AMERICAN THORACIC SOCIETY DOCUMENTS

# Air Pollution Monitoring for Health Research and Patient Care

## An Official American Thoracic Society Workshop Report

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## Abstract

Air quality data from satellites and low-cost sensor systems, together with output from air quality models, have the potential to augment high-quality, regulatory-grade data in countries with *in situ* monitoring networks and provide much-needed air quality information in countries without them. Each of these technologies has strengths and limitations that need to be considered when integrating them to develop a robust and diverse global air quality monitoring network. To address these issues, the American Thoracic Society, the U.S. Environmental Protection Agency, the National Aeronautics and Space Administration, and the National Institute of Environmental Health Sciences convened a workshop in May 2017 to bring together global experts from across multiple disciplines and agencies to discuss current and near-term capabilities to monitor global air pollution. The participants focused on four topics: *1*) current and near-term capabilities in air pollution monitoring, *2*) data assimilation from multiple technology platforms, *3*) critical issues for air pollution monitoring in regions without a regulatory-quality stationary monitoring network, and *4*) risk communication and health messaging. Recommendations for research and improved use were identified during the workshop, including a recognition that the integration of data across monitoring technology groups is critical to maximizing the effectiveness (e.g., data accuracy, as well as spatial and temporal coverage) of these monitoring technologies. Taken together, these recommendations will advance the development of a global air quality monitoring network that takes advantage of emerging technologies to ensure the availability of free, accessible, and reliable air pollution data and forecasts to health professionals, as well as to all global citizens.

**Keywords:** air pollution; environmental monitoring; satellite imagery

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## Contents

## Introduction

The technological capability to measure and record levels of outdoor air pollution is rapidly expanding with an increasing number of agencies and individuals developing various air quality monitoring technologies. However, there remain significant resource and technological limitations to reliably monitoring outdoor air pollution in many parts of the world. In addition, many of these experts work in relative isolation, limiting the potential use of their technological and quantitative developments. These divisions are particularly evident across monitoring fields, including remote sensing using satellite technology, use of regulatory and nonregulatory air quality networks for stationary monitoring, computational air quality modeling, and use of low-cost sensor systems. Integration between technology groups is essential to maximizing the potential public health benefit of these technologies.

On May 20, 2017, in Washington, DC, the American Thoracic Society (ATS) held a workshop as part of a coordinated effort between the ATS, the U.S. Environmental Protection Agency, National Aeronautics and Space Administration (NASA), and National Institute of Environmental Health Sciences, bringing together experts from multiple disciplines and agencies to discuss advances in air pollution monitoring that are relevant for scientific research and patient care. Specific issues that were considered include current capabilities and limitations of existing technologies, how an array of measurement tools can be integrated and their data standardized, how to address challenges in low- and middle-income countries (LMIC), and how best to communicate data to at-risk populations.

## Conceptual Framework and Key Assumptions

Most high-income nations already have ground monitoring networks in place, with varying levels of spatial coverage, producing accurate and consistent data for common pollutants (i.e., particulate matter [PM], nitrogen oxides [$NO_x$], sulfur dioxide [$SO_2$], ozone [$O_3$], and carbon monoxide [CO]) as well as other pollutants of interest for regulatory compliance and other purposes. However, these regulatory-quality networks are much sparser in LMICs that may lack sufficient resources to implement and sustainably operate such monitoring networks. Owing to the high per-monitor and operating costs of these networks, there are spatial and, if monitors are only operated sporadically, temporal limitations in accurately reflecting exposures that are essential for medical research and patient care.

In addition to complementing any existing monitors, new and emerging air quality monitoring technologies may allow LMIC to begin to characterize outdoor pollution concentrations in the absence of regulatory-quality monitoring networks. These technologies include satellite remote sensors and global atmospheric models, from which the data are typically free for the end user (e.g., from NASA and the European Space Agency). Similarly, emerging nonregulatory stationary sensors and low-cost portable sensors have potential for expanding monitoring in LMIC, as well as enhancing the spatial resolution of traditional networks where these exist. Data derived from low-cost sensor systems offer the potential for finer spatial, and in some cases temporal, scales; however, their reliability and accuracy merit further attention.

The efforts to develop monitoring capabilities have generally occurred without much input from health professionals, resulting in decisions that may not fully take into account the needs and opportunities for collecting data in ways that are most useful for health research and patient care. This workshop was convened among health and air quality experts to improve understanding of how different technologies can be brought together to better monitor and disseminate global air quality data.

