM_{2.5}$ estimates, with the color of country borders indicating population-weighted distance to the nearest $PM_{2.5}$ monitor. Many developed countries with relatively low $PM_{2.5}$ concentrations have population-weighted average distances to the nearest monitor of 10–50 km, with the average distance to nearest monitor for Canada and the United States of 22 km, for Western Europe of 25 km, and for Central Europe of 34 km. However, many of developing countries with high $PM_{2.5}$ concentrations have population-weighted distances to the nearest monitor

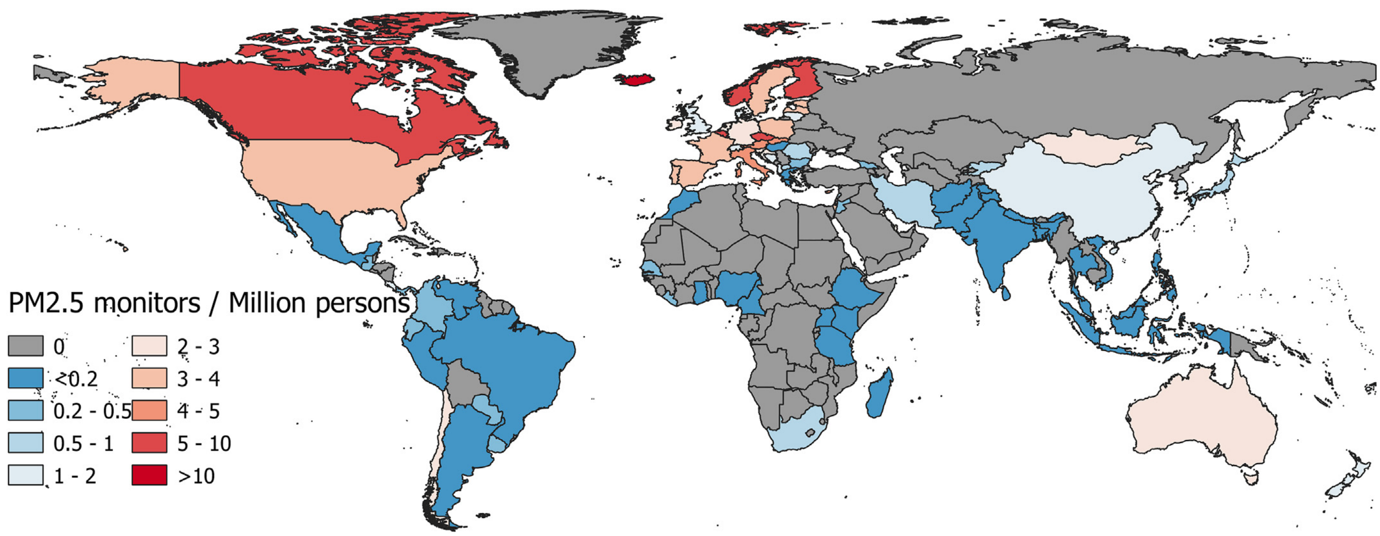

Fig. 1. Number of $PM_{2.5}$ monitors per million inhabitants by country for any of the years 2010–2016.

