Atmospheric Environment 215 (2019) 116794

Contents lists available at ScienceDirect

Atmospheric Environment

journal homepage: www.elsevier.com/locate/atmosenv

Opportunities and challenges for filling the air quality data gap in low- and middle-income countries

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ARTICLE INFO

Keywords:
Air quality monitoring
Sensors
Remote sensing
PM2.5
Lowand middle-income countries

ABSTRACT

Given the millions of people suffering from air pollution, filling the air quality monitoring gap in low- and middle-income countries has been recognized as a global challenge. To meet this challenge and make it work will require private enterprise, multiple levels of government, international organizations, academia and civil society to work together toward the common goal of characterizing, understanding better, and then reducing, the air pollution that causes sickness and preventable death for millions of people each year in lowand middle-income countries around the world. This article offers concrete next steps on how to make progress toward increasing air quality monitoring using a combination of emerging technologies, adaptation to country-specific conditions, and building capacity towards the development of lasting institutions.

Nothing is more fundamental to life than breathing. Yet for millions of people around the world, particularly those in low- and middle-income countries (LMICs), air pollution causes sickness and premature death (Fig. 1). Most of the world's most populous – and most polluted – cities are in low- and middle-income countries. Yet in many cases, citizens of LMICs are unaware of the severity of the risks of air pollution or, if aware, lack the information needed to address the problem. Other factors can exacerbate this situation, such as absent or unreliable measurement data, limited access to data, and ineffective communication strategies. Citizens of LMICs may not know dirty air is making them and their children sick or that there are actions they can take to protect themselves. Levels of air pollution in LMIC cities often dwarf those in high-income countries. Air pollution can be so pervasive that changing behaviors to avoid exposure simply is not possible without sustained national regulation to address air pollution. And in LMICs, weak or absent monitoring programs and scientific institutions makes addressing air pollution even more challenging.

Fine particulate matter ($PM_{2.5}$) accounts for the majority of the burden of disease attributable to ambient air pollution (Cohen et al., 2017), and accordingly, those LMICs that do monitor air quality tend to focus on either $PM_{2.5}$ or PM_{10}. However, there is growing concern regarding ground-level ozone concentrations, which are not frequently monitored in LMICs. Governments and international organizations are engaged in finding solutions to the health concerns associated with air pollution, yet have been faced with a lack of high quality air quality data in low- and middle-income countries on which to base policy decision-making. To begin to fill these data gaps, in July 2017, the World Bank and the United States Environmental Protection Agency convened practitioners and experts from government, private sector, multilateral organizations, and academia in LMICs and non-LMICs to explore potential solutions. Meeting attendees collaborated on a discussion draft "*Filling the Gaps: Improving Measurement of Ambient Air Quality in Low and Middle-Income Countries*".[1]

In Europe and North America, nearly all urban areas have a few reference grade ambient air quality $PM_{2.5}$ monitors, and large cities have a dozen or more, with approximately one monitor per 100,000–600,000 residents (World Health Organization, 2018). These monitors have provided the data needed to achieve robust policies and substantial decreases in $PM_{2.5}$ concentrations (Maas and Grennfelt, 2016). But across urban areas in Africa, the average is one monitor per

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[1] http://pubdocs.worldbank.org/en/425951511369561703/Filling-the-Gaps-White-Paper-Discussion-Draft-November-2017.pdf.

https://doi.org/10.1016/j.atmosenv.2019.06.032
Received 22 February 2019; Received in revised form 8 June 2019; Accepted 16 June 2019
Available online 18 June 2019
1352-2310/

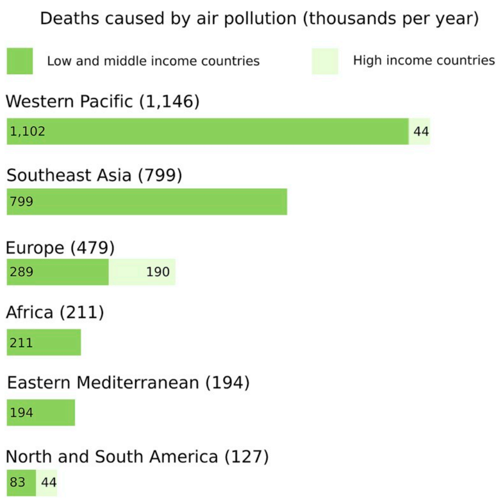

Fig. 1. Deaths attributable to ambient fine particulate matter ($PM_{2.5}$) by country income as calculated by the World Health Organization Global Burden of Disease report (World Health Organization, 2016). More than 90% of deaths attributable to air pollution occur in low- and middle-income countries.

