Satellite data to support air quality assessment and management

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Abstract

Satellite data have long been recognized as valuable for air quality applications. These applications are in a stage of rapid growth: new geostationary satellites provide hourly or sub-hourly data; improvements in algorithms convert measured wavelengths into retrievals of atmospheric constituents; advances in machine learning support improved estimates of near-surface pollution; and growing interest among air quality managers has led to a range of new satellite data applications. Considering mainly activities in the United States under the Clean Air Act, we discuss proven applications relevant to air quality management, including: informing epidemiological studies and health risk assessments for setting regulatory standards; evaluating regulatory models; constraining emissions inventories; supporting Exceptional Event Demonstrations through tracking wildfire plumes and other sources; characterizing emission patterns and ozone-forming chemistry for State Implementation Plans; improving air quality forecasting; and tracking long-term trends to evaluate regulatory impact. Air quality professionals are increasingly using satellite data for these and related analyses, but barriers remain. This review provides a summary of satellite products used in applications for air quality and related health assessments; progress in using satellite observations for deriving surface-level air quality information across scales; and their use in air quality management. Implications: The review covers advancements in satellite data for air quality applications over the last 15 years. Success with satellite applications, especially for PM2.5 and NO2, include use in health risk assessment, constraining emissions inventories, and supporting tracking short- and long-term trends with regulatory relevance. Solutions co-developed between researchers and practitioners show promise for continued improvements in the use and value of satellite data for air quality applications.

Introduction

The potential for satellite data to support air quality applications can be traced back to the 1960s, with the first instruments detecting clouds in the atmosphere (Vonder Haar and Suomi 1969). As technology advanced, aerosols and tropospheric trace gases were detected (Fishman, Balok, and Vukovich 2002; Limaye et al. 1991; Martin 2008), with potential for space-based data to inform air quality management on Earth.

When Raymond Hoff and Sundar Christopher presented their 2009 AWMA Critical Review of satellite capabilities for air quality detection, they concluded that satellite data products were in their infancy for air quality applications, considering both the length of the data record (as of 2009 there had been 10 years of data for aerosol optical depth, AOD), as well as the advancement of methods needed to support information needs. They concluded that retrievals of AOD, a unitless measure of light absorption by particles in the atmosphere, did not reliably indicate near-surface fine particulate matter (PM2.5) concentrations, but combining satellite data and models held potential to improve this characterization (wavelength measurements from space-based instruments are translated into data products called retrievals, which map a geophysical quantity of interest). Hoff and Christopher (2009) identified the value of AOD, especially from the Moderate Resolution Imaging Spectroradiometer (MODIS, aboard both the Terra and Aqua satellites, launched in 1999 and 2002 respectively) to support qualitative aspects such as defining transport patterns, identifying fires and dust storms, and visualizing large-scale pollution features applicable to public outreach and Exceptional Event Demonstrations (EPA 2019).

Hoff and Christopher (2009) also discussed successes in estimating columnar abundances of several trace gases. Retrievals related to nitrogen dioxide (NO2), formaldehyde (HCHO), and sulfur dioxide (SO2) have since been increasingly used for model evaluation, regional trend analysis, ozone sensitivity, and emissions characterization. Visualizations of large-scale trends in satellite-derived annual average NO2 columns across the contiguous United States have been incorporated into the annual “Our Nation’s Air” report from the Environmental Protection Agency (EPA), and characterizing hotspots and air quality improvement over time. Hoff and Christopher (2009) also cited examples of satellite data supporting field campaigns, such as those illustrated in Figure 1 for a multi-agency field campaign in 2023, where the top-down view from satellites complements in-situ measurements and models.

This Critical Review revisits the topic of satellite data for air quality applications, with a focus on progress since Hoff and Christopher (2009). While the air quality applications of space-based data may have been in their infancy in 2009, they have now reached a stage of rapid growth with potential for wide application. Mature products support real-world use, and capabilities are expanding with more sophisticated satellite instruments, accessible data sharing platforms, and effective user engagement programs. Despite the rapid growth and transitions, barriers remain, limiting the full integration of satellite data into air quality management.