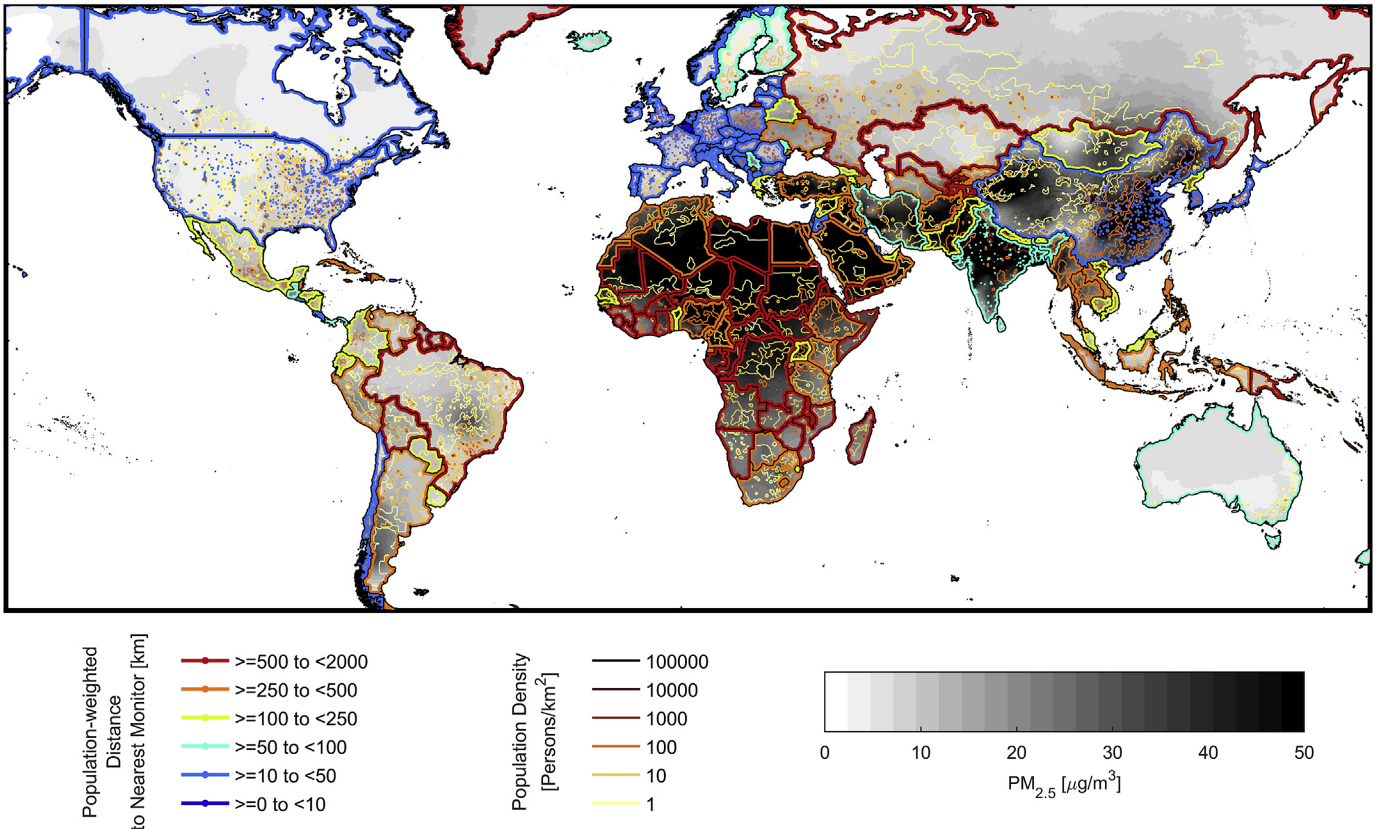

Fig. 2. Country-mean population-weighted distance to nearest $PM_{2.5}$ monitor as indicated by the colors of country borders, and by the colored dots at $PM_{2.5}$ monitor locations. Background greyscale indicates global estimates of $PM_{2.5}$ concentrations (Shaddick et al., 2018b). Thin within-country contours indicate regional population density. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

that exceed 100 km. The average distance to the nearest monitor is about 500 km in Central Asia as well as in eastern and western sub-Saharan Africa, is 690 km in Eastern Europe, and exceeds 1000 km in central Africa. Globally, the population-weighted mean distance to the nearest monitor is 220 km, far too large a distance to represent local air quality.

Fig. 3 evaluates the quality of the global $PM_{2.5}$ estimates versus ground-based monitors, indicating an overall high degree of consistency, with an overall out-of-sample population weighted root-mean-square-error of 12 $\mu g\, m^{-3}$. However, the bias at individual monitors often exceeds 10 $\mu g\, m^{-3}$ and can exceed 50 $\mu g\, m^{-3}$, far too high for air quality management. It is possible that some of this mismatch arises from monitor placement and spatial representativeness, but insufficient monitoring or available site information exists to assess that possibility. Furthermore, several major cities have estimates of high $PM_{2.5}$ concentrations (Table 1), but lack ground-based monitors, providing evidence that insufficient ground-based monitoring exists for air quality management. Indeed, the city with the highest $PM_{2.5}$ concentration may be unmonitored. The ability to answer basic questions about air quality, such as identifying the city with the highest $PM_{2.5}$ concentration, serves as an indicator of scientific progress to assess the impacts of human actions on air quality, to reduce the dramatic welfare costs of $PM_{2.5}$ exposure, and to track progress of policies and interventions designed to reduce the impacts of $PM_{2.5}$.