4.5 million residents (Carvalho, 2016). When examining all of sub-Saharan Africa, there is just 1 ground-level monitor per 15.9 million people (WHO Global Ambient Air Quality Database, 2016). While several mega-cities in LMICs have invested in monitoring networks that measure air quality and provide data to the public, there are still hundreds of LMIC cities worldwide with limited or no air quality measurements. In some cases where air quality is measured, the data may not be shared broadly with the public or the public advisories may not be clearly communicated.

Based on the available data, recent reports estimate that air pollution in LMICs is dangerously high. In Africa alone, each year without clean air means premature death for over 700,000 people at a cost of over $200 billion (from indoor and outdoor air) (Roy, 2016). Globally, the numbers are even more stark. A World Bank study found that the global cost of ambient $PM_{2.5}$ air pollution in 2016 was US$ 5.7 trillion, or equivalent to 4.8% of global GDP (World Bank, *forthcoming*).

What if every city with a population over 100,000 in an LMIC, currently without any $PM_{2.5}$ monitor, had a reliable $PM_{2.5}$ monitor established and can make the data publicly available? What if people in LMICs knew, every day, the level of pollution they would be breathing? With approximately 1900 LMIC cities without $PM_{2.5}$ monitoring (World Health Organization, 2016) and approximating the cost to install and maintain a regulatory-grade monitor at $100,000 USD per year, this would equate to a rough estimate of $200 million USD per year, or 0.004% of the global cost of air pollution. This funding combined with technology exchange, training, capacity building, and development of locally relevant health messaging can help motivate the mitigation strategies needed to reduce exposures and minimize the health risks associated with air pollution. In this way, a concerted strategy by the international community to expand air quality monitoring has great potential to inform air quality policies leading to the reduction in deaths attributable to $PM_{2.5}$.

1. Growing recognition of the dangers of unhealthy air

When people consider health challenges in the developing world, often the first issues that come to mind are malaria and HIV/AIDS. Yet air pollution is responsible for more premature deaths every year than these two diseases combined (Lelieveld et al., 2015; Global Burden of Disease Collaborative Network, 2018). As pollutant emissions increase in many LMICs, even the average citizen may begin to see that the air is dirtier than it used to be. But they may not connect that observation to changes in health. At the government level, there is a growing acknowledgment of the problem. This is due in part to the visibility of high pollution episodes and international air quality resolutions,[2] and also to public awareness efforts such as the United Nations' Breathe Life[3] and Clean Air Asia's Hairy Nose campaign.[4] Reducing air pollution is also a specific target of the United Nations Sustainable Development Goal 11 which includes $PM_{2.5}$ reporting requirements.

2. The air measurement challenge is fundamentally different in LMICs

In the United States, state, tribal, and federal agencies built the current air monitoring systems over the course of 50 years. They invested millions of dollars in equipment, human capital, and institutional frameworks to deploy and maintain monitoring stations and process, analyze, and report the data. In addition, there is ready access to electricity, telecommunications, and other infrastructure along with a long-standing system of relatively well-staffed federal, state, local, and tribal environmental organizations to ensure ongoing operation and maintenance. In contrast, most LMICs with little or no existing air quality data may have little or irregular electricity, limited or no laboratory or analytical capacity, small staff size with limited capacity, and little or no financial resources to devote to air quality characterization activities. These factors, along with other considerations such as monitoring goals, available data managements systems, legal authorities and financing means there is no "one size fits all" approach to building an air quality measurement system in LMICs. Determining the best monitoring technology may be unique to each situation.