Most air quality information has historically derived from ground-based, regulatory monitors, which provide data on regulated pollutants that may exceed air quality standards (Bachmann 2007; Chow 1995; Demerjian 2000). In the U.S., these are supplemented by surface networks that address effects on visibility, climate, and ecosystems, along with a growing number of low-cost monitors (Hidy et al. 2017). Limitations of these networks were reviewed by Scheffe, Brook, and Demerjian (2011) and include an inability to resolve urban air quality gradients in cities and associated demographic impacts; limited characterization of particulates; uncertain NO2 observations; limited coverage of volatile organic carbon (VOC) measurements; and limited or no observations of other key species. The U.S. had over three thousand compliance monitors active in 2024, which still provides relatively sparse coverage (Diao et al. 2019; Y. Wang, Marshall, and Apte 2024). Monitoring of NO2 is even more limited, with 66% of urban areas lacking data (Kerr et al. 2023). Supporting Figure 1 shows a large number of monitors in urban areas in the eastern U.S. and California, with fewer stations in rural and mountainous regions. Several of these areas are affected by wildfire smoke (Reid et al. 2016) and oil and gas extraction emissions (Macey et al. 2014). Despite its gaps, the U.S. monitoring network is more extensive than those in most other countries, with 71 of 198 studied United Nations countries having no regular PM2.5 monitoring at all (OpenAQ 2024).

Concerns about in-situ NO2 monitoring have played a major role in the comparison of satellite tropospheric column NO2 with ground-monitor data. In-situ NO2 measurements have had spatiotemporal biases due to interference from other nitrogen-containing compounds, which can affect the fidelity of surface NO2 measurements (Lamsal et al. 2015). Given these known errors, the satellite-to-monitor NO2 comparisons have been treated differently by researchers, with some correcting the monitors prior to comparison (e.g., Cooper et al. 2020; Laughner, Zhu, and Cohen 2019; J. Liu et al. 2021; Silvern et al. 2019), and others using the monitor data in the same format that they are used for regulatory applications (e.g., Appel et al., 2017; Chai et al. 2013; Duncan et al. 2013; Harkey and Holloway 2024; Goldberg et al. 2021; Penn and Holloway 2020; Novotny et al. 2011; E.J. Kim et al. 2024; Qin et al. 2019; Jiang et al. 2018). Newer "True NO2" monitors have been recommended by the United States Environmental Protection Agency (US EPA 2020) such that this problem may be avoided, but the True NO2 monitors have not shown improved agreement with satellite tropospheric column NO2 (Acker, Holloway, and Harkey 2025).

With increasing resolution, satellite data are better able to identify intra-urban variability in NO2 (Karner, Eisinger, and Niemeier 2010). While photochemical grid models can resolve down to ~10 km scale for longer term simulations relevant to air quality management, satellite instruments can provide data down to ~1 km resolution. Figure 2 compares data coverage provided by monitors, models, and satellite data products for Baltimore, Maryland, illustrating the ability for column values from the satellite to resolve fine-scale NO2 gradients, gap-fill between in-situ monitors, and support comparison with demographic data. Satellite values may not align with observations in microscale environments with high emissions or with complex chemistry, as evident in the westernmost monitor in Figure 2. While the monitor captures high NO2 levels in near-road conditions, modeled estimates and satellite measurements are relatively low.

The main benefit of satellite data for air quality is contiguous spatial coverage, complementing surface monitors (Brauer et al. 2019; Duncan et al. 2014), with the potential to identify areas where monitors may be needed (Yu et al. 2018), improve health risk characterization (Holloway et al. 2021), evaluate air quality models (Canty et al. 2015; Harkey et al. 2015; Kemball-Cook et al. 2015), refine emissions inventories (Streets et al. 2013), and inform tools for real- time air quality alerts (Al-Saadi et al. 2005). In contrast to monitors, space-based instruments provide column abundance rather than surface concentrations; allow detection only during daylight (and for many instruments, only once- per-day); support a limited subset of pollutants due to light absorption characteristics; and vary widely in uncertainty across data products (Duncan et al. 2014).

Because satellites look down on Earth from space, they report metrics of chemical abundance akin to the vertical sum of a pollutant in the column, known as vertical column density (VCD, Bucsela et al. 2006) or measurements of light extinction due to aerosol abundance (especially AOD, Wei et al. 2020). One way to think about the satellite's view of air pollution is to consider a hiker looking down at fish in a pond. The hiker may be able to count the fish, but probably could not estimate their depth.

Much of the work to connect satellite data with air quality considers methods to overcome this column-vs.-surface perspective, which has advanced most quickly for PM2.5 and NO2. The detection of surface-level ozone concentrations from satellite-measured columns is difficult due to the uncertainty introduced by separating stratospheric and tropospheric contributions (Miles et al. 2015). Similarly, HCHO and SO2 are routinely measured by satellites but have weaker spectral signatures and are more sensitive to background noise, leading to higher retrieval uncertainties (De Smedt et al. 2018; Theys et al. 2017).

