Stereoscopic Monitoring

A Promising Strategy to Advance Diagnostic and Prediction of Air Pollution

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ABSTRACT: Monitoring and modeling/predicting air pollution are crucial to understanding the links between emissions and air pollution levels, to supporting air quality management, and to reducing human exposure. Yet, current monitoring networks and modeling capabilities are unfortunately inadequate to understand the physical and chemical processes above ground and to support attribution of sources. We highlight the need for the development of an international stereoscopic monitoring strategy that can depict three-dimensional (3D) distribution of atmospheric composition to reduce the uncertainties and to advance diagnostic understanding and prediction of air pollution. There are three reasons for the implementation of stereoscopic monitoring: 1) current observation networks provide only partial view of air pollution, and this can lead to misleading air quality management actions; 2) satellite retrievals of air pollutants are widely used in air pollution studies, but too often users do not acknowledge that they have large uncertainties, which can be reduced with measurements of vertical profiles; and 3) air quality modeling and forecasting require 3D observational constraints. We call on researchers and policymakers to establish stereoscopic monitoring networks and share monitoring data to better characterize the formation of air pollution, optimize air quality management, and protect human health. Future directions for advancing monitoring and modeling/predicting air pollution are also discussed.

<https://doi.org/10.1175/BAMS-D-20-0217.1>

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In final form 29 October 2020

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Exposure to outdoor air pollution has been recognized as a preeminent global health concern, responsible for 4.2 million deaths every year (WHO 2020). More than 90% of the world's population are breathing hazardous air, especially people in China and India (WHO 2020). The major culprits include fine particles that can penetrate deep into lungs, heart, and bloodstream, and ozone that impairs lung tissues, respiratory tract (Dominici et al. 2006; Li et al. 2019), etc. Air pollutants have also been linked to damage to ecosystems (including reduced crop yields; Unger et al. 2020), to climate change, and to welfare losses (Haywood et al. 1999; Ramanathan et al. 2001). On top of that, recent in situ measurements suggest a role of aerosols in the transmission of SARS-CoV-2 (Liu et al. 2020).

Monitoring and modeling/predicting air pollution are crucial to understanding the links between emissions and air pollution levels, to supporting air quality management, and to reducing human exposure (Kumar et al. 2018). In 1961, the United Kingdom established the world's first national air quality monitoring network after the introduction of the 1956 Clean Air Act. This has evolved over the years into the current Automatic Urban and Rural Network (AURN; Stedman et al. 1997), which consists today of more than 100 sites across the United Kingdom. Other developed countries in Europe and North America have also established densely distributed observation networks. However, there remain large parts of the world with little or no monitoring of air pollution. China has made notable achievements over the past several years (Gao et al. 2018; Zhai et al. 2019), with the number of monitoring sites exceeding 1600 across China in 2020 (Lu et al. 2020). Several countries, including China, the United States, and the United Kingdom, offer daily broadcasts of air quality levels and forecasts (Kumar et al. 2018), and the Copernicus Atmosphere Monitoring Service (CAMS) issues information around the globe (Roberts et al. 2015).

Yet, current monitoring networks and modeling capabilities are unfortunately inadequate to understand the physical and chemical processes above ground and to support attribution of sources. Conventional monitoring networks are designed to describe only the near-surface features of atmospheric composition. However, many important processes that determine formation, transport, and fate of air pollutants occur above the surface, often in distinct vertical layers between 2 and 8 km above the surface. Aircraft observations indicate that prevalent brown carbon (BrC) can absorb more shortwave radiation than black carbon at altitudes above 5 km (Zhang et al. 2017). If such a strong absorption by BrC were ignored, sources of anthropogenic climate forcing would have been missed (Zhang et al. 2017). Furthermore, often there is unequal allocation of monitoring sites in rural and less-settled areas (Lu et al. 2018). Activities in rural regions, such as agricultural burning, have been linked to significant modulation of weather and regional climate (Ding et al. 2013). However, it is challenging to examine their influences on air quality, climate, and health with current monitoring networks. The depiction of air pollutants in the vertical in current chemical transport models is recognized as an important deficiency (Solazzo et al. 2013), which needs vertical observational constraints. The fragmented and incomplete sketch of the evolution of air pollution provided by current

observation networks and large uncertainties in current chemical transport models hinder our ability to better understand and manage air pollution.