## Workshop Agenda

Workshop participants presented information as part of four sessions, each one followed by group discussion. Topics of discussion included current capabilities and future aspirations for air pollution monitoring, data assimilation from multiple technology platforms, critical issues for air pollution monitoring in regions without a regulatory-quality stationary monitoring network (particularly in LMIC), and risk communication and health messaging. Presenter names are listed at the end of the document immediately before the REFERENCES. The information presented and discussed in these sessions is summarized below together with recommendations that naturally flowed from the discussion.

### Current Capabilities and Near-Future Aspirations for Air Pollution Monitoring

Current technologies for monitoring particulate and gaseous air pollutants go far beyond traditional regulatory monitoring networks and now include remote sensing of air pollutants using instruments on satellites, low-cost portable sensors, nonregulatory monitoring networks, and air quality model simulations. Each of these technologies has strengths and weaknesses when considered in the context of monitoring air pollution for health research and in disseminating clinically relevant information to the public. These limitations range from technical (e.g., data accuracy, spatial coverage, spatial and temporal resolution) to practical (e.g., cost, general awareness of data availability, difficulty accessing and using data).

Various monitoring technologies can be distinguished by the spatial and temporal scales at which their data are reliably generated. Figure 1 summarizes the current capabilities of regulatory-quality monitors, nonregulatory stationary sensors, low-cost portable monitors, remote sensing from satellites, and global atmospheric models as a function of the spatial scale (resolution and coverage) and temporal scale at which data can be used to conduct health research studies with the eventual goal of improving patient care. Figure 1 not only demonstrates how these various monitoring technologies can complement each other but also emphasizes that no one technology group alone is able to provide the full range of temporal and spatial coverage needed in health research and for use in public communication.

In general, continuous or near-continuous monitoring approaches for PM and gaseous pollutants (e.g., $O_3$, $NO_x$, $SO_2$, and CO) are widely developed in high-income countries. They are typically designed to serve regulatory purposes for monitoring compliance with air quality standards because of their ability to capture ambient concentrations with high degrees of temporal accuracy and precision. Although these networks are highly relied on in health research, they can have limited spatial coverage in most areas and are sometimes specifically designed for an urban background emphasis without a focus on near-source environments where people are exposed to high pollution levels.

There has been great interest in the potential of low-cost sensor systems comprised of stationary and portable sensors that typically employ optical methods for counting particles and estimating PM mass or metal oxide and electrochemical approaches for measuring gas species. Owing to their lower investment costs and setup time, deployment of these types of nonregulatory monitors as part of a stationary network can improve the spatial characterization of highly variable pollution exposures within a city and can be used in a greater number of locations around the world. Similarly, deployment of air quality instruments as part of mobile monitoring platforms is promising for monitoring with greater temporal and spatial resolution, often continuously and in real time, capturing transient or short-term peaks in concentrations at the street level.

However, large variability in performance between units and within the same unit over time is currently a challenge for nonregulatory monitors and low-cost portable sensors (1, 2). Statistical approaches to manage and improve these data continue to develop, and data quality is greatly improved when using best practices such as *in situ* calibration or quantitative correction techniques (3–5). The typically short functioning lifespan of these sensors presents complications in evaluating air quality trends at longer time scales. However, even without a breakthrough in sensor technology that may improve data quality, these sensors already can be a valuable resource, particularly when integrated with more robust air pollution monitoring technologies (6, 7).

No other technology can approach the unique advantage of satellite data in terms of spatial coverage. In the past, this benefit was offset by substantial limitations in spatial resolution, but each generation of satellite technology has resulted in substantial improvements. NASA, the European Space Agency, and other space agencies together operate a large network of satellites that provide global observations which are being used to support environmental and public health science and research, including air pollution monitoring, exposure assessment, and air quality forecasting. Although remote sensing data have been used successfully in models to infer and simulate surface-level pollution concentrations across the globe (8–13), there remain important limitations to accurately monitoring certain gaseous pollutants and PM. For example, satellite data give little information on the vertical structure, including surface concentrations, of $O_3$, and they do not provide data on