Potts, Ferranti, and Hey (2024) identified barriers to broader utilization of satellite data, with issues considered to be "major" by 50% or more of survey respondents including: column data from satellites, rather than surface; limited staff resources and time to develop satellite expertise; inadequate spatial resolution; lack of training to analyze satellite data; data storage requirements; data uncertainties; unknown implications for regulatory practices; difficulty in identifying data for specific applications; lack of data with cloud cover; complicated data acquisition; inadequate temporal resolution; and difficult data formats.

Milford and Knight (2017) found that barriers reported by air quality managers included limited satellite data coverage or frequency, data uncertainty, and limited staff resources and time. The two most frequent applications were the use of National Oceanic and Atmospheric Administration (NOAA) air quality forecasts for public information (61% of respondents), and visible smoke products for public information (46% of respondents). When asked about the use of air-quality relevant satellite retrievals, including AOD from MODIS and trace gases like NO2, HCHO, and SO2 from Ozone Monitoring Instrument (OMI launched in 2004), the most frequent response was that these products were not used at all (35% AOD, 43% gas retrievals). Some respondents noted use for public information (28% AOD, 20% gas retrievals), control strategy development (15% AOD, 20% gas retrievals), and other applications (22% AOD, 18% gas retrievals) (Milford and Knight 2017).

Scientific activity involving air quality and satellite data may be characterized by peer-reviewed research papers, shown in Figure 3. AOD, PM2.5, and NO2 are the most widely studied data products from satellites, with expansive growth across a range of air applications. Interest in satellite detection of methane is growing rapidly, including data from high-resolution commercial satellites (e.g., McLinden et al. 2024) to support emissions characterization.

This review addresses the successes of data and applications for air quality decision-making, and future directions to expand applications further. We provide an inventory of satellite products used in air quality applications "Inventory of satellite data for air quality"; a summary of progress in inferring surface applications from satellite columns, especially for PM2.5 and NO2 "Inferring near-surface concentrations from satellite columns"; and a review of major air quality applications across scales, including links with the air quality management lifecycle "Major air quality applications." We conclude with a consideration of how emerging research can support information needs "Conclusion."

Inventory of satellite data for air quality

Most satellite instruments relevant to air quality operate as passive sensors, measuring solar radiation reflected from the surface of the Earth. Because gases absorb specific wavelengths as sunlight travels from the surface of the Earth and scattered by the atmosphere, satellite data can be used to produce retrievals of aerosol characteristics like AOD, and gases with detectable absorption features, especially NO2, SO2, O3, HCHO, CO, ammonia (NH3), and glyoxal (C2H2O2). These measurements require daytime conditions and can only be made in cloud-free conditions, limitations that lead to uncertainties and potentially biases. For example, by filtering out cloudy days, which tend to have higher levels of NO2, there is a possibility of clear-sky bias (Geddes et al. 2012; Goldberg et al. 2025).

The temporal resolution of satellite instruments depends on the satellite's orbit. Polar orbiting, also known as low Earth orbiting (LEO), satellites provide global data, but typically only with one snapshot or less per day for a given location. Geostationary satellites move with Earth's rotation, scanning over a fixed area multiple times per day, like Tropospheric Emissions: Monitoring of Pollution (TEMPO) launched in 2023 (Zoogman et al. 2017), the Geostationary Environment Monitoring Spectrometer (GEMS) satellite over Asia launched in 2020 (J. Kim et al. 2019), and the planned Sentinel-4 satellite over Europe (Timmermans et al. 2019). TEMPO represents the most advanced satellite data for air quality applications over the U.S., providing hourly column data on gases and aerosols during the daytime. Figure 4 shows an NO2 VCD retrieval from TEMPO, illustrating the lack of data in the presence of clouds, over highly reflective surfaces like snow, and out of the satellite's field of view.

Available data products

Table 1 summarizes current instruments providing data on aerosols and/or gas-phase pollutants relevant to air quality, categorized based on satellite orbit (which determines spatial domain and temporal coverage), followed by whether the data products are mainly used for aerosol analysis or gas-phase products (recognizing that many instruments detect both). Readers are referred to several comprehensive review papers for more detail, especially Ma et al. (2021), Gonzalez Abad et al. (2019), Sogacheva et al. (2020), and Wei et al. (2020).