Stereoscopic monitoring, a strategy to depict three-dimensional (3D) distribution of atmospheric composition is needed to reduce the uncertainties, and to advance diagnostic understanding and prediction of air pollution. The stereoscopic monitoring strategy can be achieved with advanced passive and active remote sensing instruments. In its development, information from multiple platforms will be synthesized, including ground-based, vehicle-based, and satellite-based data. Satellite-based remote sensing, particularly geostationary satellites, is skilled in obtaining the horizontal distribution of column atmospheric composition during daytime (Kim et al. 2020). Vertical distribution of atmospheric composition can be probed with well-designed operation of ground-based instruments. For example, a Multi-Axis Differential Optical Absorption Spectroscopy (MAX-DOAS) instrument was operated in three modes (measures solar scattered photons from any pair of elevation angle and azimuth angle, measures any set of azimuth angles at constant elevation angle, and measures direct solar beam) to obtain a 3D view (Ortega et al. 2015). With inputs of planned geostationary satellites, the temporal resolution of a stereoscopic monitoring system can reach hourly during daytime, and horizontal resolution can be higher than 10 km (Kim et al. 2020). The vertical resolution of a stereoscopic monitoring system can be 100 m within boundary layer, and 500–1,000 m at higher layers (Su et al. 2020). With well-designed placements of ground-based instruments and synthesis of information from multiple platforms, 3D distribution of atmospheric composition can be presented intuitively and quantitatively, and the sources, evolution, and transport processes of air pollution can be identified dynamically (H. Liu et al. 2016).

Why is stereoscopic monitoring needed?

First, current observation networks provide only partial view (phenomena observed mostly at the surface, and in populated regions) of air pollution and this can lead to misleading air quality management actions. Management of air quality is usually bounded by political boundaries, while air pollutants are inclined to travel across cities, countries, and even continents. Quantitative evaluation of transboundary air pollution is needed by policymakers, but nonetheless challenging, due to a lack of a well-grounded 3D characterization of air pollutants. Inappropriate observation systems (only a few sampling locations) and uncertain models (unsure emission rates, nonlinear nature of chemistry, etc.) are being used extensively to draw disputable policy implications. For instance, an air pollution episode induced by transport of aerosols from the free troposphere is not likely to be tackled by reducing local human-made sources (Colette et al. 2008). Besides, a recent investigation with vertical observations of air pollutants indicates that appreciable inconsistencies between column and near-surface net transport fluxes exist (Hu et al. 2020). If policymakers trust in measurements of surface or column properties only, it is conceivable that the relative significance of local sources could be overvalued/downplayed.

Second, satellite retrievals of air pollutants are widely used in air pollution studies, but too often users do not acknowledge that they have large uncertainties (Goldberg et al. 2019). The uncertainties of satellite retrievals result from both the uncertainties in observed slant column density (SCD) and calculated airmass factor (AMF). The calculation of AMF is the largest source of uncertainty in satellite retrievals of many trace gases, including nitrogen dioxide (NO_2) and formaldehyde (HCHO) (Lorente et al. 2017). The accuracy of AMF is affected by various factors, including surface albedo, clouds, and profile shape (De Smedt et al. 2018). The uncertainties of some of these factors can exceed 50% (De Smedt et al. 2018). The standard official Ozone Monitoring Instrument (OMI) retrievals were derived with a priori profile shapes from a monthly averaged and year-specific coarse-resolution global model simulation (Goldberg et al. 2019). When airmass factors inferred from high-resolution air