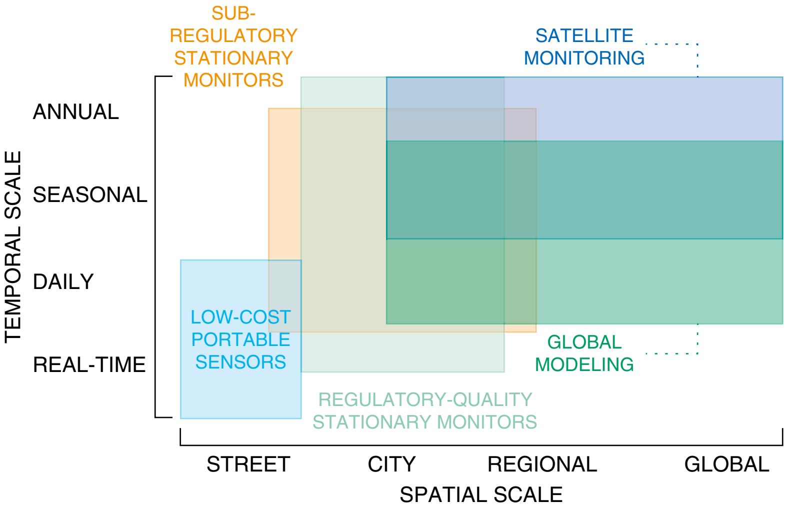

**Figure 1.** Illustrated summary of air pollution monitoring technologies by effective spatial and temporal scales for health research and patient care. This figure is for illustrative purposes only and reflective of general abilities of these technologies to provide air quality information for health research and patient care. The limitations for regulatory-quality monitors to have greater spatial coverage and greater fine-scale spatial resolution is economical, not technological. Lower-cost nonregulatory monitors can therefore help increase both coverage and resolution, but data quality issues potentially prevent these monitors from being highly reliable for health studies at very short (e.g., hourly) or very long temporal scales (e.g., multiyear). Remote sensing using satellite data and pollution estimates derived from global models have similar temporal and spatial resolutions; however, global models can make estimates every day, regardless of cloud cover, whereas satellite data have an advantage at longer time scales owing to being a measured quantity rather than a modeled concentration that is limited by the quality of model inputs.

numerous pollutants, such as most volatile organic compounds. Satellites currently do not give information on aerosol size fractions or speciation (e.g., sulfate, organic aerosol, nitrate), including mixed-phase PM (e.g., black carbon coated by sulfate and heavy metals), which would be helpful to estimate their impacts on human health. Despite improvements, the current spatial resolutions of some datasets are insufficient to capture sharp gradients in pollutant concentrations, such as at street level, including short-lived pollutants (e.g., $NO_2$). Continued conversations between health researchers, exposure scientists, and scientists affiliated with space agencies are key to improving these limitations and harnessing the vast potential of these platforms and modeling tools.

An additional limitation in using satellite remote sensing for health research has been the inability to reliably monitor air pollution at short-term temporal scales. This is due in part to measurement deficiencies (e.g., no data on a cloudy day or collecting relevant data at night) as well as to the limitations of orbiting satellites to provide more than one measurement per day. However, as shown in Figure 2, several recently launched and upcoming satellites offer substantial improvements, including greater spatiotemporal resolution, which will open new and exciting possibilities for the use of these data in health studies. In particular, the upcoming Tropospheric Emissions: Monitoring of Pollution (TEMPO) (14), Sentinel-4 (15), and Geostationary Environment Monitoring Spectrometer (GEMS) (16) missions will provide hourly measurements of gaseous pollutants over much of the Northern Hemisphere, and the upcoming Multi-Angle Imager for Aerosols (MAIA) mission (17) will provide multiple daily measurements of particle pollution, including some composition information, for select locations around the world. These upcoming missions represent a significant step forward in the temporal resolution of remotely monitored pollution and, combined with the much-improved spatial resolution, will open the door for widespread use of air pollution data from satellites by health researchers in a way that has not previously been possible.

Another promising source of air quality information is global atmospheric models that simulate the complex chemistry and transport of pollutants (e.g., particulates and gaseous pollutants). The spatiotemporal resolution of global simulations is rapidly approaching that of established regional air quality models. Initial conditions are determined by constraining meteorological data (and sometimes atmospheric pollutant data) from both *in situ* and satellite observations to produce a credible representation of air pollution concentrations at a given point in space and time (18). The performance of these models depends on the representation of atmospheric dynamics and air pollution chemistry, which is often limited by spatiotemporal resolution. In addition, the accuracy of these simulations requires time-varying emission estimates as well as high-quality air quality data with which the simulations may be evaluated.