Advancing algorithms can improve the quality and scope of data products, even from existing satellite instruments. For each of the instruments listed in Table 1, there may be multiple products or retrievals created, often at higher resolutions than the resolution specified by the instrument itself. For example, the MODIS instrument provides aerosol data at 10 km, but aerosol products based on MODIS are developed using different methodologies to optimize specific aspects of performance and achieve higher resolution, including 3 km from Dark Target (Levy et al. 2013), Deep Blue (Hsu et al. 2013), and combined Dark Target-Deep Blue (Sayer et al. 2014), and 1 km from the The Multiangle implementation of atmospheric correction (MAIAC) product (Lyapustin et al. 2011, 2018). The higher resolution of the MODIS MAIAC product has enabled health-related studies on surface PM2.5 (C. Li et al. 2023; Wei et al. 2023).

For gas-phase species, a three-step process is used to convert the satellite-measured irradiance spectra to familiar VCD products (González Abad et al. 2015; Seo et al. 2024). First, Level-1 irradiance spectra are converted to slant column densities (SCDs, an estimate of abundance of a species along the observational path). SCDs are calculated based on the characteristic absorption spectra of individual trace gases, using techniques such as differential optical absorption spectroscopy. As an example, TEMPO's retrieval algorithm uses a 405–465 nm fitting window for NO2 and a 328.5–356.6 nm fitting window for HCHO (TEMPO 2024). Second, VCDs are calculated from SCD using a local conversion factor, called an air mass factor (AMF). The AMF depends on surface albedo, viewing geometry or the solar zenith angle, vertical terrain, cloud parameters (such as cloud fraction and pressure), corrections for aerosols, and the assumed ("a priori") vertical profile of the measured species, generally modeled with a radiative transfer model and chemical transport model (e.g., Lee et al. 2009; Lorente et al. 2017). The relationship of the AMF to viewing angle, wavelength, surface albedo, and vertical location of the absorbing layer may be explored with an online calculator developed by the University of Bremen (2018), which the reader may find useful to build understanding of this important, but non-intuitive aspect of satellite retrievals. Finally, different species may use different techniques to isolate the tropospheric abundance or include background levels. With NO2, for example, model-calculated estimates of stratospheric NO2 are subtracted from the total VCDs to yield tropospheric VCDs, whereas for HCHO, a background correction adds HCHO from a reference spectrum to create the final VCD (TEMPO 2024). The retrieval process introduces different sources of uncertainty to the VCD estimation (e.g., Chatterjee et al. 2024). Depending on the trace gas and instrument, tropospheric VCDs can be calculated with a precision of 35–60% (Boersma, Eskes, and Brinksma 2004; Lorente et al. 2017). The largest contribution to this uncertainty comes from the application of the AMF, which has been found to contribute up to half of the total VCD uncertainty, which in turn depends on the model representation of a priori vertical profiles (Palmer et al. 2001).

Future missions are planned to expand capabilities, such as Multi Angle Imager for Aerosols (MAIA, Diner et al. 2018) designed to support the development of speciated, ground-level PM2.5 for health studies. In combination with collocated surface monitor and chemical transport model data, MAIA mission will provide the capability of converting fractional AOD to near- surface PM10, PM2.5 and speciated PM2.5 including sulfate, sulfate, nitrate, organic carbon (OC), and elemental carbon (EC).

Satellites with research objectives, like most NASA missions, have limited lifetimes that do not meet data continuity requirements of long-term air quality monitoring. The NASA TEMPO satellite has a baseline mission of 20 months, with options to extend for 10+ years, while the NOAA GeoXO is planned to continue the capabilities of GOES satellites, as well as to add new capabilities informed by TEMPO (Lindsey et al. 2024).

Aerosol instruments and retrievals

The MODIS instrument, aboard both the NASA Terra and NASA Aqua satellites, has been the workhorse of satellite data relevant to PM2.5, with 36 spectral channels, morning and afternoon overpass times, and a wide, 2,400 km swath allowing global coverage every 1–2 days (Remer et al. 2008). Higher resolution analogs of MODIS data are available from the Visible Infrared Imaging Radiometer Suite (VIIRS) with spatial resolution of 750 m, launched in 2011, aboard the Suomi National Polar-orbiting Partnership (S-NPP) from NASA, and from a second VIIRS with launched in 2017, followed by NOAA-20 launched in 2017 and NOAA-21 launched in 2022. VIIRS, designed as a MODIS successor, covers similar spectral channels, with an overpass time of 13:30 local time. Its 3,000 km swath allows for daily global coverage. VIIRS aerosol retrievals are based on MODIS algorithms, including the 0.75 km resolution intermediate product (IP) and the 6 km resolution environmental data record (EDR), largely based on Dark Target algorithm (Jackson et al. 2013). The VIIRS Deep Blue aerosol product has become available and evaluated (Hsu et al. 2019; Lee et al. 2024). Additionally, the MAIAC algorithm has been adapted for VIIRS on S-NPP and NOAA-20 (Lyapustin et al. 2023; Román et al. 2024). A comparison of datasets from MODIS to VIIRS has been examined by several studies (Hammer et al. 2023; Román et al. 2024).