Harmonized network

Progress in advancing knowledge about the global distribution of $PM_{2.5}$ and its chemical composition will require a harmonized network that integrates different types of monitoring equipment (regulatory networks, low-cost monitors, satellite remote sensing, and research-grade instrumentation) with atmospheric and statistical models. National regulatory networks serve as the foundation for air quality measurement and management with precise, local, real-time information that is readily communicated to the public. In addition, advanced monitors can provide information on $PM_{2.5}$ chemical composition which can be used to evaluate and improve chemical transport models and provide critical information on source contributions to inform air quality management.

Despite laudable recent increases in $PM_{2.5}$ monitoring in several countries, we calculate that thousands of new monitors would be needed to achieve even a basic global goal of one monitor per million inhabitants. For example, more than 1,300 monitors would be needed in India with an additional 1,000 monitors in Bangladesh, Pakistan, Indonesia, and Brazil, whereas there are currently less than 275 in total in these five of the world's ten most populated countries. Even more resources would be needed to reach the monitoring levels of more densely monitored countries with several monitors per million persons (Fig. 1). Barriers to coverage have been the high cost of purchasing and operating monitors, and technical capacity to operate and maintain monitoring networks. Low-cost monitors are emerging with exciting prospects to augment regulatory monitoring networks and to support citizen science, but outstanding questions remain about their reliability, durability, and accuracy, especially for sensor networks that are not integrated with traditional regulatory monitoring networks (Snyder et al., 2013; Jiao et al., 2016). Satellite observations currently are the only observational approach able to provide global coverage with sufficient spatial resolution. However, these observations measure an atmospheric column for cloud-free conditions during daytime and require additional information from chemical transport models to infer global annually-representative ground-level concentrations (van Donkelaar et al., 2010). Ground-based measurements that also measure aerosol

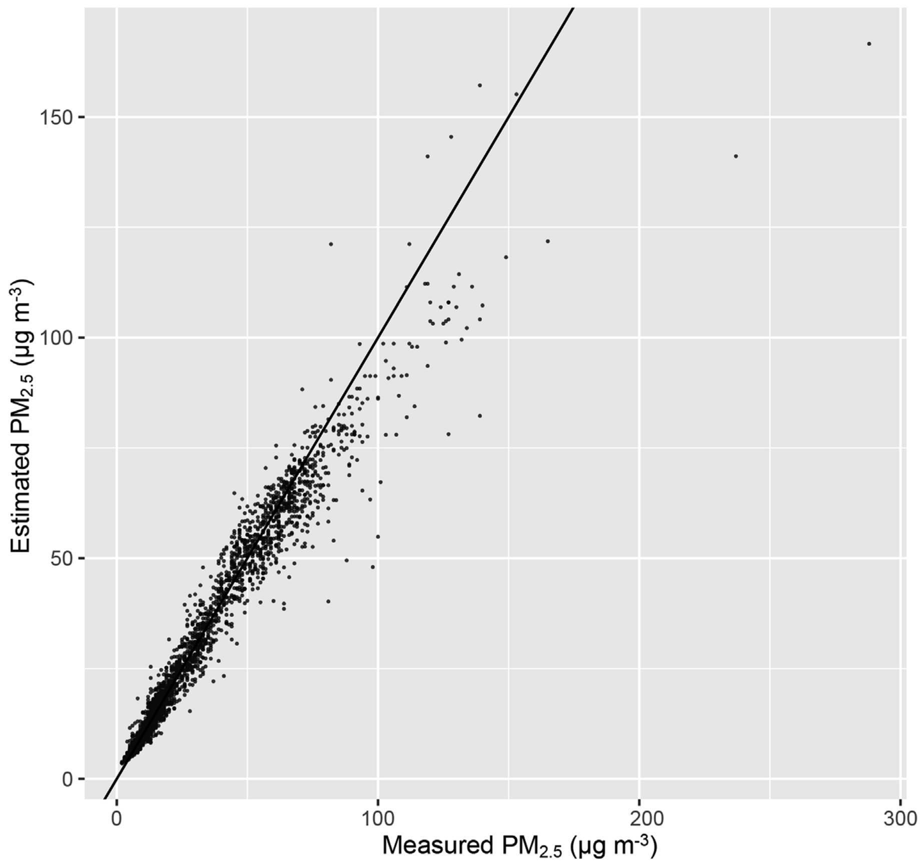

Fig. 3. Performance of current global estimates of $PM_{2.5}$. Scatter plot of annual mean ground-based monitor $PM_{2.5}$ concentrations versus recent global estimates (Shaddick et al., 2018b). The 1:1 line is solid.

Table 1
Example major cities with high estimates of $PM_{2.5}$ concentrations, but without ground-based $PM_{2.5}$ monitors.