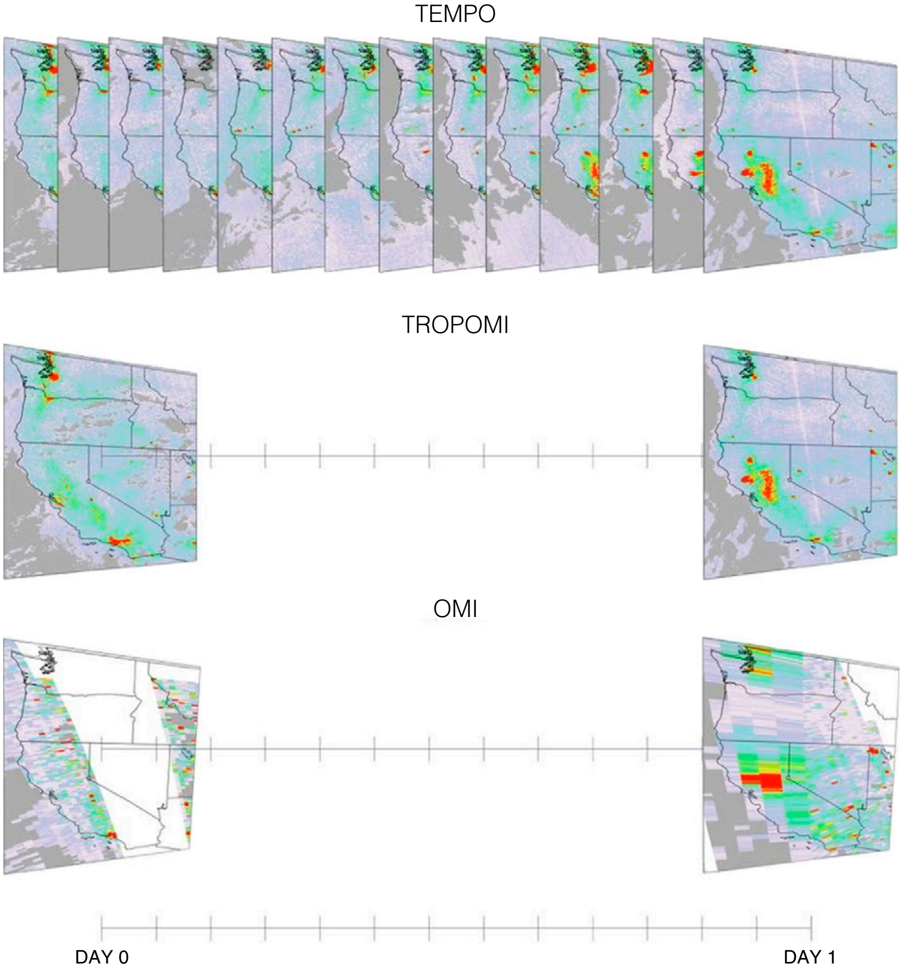

**Figure 2.** Depiction of spatial resolution and temporal frequency of current and upcoming satellite missions. The TROPOspheric Ozone Monitoring Instrument (TROPOMI) was launched in 2017 and currently provides measurements for $NO_2$, $SO_2$, and other pollutants at a sub-urban resolution of approximately 3.5 × 7 $km^2$, which is much better than the relatively coarse spatial resolution of the Ozone Monitoring Instrument (OMI), which was previously the best available technology when launched in 2004. However, both OMI and TROPOMI are orbiting satellites and therefore can provide only a single measurement per day at approximately 14:00 hours local time. The soon–to-be-launched geostationary satellites over North America (Tropospheric Emissions: Monitoring of Pollution [TEMPO]), Europe (Sentinel-4), and Asia (Geostationary Environment Monitoring Spectrometer [GEMS]) will monitor similar pollutants at an even better spatial resolution (approximately 2.2 × 4.7 $km^2$ for TEMPO) but will provide much higher temporal resolution with measurements occurring every daylight hour.

Despite the challenges and complexity of these models, air quality simulations are currently a viable source of information for health professionals. Similarly to remote-sensing data from satellites, the primary advantage of a model simulation is spatial coverage (with similar spatial resolution). Furthermore, with their ability to forecast pollution values several days in advance, these models are currently better suited than satellite technology to providing temporal information useful in health research and, most important, risk communication.

Ultimately, the goal of integration across multiple technology groups is that the strengths of each technology can complement each other to advance understanding of air pollution from the global to the local scale and from real-time measurements to long-term trends. As depicted in Figure 1, taken together, these approaches provide complementary time and space resolution in monitoring coverage. For example, there is great potential to integrate satellites with traditional ground monitoring networks as well as land use data to provide additional spatial and temporal coverage (19, 20); these efforts can be further enhanced with dense sensor networks and/or mobile monitoring (21, 22). Integration of these models with mobility information obtained from surveys or from tracking via mobile phones (23) can also account for individuals' behaviors and time–activity patterns to more accurately reflect exposure for large populations and to further estimate inhaled dose of air pollutants, the metric more relevant for health outcomes than external concentrations, especially for sensitive subpopulations.