A major advance in aerosol detection has been the discernment of qualitative aerosol types from satellite data with “multi-angle” data taken from multiple sensors (Dubovik et al. 2019). The Multi-angle Imaging SpectroRadiometer (MISR) on NASA’s Terra satellite utilizes nine cameras to enable retrievals of aerosol size, single-scattering albedo, and shape, which can be used to constrain aerosol mixtures with varying size, shape and optical properties (Kahn and Gaitley 2015; Kahn et al. 2007, 2009). With a swath width much narrower than MODIS (380 km), MISR provides global coverage approximately once per week, with more frequent observations in polar regions. With improved retrieval algorithms, the horizontal resolution of MISR AOD products have increased from 17.6 km (Diner et al. 2005) to 4.4 km (Garay et al. 2020). Recent work further provides constraints on plume age, particle size and shape, and light absorption properties (Junghenn Noyes et al. 2022). MISR can retrieve plume height from parallax (Junghenn Noyes et al. 2020; Val Martin, Kahn, and Tosca 2018), a capability that has been used in field studies to examine the plume injection heights from biomass burning (Val Martin et al. 2010, 2012). Similar capabilities are available on the recent Plankton, Aerosol, Cloud, ocean Ecosystem (PACE) satellite (Werdell et al. 2019), and planned for the upcoming Multi-Angle Imager for Aerosols (MAIA) mission (Diner et al. 2018).

The Cloud-Aerosol Lidar with Orthogonal Polarization (CALIOP) instrument aboard the Cloud- Aerosol Lidar and Infrared Pathfinder Satellite Observations (CALIPSO) satellite also provides advanced vertically resolved information on aerosol type with the trade-off of reduced spatial coverage. It is also the only satellite instrument that provides global three-dimensional vertical profiles of aerosols (Winker et al. 2013; Yu et al. 2010). CALIOP was launched in 2006 (Hunt et al. 2009) and decommissioned in 2023, but the data may be used for retrospective analysis to provide aerosol classification from six types – desert dust, smoke, clean continental, polluted continental, clean marine, and polluted dust (Winker et al. 2009) based on the two wavelength backscatter measurements, volume depolarization ratios, surface type, geographic location and aerosol layer altitude (Omar et al. 2009). Because the data directly inform the vertical structure of aerosols, they can be useful for Exceptional Event Demonstrations (Geigert 2018) if the overpass coincides with an event of interest.

Aerosol layer height may also be derived from satellites with better global coverage through a new method to assess aerosol abundance using molecular oxygen (O2) absorption bands, as aerosols increase O2absorption through a longer pathlength. The Tropospheric Ozone Monitoring Instrument (TROPOMI) operational product uses O2 A band (760 nm) to derive aerosol layer height (Nanda et al. 2020), and combining O2 A band and B band (688 nm) showed even better performance (Chen et al. 2021). The approach of combining O_2 A and B bands has been applied to observations from the Earth Polychromatic Imaging Camera (EPIC) aboard the Deep Space Climate Observatory (DSCOVR, Xu et al. 2017, 2019). Aerosol layer height can be also derived from the absorption of O_2-O_2 dimer, as demonstrated from GEMS satellite (Park et al. 2016). Aerosol layer height products from O_2 absorption bands are useful to investigate wildfire plumes (H. Kim et al. 2025; Y. Li et al. 2023) and dust (Lu et al. 2023).

Over North America, geostationary satellites from NOAA offer multispectral imaging similar to MODIS and VIIRS at a higher resolution, with the Advanced Baseline Imager (ABI) providing AOD every 10 minutes across the observed domain, and every 5 minutes over the continental United States (Zhang and Kondragunta 2021). The ABI is aboard three Geostationary Operational Environmental Satellites (GOES; where GOES-16 orbits as GOES-East, GOES-18 orbits as GOES-West, and GOES-17 serves as backup), each with 2 km spatial resolution and full disk scans every 15 minutes. These instruments retrieve AOD using a method similar to the MODIS Dark Target algorithm (Kondragunta et al. 2020). Advanced Himawari Imager (AHI) on Himawari-8 and Himawari-9 also provides AOD at 0.05 degree (Yoshida et al. 2018).