City, Country	$PM_{2.5}$ (μg/m^3)
Allahabad, India	137
Riyadh, Saudi Arabia	137
Lucknow, India	120
Asyut, Egypt	112
Ahvaz, Iran	97

abundance throughout the atmospheric column are needed to connect columnar satellite observations with the ground-level concentrations of relevance for human health (Snider et al., 2015). These ground-based measurements could also serve as anchor points to dense low-cost monitoring networks (Gao et al., 2015), mobile monitoring approaches (Apte et al., 2017), or hybrid models (Beckerman et al., 2013) to assess exposure at fine spatial resolution in the surrounding area. Ground-based monitoring is critical for air quality forecasting (Kumar et al., 2018). Additionally, targeted research grade measurements of the atmospheric vertical profile (e.g. by aircraft (i.e. Crawford et al., 2014) or lidar (i.e. Welton et al., 2001)) can offer information to develop and improve estimates based on atmospheric models. Readily available data in near-real-time such as being facilitated by OpenAQ is another important component of air quality management. Interpretation of measurements from such harmonized, but complex networks will require increased coordination amongst local, national, and international institutions, and for atmospheric and health scientists to work increasingly closely together (West et al., 2016).

Case study for India

As described in Brauer et al. (submitted), ambient air pollution is a leading risk factor for disease burden in India with ambient $PM_{2.5}$ estimated as a leading risk factor for mortality, with one million attributable deaths in 2017 (Stanaway et al., 2018). The national population-weighted annual average $PM_{2.5}$ level in India of 76 μg m^{-3} is more than double the World Health Organization Interim-Target 1 (35 μg m^{-3}) with approximately 90% of the population living in areas above this level and 99.9% living in areas above the WHO Guideline. Based on the measurements of $PM_{2.5}$ collected as part of the World Health Organization Global Ambient Air Quality Database (WHO, 2018), about 40 cities contained $PM_{2.5}$ measurements in India in the 2010–2016 period. The population-weighted average distance to the nearest monitor is over 70 km. This monitor density is only ~0.14 monitors/million persons (1 monitor for every 6.8 million people). Substantial time and resources would be needed to reach basic levels of monitoring (e.g. 1 monitor per million persons).

A hybrid monitoring approach could accelerate the availability and quality of information about $PM_{2.5}$ within India. Such an approach could build upon recent advancement in satellite-based assessment of air quality, and the emergence of strategically located ground-based monitoring stations that combine measurements of $PM_{2.5}$ chemical composition with sun-photometer measurements of aerosol optical depth to improve the accuracy of satellite-based estimates from both global and regional perspectives (Snider et al., 2015). Such strategic measurement nodes can also provide important evaluation data for chemical transport model simulations and provide necessary inputs for receptor modeling source apportionment. This information on source contributions could inform forecasting and evaluation of air quality management options and initiatives.

Ideally, each strategic monitoring station would be located in each of the 11 distinct airsheds within India identified by Brauer et al. (submitted). Linking of these strategic monitoring stations with new or existing traditional air quality monitoring stations within each airshed would provide additional information on spatial variability in pollutant concentrations at high temporal resolution, and would link the network directly to satellite-based estimates. Monitor density could be weighted towards areas with higher population density and towards areas with greater variability in satellite-based estimates.

A path forward

Despite the implications of $PM_{2.5}$ and recent growth in $PM_{2.5}$ monitoring, we find that insufficient information exists for air quality management, or even to identify a basic question such as the location of the city with the highest $PM_{2.5}$ concentration. The ability to answer this basic question serves as an indicator of scientific progress to assess global human exposure to air pollution and as an important component of efforts to reduce its impacts. Reliable global estimates of the spatial and temporal distribution of $PM_{2.5}$ concentrations will help raise awareness about the severity of the problem, help identify hot spots, track progress, and inform local air quality management planning. While $PM_{2.5}$ is the most important pollutant from a global health perspective, and its mass is most widely monitored, monitoring of its chemical composition and of additional pollutants will be needed to support air quality management and should also be integrated into such a hybrid framework. Exciting prospects exist for aspects of this network including advances in low-cost monitors, planned satellite missions, and targeted field campaigns. Further development of this harmonized network has the potential to advance global exposure estimates that are needed for major assessments such as the Global Burden of Disease and the United Nations Sustainable Development Goals.

Declaration of interests

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.

Competing financial interests

The authors have no competing financial interests.

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