Another challenge is the difference in pollutants, their sources, and the nature of the health effects. The Global Burden of Disease focuses on the health impacts of $PM_{2.5}$ and ozone. Globally, exposure to $PM_{2.5}$ causes more than 10 times more deaths than ozone (Cohen et al., 2017) and most LMICs report higher exposure to $PM_{2.5}$ than ozone. In addition to ozone and $PM_{2.5}$, other studies have linked coarse particulate matter (PM_{10}) and nitrogen dioxide (NO_2) to health effects in children, such as reduced lung function (Gehring et al., 2013) and incidence of asthma (Chen et al., 2015). Many of the largest cities in LMICs have high levels of new cases of childhood asthma attributable to NO_2 (Achakulwisut et al., 2019). These studies are informed by annual average pollutant concentrations. Measurement strategies that are consistent across time and across different locations are critically needed to support health assessment and to guide air quality policy decision-making to improve human health. There is also a need for rapidly available measurements that can inform current conditions and alert the public to take action during air pollution episodes. While the efficacy of such programs has been called into question (Chen et al., 2018), studies in Santiago, Chile have reported reductions in air pollutant concentrations (Mullins and Bharadwaj, 2014) and a study in Hong Kong reports reductions in hospitalizations (Mason et al., 2019) due to public alerts. Part of the success of these programs can be attributed to a quasi-experimental design, where different approaches can be tested and iteratively improved. Note that the program in Chile uses PM_{10} measurements and the Hong Kong air quality index includes ozone, $PM_{2.5}$, NO_2, and sulfur dioxide (SO_2). Rapid development, changing emissions, and the need for iterative experimentation means that LMICs need flexible monitoring strategies that can address multiple pollutants.

[2] First United Nations Environment Assembly (UNEA) Resolution 7 on Air Quality (https://www.unenvironment.org/resources/report/unea-1-resolution-7-air-quality) and UNEA-3 Resolution on Preventing and reducing air pollution to improve air quality globally (http://www.ccacoalition.org/en/resources/preventing-and-reducing-air-pollution-improve-air-quality-globally-resolution-adopted-2017).

[3] http://breathelife2030.org/.

[4] http://cleanairasia.org/node11316/.

Given the substantial cost of measuring air quality using traditional regulatory-grade monitors, and the rapidly evolving needs of LMICs, there is increasing attention on new technologies – low cost sensor devices and other sources of data, such as satellite-based measurements. Exploring these newer technologies may provide an opportunity to provide valuable information sooner and at a lower cost for areas where deploying a full monitoring station is not feasible. The fundamental question is whether these new technologies can offer LMICs a reliable and credible path to "decision-grade" air quality data, capable of supporting and enabling policies to improve air quality.

3. Leveraging emerging technologies: opportunities and challenges

Much has been written about opportunities to skip over mid-20th century technology on the path to modernity (Aker and Mbiti, 2010; Tchouassi, 2012; Amankwah-Amoah, 2015). For example, in the developing world, mobile phones have become ubiquitous, while wired phone networks are less common. Air quality monitoring may offer a similar opportunity. Recent advances in low-cost sensors and satellite-based remote sensing hold much promise for monitoring the levels of $PM_{2.5}$ over the majority of the earth's surface where little information is currently available. Sensors are smaller, have lower power requirements, and can be easily deployed in nearly any setting. While historically, air quality monitoring has relied on expert judgement to site instruments to represent city-wide average concentrations or other policy-relevant metrics, sensors are being deployed in large numbers, often by citizens, saturating the landscape to capture the variability in the air we breathe.

On the other end of the cost spectrum, a constellation of polar-orbiting satellites carrying remote-sensing instruments is creating a global view of air quality every day. Multiple space-based measurements and global chemical transport models have been combined to create annual-average estimates of $PM_{2.5}$ at close to $10\,km^2$ spatial resolution (van Donkelaar et al., 2016). Both the underlying satellite-based observations and models used for estimating surface $PM_{2.5}$ concentrations are continuously improving. Launched in October 2017, TROPOMI is collecting data at $7\,km^2$. The Multi-Angle Imager for Aerosols (MAIA), currently in development, is designed to also provide information on the particle size distribution and chemical composition at 1 km spatial resolution (Diner et al., 2018). Geo-stationary satellites are planned that can provide information on air quality conditions throughout the day, as opposed to a few times a day from the current polar-orbiting satellites. Improved statistical methods have been developed (e.g. Shaddick et al., 2017; Larkin et al., 2017) for combining space-based observations with ground-based measurements, chemical transport models, and land use data to estimate air quality conditions at finer scales.