quality simulations are used instead, retrieved NO_2 column values often significantly exceed standard columns and are in better agreement with values based on NO_2 measurements from other platforms (Goldberg et al. 2019). Similar improvements are found for other satellite products and over other regions (W. Liu et al. 2016). Our recent investigation (Su et al. 2020; Xing et al. 2017) demonstrates that using ground-measured HCHO profiles as a priori in the calculation of AMF can remarkably improve the accuracy of retrieved HCHO column. The results indicate also that the improvement in the estimation of retrievals of HCHO is attributed largely to the updated prior and AMF (60%), while the influence of SCD retrievals is relatively minor (0.15%) (Su et al. 2020). Thus, we expect that a stereoscopic monitoring system would reduce the uncertainties in priori profiles, and further improve satellite retrievals.

Third, air quality modeling and forecasting require 3D observational constraints. Despite advances over the past several decades, it is challenging to accurately simulate and predict air pollutants, due to large uncertainties in emission inventories (Gao et al. 2017), imperfect model parameterization, etc. We demonstrated that assimilating surface $\text{PM}_{2.5}$ measurements can overcome the limitation of missing data of satellites during heavy haze to improve the simulation of aerosol (Gao et al. 2017; Feng et al. 2018). We also exemplified the improvements with assimilation of geostationary satellite retrievals (Saide et al. 2014). However, vertical profiles of air pollutants have not been well constrained, mainly due to lack of observations. Difficulty in capturing the vertical structures of air pollutants is recognized as a long-standing deficiency of current chemical transport models (Solazzo et al. 2013). A stereoscopic description of air pollutants would greatly enhance the accuracy of air quality models. Attempts have been made to assimilate vertical profiles of aerosol extinction from lidar observations, and validation indicates potential improved products of detailed 3D and time-varying structure of aerosol (Sekiya et al. 2010). $\text{PM}_{2.5}$ vertical profiles retrieved from several lidars operated in China were also assimilated into a regional air quality model, and the improvements were demonstrated with enhanced correlation with observations and reduced errors (Xiang et al. 2020). Similar improvements, especially the vertical distribution of $\text{PM}_{2.5}$ in models, are also found in another investigation (Cheng et al. 2019). Three-dimensional observations of atmospheric composition can also be used in inverse methods to localize the sources and to aid on regulations of emissions (Shi et al. 2020; Yumimoto et al. 2008). For example, an inversion model was developed to estimate the emission rate of CO_2 with lidar-observed profiles of CO_2 concentrations (Shi et al. 2020).

The need for vertical profile information has been widely recognized (NRC 2009), yet limited advancements have occurred, particularly for observations of atmospheric composition. Over recent years, we have set up of network of MAX-DOAS in more than 20 stations across China (locations are marked in Fig. 1). We call on researchers and policymakers to establish stereoscopic monitoring networks and share monitoring data to better characterize the formation of air pollution, optimize air quality management and protect human health.

Current monitoring, limitations, and prospects

Despite the fact that air quality in a considerable number of countries and regions goes still unmonitored, it is a good time for countries that have already established densely distributed surface networks to undertake stereoscopic monitoring. The Geostationary Environment Monitoring Spectrometer (GEMS) was launched on 19 February 2020 to monitor air quality over East Asia at an unprecedented spatial and temporal resolution from a geostationary Earth orbit for the first time (Kim et al. 2020). Similar satellites will be launched soon to watch air quality over North America [NASA's Tropospheric Emissions: Monitoring of Pollution (TEMPO)] and Europe (ESA's *Sentinel-4*). These geostationary efforts would monitor the horizontal distribution of air pollutants at high temporal resolution during daytime, and their capability could be further enhanced with measurements of vertical profiles and big-data analytics (Reid et al. 2015).

Fig. 1. Locations of MAX-DOAS network in China.