## Data Assimilation within and across Multiple Technology Platforms

The challenges in integrating air pollution measurements from multiple technology platforms lie in both the various technologies and diverse needs of users. For example, users in the air quality management community may have very different information needs from epidemiologists or clinicians. These stakeholders are often trained in different disciplines (e.g., atmospheric chemistry, public health, or medicine). Their roles can vary from full-time researchers with institutional support to practitioners with limited resources and time to explore new and complex datasets other than easy-to-use products.

For the past decade, advanced spatial statistical models have emerged as a promising solution to integrate satellite remote sensing data, ground measurements from regulatory monitors, and model simulations (24, 25). Most recently, machine learning approaches have also been applied in the exposure modeling setting as a promising way of integrating a large amount of air quality measurements with meteorological and land use information (26, 27). Both the statistical models and machine learning approaches have the potential to consider the noisier data from emerging low-cost sensor systems, although such methods have room for further development (28, 29).

Although many scientific domains have adopted robust data standards that facilitate the finding and exchange of data, this is not yet true for nascent technologies used in low-cost air monitoring sensors. Fortunately, data and metadata standards for environmental sensing already exist (30–32), and in the case of the Open Geospatial Consortium, they go even further by defining services for access, query, and tasking of sensors, forming a suite of data standards and web services called "Sensor Web Enablement."

Though the difficulty in obtaining concurrence from all the stakeholders cannot be underestimated, the benefits of adopting common data standards are numerous. The ability to harmonize and easily integrate data streams from portable air sensors and physiological monitors will open new doors for health research and disease management. Reliance on and use of proprietary data structures and closed systems will detract from the scientific and public health benefit that low-cost sensor technologies may offer. Efforts to adopt common standards should focus on enabling end users to find and access the data, understand the nature and content of the data, ascertain the data's applicability outside the original purpose, and restructure the data for analysis and integration.

## Critical Issues for Air Pollution Monitoring in Regions without a Regulatory-Quality Stationary Monitoring Network (Including in LMIC Locations)

In selecting a monitoring technology for use in health research or patient care, the degree of accuracy and precision required for the intended use can guide the choice of instrument or data. These can generally be grouped into citizen science and educational purposes (when relative concentrations and trends can be informative) or into exposure and health research or regulatory monitoring for compliance with air quality standards (when more stringent data quality requirements are needed). In selecting the appropriate technologies, it is important to remember that in some low-income locations without extensive ground-based monitoring, simply understanding changes in exposure measurement data over time and space may be nearly as powerful as regulatory-quality data (33).

Given the paucity of regulatory-grade air pollution observations, collecting air quality data in LMIC for health research and patient care may benefit from inclusion of nonregulatory sensors, satellite instruments, and atmospheric models. Despite their limitations in accuracy and consistency, the complementary data derived from low-cost sensors, satellite instruments, and atmospheric models have the potential to aid health research and patient care in these regions of the world, especially as the quality of these instruments and models improves over time.

For example, low-cost portable sensors may provide an opportunity to quickly and easily understand where and when an individual is exposed to higher or lower levels of air pollution. The hope is that this information may, in itself, be enough to inform changes in behavior that will result in associated changes in exposure.

Because air monitoring information is increasingly accessible in LMIC, it is important that health studies in these locations be pursued rather than only relying on concentration response functions from wealthier countries to assess risks and health impacts. The key challenge for health research in these locations moving forward may be the availability and accessibility of health data for use in these studies. Matching health data with the precision of the collection of exposure data is often a challenge, and collection of a few robust measures is likely better than more individualized but poor quality measurements. In addition, collection of existing data sources (e.g., social data) in addition to exposure- and individual-level data may be hugely informative for health studies in these locations.