However, both low-cost sensors and satellite-based instruments estimate the $PM_{2.5}$ concentration using optical measurements (light scattering and/or absorption). Fine particulate matter is a complex mixture of extremely small particles and liquid droplets composed of a combination of dust, soot, salts, organic compounds, and water (US EPA, 2018a). Each of these interact with light in different ways. Relating the optical measurement to a mass concentration requires calibration. Because the mixture of $PM_{2.5}$ depends on the mixture of contributing emission sources, particle size distribution, temperature, and relative humidity, the calibration should be performed in conditions where the measurements are made. For low-cost sensors, this means co-locating with reliable measurement techniques with well-defined quality assurance protocols. Calibration in the lab is not sufficient (Castell et al., 2017;Rai et al., 2017). In the case of $PM_{2.5}$ concentrations estimated by satellite-based remote sensing, the accuracy improves in areas where surface-based measurements are also available (Shaddick et al., 2018). However, where high quality ground-level measurements are absent, satellite estimates of ground level $PM_{2.5}$ values should be assigned a higher uncertainty (Alvarado et al., this issue).

The extent and frequency of calibration depends on the goals for the measurements (Lewis et al., 2018). For raising awareness about air quality, surveying an area to detect unpermitted emission sources, identifying areas with exceptionally high levels of pollution in need of further investigation, or other uses where rapid deployment is critical, deployed sensors may only need to distinguish high concentrations from low concentrations. For enforcing regulatory limits, legal requirements may demand a higher level of certainty from the measurements, for example duplicate instruments and frequent calibration. Measurement artifacts may be addressed through recent advances in calibration strategies, deploying machine learning approaches (Zimmerman et al., 2018) and co-located measurements of multiple pollutants (Kim et al., 2018); however, data processing needs to be done with care to ensure the final data are useable for a particular objective (Hagler et al., 2018). Despite these advances, many sensors have limits to their accuracy and other measurement parameters (Zamora et al., 2019), which should be considered depending on the goals of the air quality monitoring network (Lewis et al., 2018; US EPA, 2018b).

Each approach to monitoring air quality has unique advantages and when deployed together could potentially compensate for weaknesses. This hybrid approach could deploy a few reference monitoring stations (1–3) paired with a network of low-cost sensors (twenty or more). The reference monitors would use well-tested measurement techniques, including rigorous quality assurance protocols that include a known quantification of measurement uncertainty. The network of low-cost sensors could provide spatial and temporal coverage needed to quantify exposure, while being calibrated using the quality-controlled data from the reference monitors. The reference monitoring stations could be further used to improve the accuracy of satellite-based remote sensing data, extending the spatial coverage and filling in areas not measured using sensors. Over time, it will be important to collect measurements that can be used to identify emission sources, which could include monitors for gases or PM chemical composition. For example, the instruments deployed as part of SPARTAN have filters that can be analyzed for mass, black carbon, water-soluble ions, and metals (Snider et al., 2015), which in turn, could be used both to identify the contribution of different emission sources and to further improve the interpretation of the satellite-based remote sensing observations. If this evolving, hybrid approach is piloted and successful, it would mean a few regulatory-grade monitoring stations could be leveraged to better characterize air quality in a wider area. This less labor-intensive and less expensive approach might help LMICs cover a broader spatial area and achieve air quality monitoring goals.

Historically, air quality engineering has focused on increasing the reliability of instruments by developing consistent manufacturing standards and rigorous quality assurance protocols. The proliferation of sensor-based instruments poses a new engineering and quality assurance challenges – how to incorporate data from a large number of less reliable devices? New instrument siting protocols are needed. While existing instrument siting protocols for a single reference monitor may seek to find a location that represents average ambient conditions, a network of sensors could seek to measure the maximum spatial and temporal variability relevant to exposure. Spatial statistics methods are needed to analyze data from sensor networks and translate it into information that could be used to inform air quality management goals.

4. Sustainable solutions require investment in human capital and civil society

The pursuit of technical solutions must be paired with a sustained commitment to continuous operation and institution building in LMICs. First, continuously operating monitoring sites provide more useful information. Long-term data records are a more credible basis for decision-making, and the trend in air quality can demonstrate the success of an intervention or forecast the need for new approaches. However, sustained monitoring is expensive and labor-intensive. To be successful, it requires budget and staffing to build up the equivalent of environmental protection agencies and local monitoring units. Sustained monitoring requires training in operations and quality assurance protocols. In LMICs, it is often difficult to retain trained staff, especially if the monitoring program lacks sustained and stable funding for personnel. The supply chains for replacement parts and calibration media can break down if there is no prospect for continuous business. Monitoring equipment that is properly sited and maintained is less expensive to operate in the long run than re-starting equipment after prolonged disuse. Sustained investment is needed to achieve success.