At present, vertical profiles of air pollutants are available from several networks, including the Asian Dust and Aerosol Lidar Observation Network (AD-Net; Nishizawa et al. 2016), EARLINET (European Aerosol Research Lidar Network; Bösenberg et al. 2003), MPLNET (Micro-Pulse Lidar Network; Welton et al. 2001), the MAX-DOAS networks (MADRAS; Kanaya et al. 2014), ozonesonde networks [e.g., Southern Hemisphere Additional Ozonesondes (SHADOZ); Witte et al. 2018], and *CALIPSO* (*Cloud–Aerosol Lidar and Infrared Pathfinder Satellite Observations*; Winker et al. 2003) dataset. The number of stations and measured species are unpleasantly insufficient. These stations are sparsely settled in limited regions, such as Japan, Europe, and the tropics. Although *CALIPSO* covers regions globally, the revisiting time is too long to provide a delightful spatial map. In our previous study examining the formation mechanism of a wintertime haze episode in the North China Plain, the explored haze episode was missed entirely by *CALIPSO* data (Fig. 5 in Gao et al. 2016).

Column abundance of SO_2 , NO_2 , HCHO, glyoxal, ozone, and aerosol properties are currently being monitored by multiple satellite sensors (Kim et al. 2020). Limited amounts of ground-based instruments are measuring vertical profiles of SO_2 , NO_2 , HCHO, ozone, aerosol, etc. These species are still inadequate to elucidate the formation of air pollution, and low-cost and high-performance detection technology for free radicals and other pollutants are urgently needed (Lu et al. 2019). We call on researchers in this field to delve more deeply into retrieving new trace gases. In addition, near-surface air quality is largely affected by boundary layer meteorology, the understanding of which cannot be improved with satellites nor with surface instruments. Surface fluxes are challenging to represent, particularly in the presence of the

built environment, ocean waves, etc. Large eddies are difficult to record in observations and to represent in numerical models. Leading-edge advances in observational and modeling techniques, such as large-eddy simulation (LES), would be essential (LeMone et al. 2019) to obtain a better understanding of boundary layer processes at the same time.

Next, the data gained should be made more readily available to the modeling community for model evaluations and improvements. Chemical data assimilation is critical for such improvement, and more systems with capability of assimilating vertical profiles and multiple air pollutants are needed. Organizations such as the World Meteorological Organization (WMO) already coordinate international agreements to obtain and share data through its various data centers. But further efforts are needed to capture, expand, and share 3D monitoring data and to stimulate synthesis of data from different locations and seasons. Given the computational costs of chemical data assimilation, enhanced efforts are needed to share data assimilation systems, and to accelerate efforts to develop innovative and less expensive methods, such as machine learning.

In the meanwhile, several important technical challenges remain in remote sensing of atmospheric composition. First, the widely used MAX-DOAS and satellite instruments usually measure solar stray light, and products are provided only for daytime. Products for nighttime air quality are desired but missing. Endeavors have been made with Visible/Infrared Imager/Radiometer Suite (VIIRS) Day/Night Band (DNB) observations to retrieve nighttime aerosol optical depth. Recently, light-emitting diode (LED) and other active light sources have been used to measure nighttime air quality (Wang et al. 2020). These nighttime measurements should be embraced and included in operational networks. Second, although ozone retrievals at different layers have been provided, the quality, especially for layers near the surface, is not guaranteed yet (Huang et al. 2017). As near-surface O_3 is most important in terms of its impacts on human health, ecosystem, etc., the accuracy of ozone retrievals at lower layers need improvements. Third, there have been long-standing limitations that air pollution is unobserved by remote sensing methods in cloudy conditions. Such deficiency in data completeness hampers the understanding of air pollution and its impacts. We urge the scientific community to probe into these key bottlenecks to boost the current capability of monitoring platforms.

Developing a stereoscopic monitoring strategy, particularly enhancing monitoring of vertical profiles, is crucial to deepen our understanding of air pollution and enhance air quality forecasting services. An internationally coordinated approach with involvement of many countries in the world is needed. The atmospheric chemistry community through their International programs such as Global Atmosphere Watch (GAW), Stratosphere-Troposphere Processes and their Role in Climate (SPARC), and International Global Atmospheric Chemistry (IGAC) have important roles to play in progressing this strategy.

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