### Risk Communication, Health Messaging, and Health Research

The increased availability of nonregulatory air pollution monitoring data, including information from satellites, low-cost sensors, and portable monitors, has generated new needs for health messaging. Clear messaging on how to interpret these measurements can empower communities in identifying times and locations of high pollution concentrations even in areas where regulatory monitors are currently not available. Current efforts to develop health messaging for pollution measurements from nonregulatory monitors have typically focused on aligning the messaging with established messaging for regulatory monitors to avoid confusion when interpreting pollution values. However, in some cases, nonregulatory monitors often report measurements at very short time resolutions (e.g., 1-min averages of pollutant concentrations), whereas regulatory monitors typically report hourly or longer averages. Therefore, quantitative adjustments must be made to align health messaging on the basis of longer exposures before it can be directly applied to very short-term exposures (34). Any efforts to directly link very short-term exposure levels to regulatory health messaging without such an adjustment is not scientifically justified.

Another potential option for improving health messaging is to create independent, evidence-based messaging specifically designed for very short-term pollution exposures. However, this is particularly challenging because of a general lack of health effect studies using the same exposure times (35). It should be noted that the clinical relevance of minute-to-minute variations in pollution exposures is not manifestly apparent. Until more studies using very short exposure times are made available, and until the health relevance of these exposures is better understood, development of evidence-based health messaging for these very short exposures may be limited.

The downside of failing to develop adequate health messaging for nonregulatory air quality monitoring is the potential misinterpretation of individual- or community-level monitoring data, which could result in unneeded averting behavior to reduce exposure to air pollution. For example, studies have generally found that for most people, the health benefits of exercise outweigh the risks of ambient pollution exposure for respiratory disease (36), and time outdoors appears to be health protective (37, 38). As a result, unnecessary avoidance behavior based on misinterpreting the health risks of very short pollution exposures could potentially result in net harm rather than benefit to individuals.

Finally, because an increasing number of health studies use individual- and community-level monitoring data, investigators must consider how best to report individual and community exposure levels that were monitored as part of the study. It is important not only to effectively communicate measured pollution concentrations to study participants and communities but also to do so in a way that explains and contextualizes any relevant health risks that may accompany the monitored pollution values.

## Workshop Conclusions and Recommendations

### Integrated Approach to Air Pollution Monitoring: A New Paradigm

Rather than viewing various monitoring technologies as competing for supremacy for use in health research, it is more constructive to realize that obtaining spatially resolved estimates of short-term and long-term pollution concentrations with global spatial coverage requires combining the strengths of multiple monitoring technologies. The contemporaneous improvements in data quality that have recently been achieved with low-cost monitors, satellites, and global models have enabled this new integrated paradigm in air pollution monitoring for health research.

### Health Researchers Communicate with Satellite Agencies

The dramatic improvements in spatial resolution from satellites and, more important, the near-future availability of hourly air pollution measurements from upcoming satellite missions will open a new avenue of air pollution and health research, particularly in studies assessing the impact of short-term exposures. Continued interaction between health researchers and individuals affiliated with space agencies responsible for these satellite missions is essential to maximizing the relevance and suitability of collected air quality information.

### Data Quality Standards for Low-Cost Sensors

The value of low-cost sensors as part of an integrated system of air quality monitoring will be greatly increased if data and metadata standards are established and adhered to in order to improve aggregation and use of collected data. Not to minimize the challenge in bringing an increasingly fractured sensor industry together around common standards, the highly similar technologies being used by a large number of different participants in the industry make this an obtainable and much desired goal.

### Potential Power of Nonregulatory Data in LMIC

Locations currently without regulatory-quality monitors are encouraged to adopt and use air quality estimates from technologies such as satellites, nonregulatory monitors, and global models. Although these technologies lack the accuracy and precision of regulatory monitors typically needed as the basis of legal attainment of regulatory standards, they are currently sufficient for use in local health studies (multiple technologies), for monitoring trends in air quality (satellite), to identify of air pollution hot spots within a city (nonregulatory monitors), for daily risk communication (global models), and for assessing the effectiveness of air quality interventions (multiple technologies).

### Integration of Global Air Quality Forecasts into Local Health Communication Efforts

Dramatic improvement in risk communication is now possible in areas without stationary monitoring networks because of the availability of global models that provide hourly estimates of air pollution at city-level spatial resolutions. These values can be forecast several days in advance but still need to be effectively harnessed by public health officials to incorporate these newly available estimates into successful health communication efforts.

### Risk Communication for Very Short-Term Exposures

The availability of air quality information from a wide range of sources, with varying levels of accuracy and temporal resolution, strains risk communication efforts that have traditionally been based on regulatory or legal limits at time periods of 1, 8, or 24 hours. In addition to efforts to "translate" minute-to-minute exposures into existing risk communication constructs, additional exposure assessment and health research is needed to directly address risk communication questions regarding very short-term exposures to elevated pollution levels. ■

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