Public support for air monitoring can be an important driver for sustained government investment and low-cost sensors can play an important role in engaging the public. In LMICs without a history of air pollution and public health issues, involving citizens in the measurement and science is a powerful way to improve understanding, increase awareness, and increase public support for monitoring and action (Ngo et al., 2017; deSouza et al., 2017). Emerging low-cost sensors are more compact, mobile, and accessible, which makes getting citizens involved in air measurements more feasible. Community outreach and citizen science projects are often designed to be short-lived, but by raising public awareness, these projects can be an important part of building support for sustained investment in air quality monitoring.

5. Building a system and making it work

What is "the answer" to the serious data, knowledge and action gap around air pollution in LMICs? There is no single answer, which means there are many opportunities. We know that air quality data, communicated thoughtfully, can be a powerful tool to inform the public about the dangers of air pollution. We also know that it is not enough to simply identify pollution levels, you must also be prepared with solutions, even if those are just first steps on a long path to cleaner air. Building an air quality management system may begin with an understanding of what is in the air to allow for individual short-term adaptation, but the ultimate goal is to breathe clean air by reducing emissions.

The global air quality and health communities have an opportunity to raise awareness and take steps to meet the challenge of air pollution in LMICs. Here are some suggested concrete next steps on how to make progress toward meeting that challenge:

- Provide clear, informed guidance to LMICs on purchasing and deploying low-cost sensor devices, alongside a smaller number of higher quality, higher cost devices. Together, these could provide a wealth of data for decisionmakers in LMICs. For example, where can LMICs find trusted, transparent information related to device data ownership, device data quality over time in different environments, device replacement frequency, device calibration, siting, equipment costs, data management and analysis, and expenses for operations and maintenance?
- Develop siting protocols and calibration strategies relevant to sensor networks that support greater spatial density and unique calibration needs.
- Building further on ongoing testing of air quality sensors in the United States and Europe, conduct field testing in settings representative of LMIC conditions. What is the range of performance for emerging sensor technologies under the diversity of environmental and pollution conditions representative of LMICs?
- Design instruments that could continue to operate during times of intermittent power and data connectivity.
- Continue to support further improvements to satellite-based remote sensing and related data-fusion datasets to more accurately resolve near-surface $PM_{2.5}$ concentrations under the wide range of conditions found in LMICs.
- Develop and share best practices in data management, considering data post-processing, data integrity and transparency. Develop open source software tools for archiving, interpreting, and communicating data from sensor networks.
- Invest in the responsible air quality staff within LMICs to develop and maintain sustained air monitoring infrastructure. This includes staff training, professional regional networks for sharing best practices, shared data platforms, and supply chain viability for equipment and consumables.
- Support the development of lasting institutions for creating and dispersing air quality information, including building public support for sustained, credible monitoring. Foster the participation of LMIC stakeholders in these institutions.
- Strongly encourage the public availability of air quality information (Hasenkopf and Sereeter, 2016). As articulated in the mission of OpenAQ, "air pollution is one of the greatest environmental health issues of our time and opening up these data is a powerful step forward in our collective progress to defeat it.[5]"

Given the millions of people suffering from air pollution, filling the air quality monitoring gap in low- and middle-income countries has been recognized as a global challenge. To meet this challenge and make it work will require private enterprise, multiple levels of government, international organizations, academia and civil society to work together toward the common goal of characterizing, understanding better, and then reducing, the air pollution that causes sickness and preventable death for millions of people each year in low- and middle-income countries around the world.

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.

Disclaimer

The views expressed in this article are those of the authors and do not necessarily represent the views or policies of the U.S. Environmental Protection Agency. The findings, interpretations, and conclusions expressed in this article do not necessarily reflect the views of the executive directors of the World Bank or the governments they represent.

Further reading

Fowler et al., 2008, Pinichka et al., 2017, United Nations, 2018, World Bank, 2019.

Acknowledgements

The authors thank numerous participants in the "Filling the Gaps: Improving Measurement of Ambient Air Quality in Low and Middle-Income Countries" workshop held in July 2017. The authors acknowledge and appreciate financial support for this workshop from the World Bank-administered Pollution Management and Environmental Health multidonor trust fund (USA). The authors also thank Pat Dolwick, Jackie Ashley, Kristen Benedict, Amanda Kaufman, Lee Riddick, and Mike Koerber for helpful conversations and suggestions during the preparation of this article.

[5] https://openaq.org/.

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