Trace gas instruments and retrievals

Current instruments build on the spectrometer designs and retrieval techniques pioneered by several trace gas- observing predecessor instruments, including the European Space Agency (ESA) Scanning Imaging Absorption Spectrometer for Atmospheric Chartography (SCIAMACHY, 2002–2012) and the ESA Global Ozone Monitoring Experiment (GOME, 1995–2011), which revolutionized the field but are now retired (Martin 2008).

Successors to these instruments include ESA GOME-2 (2006-present); and the aforementioned NASA OMI (2004-present) (Boersma et al. 2007; Bovensmann et al. 1999; Burrows et al. 1999; Munro et al. 2006). While these older instruments have coarser spatial resolution than newer options (GOME-2 hase resolution of 80 × 40 km on Metop-B and -C; OMI, 13 × 24 km^2), but they have allowed for the creation of long-term data products that composite observations from multiple instruments (e.g., Hilboll, Richter, and Burrows 2013; Loyola et al. 2009), including in some cases with consistent retrieval algorithms applied across instruments (Boersma et al. 2018; De Smedt et al. 2018). These consistently retrieved products from multiple instruments have aided in estimating surface-level trace gas concentrations for use in health studies (e.g., Geddes et al. 2016) and in documenting long-term trends in urban air quality (e.g., Jin et al. 2020).

At present, a few instruments launched since Hoff and Christopher (2009) stand out for both their ability to survey trace gases at a high spatiotemporal resolution, and for their widespread use supporting the development of emissions and exposure datasets, health studies, and air quality management: TROPOMI, GEMS, and TEMPO.

TROPOMI was launched in 2017 and measures several key trace gases including NO_2, CO, HCHO, SO_2 and CH_4, in addition to aerosol layer height noted above at a spatial resolution of 5.5 × 3.5 km^2 (7 × 3.5 km^2 prior to August 2019; Van Geffen et al. 2020). Depending on clouds and surface reflectivity, TROPOMI's polar orbit enables daily global coverage but is limited to a single observation in the early afternoon, local time. By averaging over multiple days, higher spatial resolution data products may be created, a process known as "oversampling" (Goldberg et al. 2021).

GEMS and TEMPO offer observations for a similar suite of trace gases and at a similar spatial resolutions, 7 × 8 km^2 and 2 × 4.75 km^2 , respectively (Choi 2018; Naeger et al. 2021; note that oversampling, discussed above, can yield data products at an even finer spatial resolution). The key differences between GEMS and TEMPO relative to TROPOMI relate to temporal and geographic coverage. As geostationary satellites, GEMS and TEMPO provide hourly observations during the daytime, approximately eight observations per day depending on the time of year and latitude, over geographically limited regions (GEMS: East Asia, 75°-145°E and −5°S-45°N; TEMPO: North America, 168°-13°W and 14°-73°N). GEMS and TEMPO currently provide a more limited suite of data products than TROPOMI, with GEMS providing NO2, HCHO, SO2, and O3, and TEMPO providing NO2, HCHO, and O3. Because of their high spatial resolution, these current instruments are on the cusp of resolving intra-urban pollution variations, particularly for NO2.

Navigating the landscape of satellite products

Beyond the scientific characteristics of satellite instruments, effective application requires that potential users have awareness and ability to select an appropriate data product. If web-based tools cannot meet the needs of a particular application, advanced data analysis skills may be required to download, visualize, and interpret data (Duncan et al. 2021; Earth Science Information Partners ESIP 2022, 2023).

The National Aeronautics and Space Administration (NASA) Air Quality Applied Sciences Team (AQAST, Jacob, Holloway, and Haynes 2014) and two follow-up Health and Air Quality Applied Sciences Teams (HAQAST, Holloway, Jacob, and Miller 2018) have worked for over a decade to connect satellite data and other NASA products with the needs of air quality and health professionals. Members of these teams were selected through competitive peer-reviewed funding cycles by NASA, with a range of outreach initiatives to the professional air quality community (NASA HAQAST 2021).

An evaluation of AQAST was conducted by Milford and Knight (2017), via a survey of air quality managers who had been involved in meetings or collaborative projects ("participants," with survey invitations sent through AQAST communication channels) and of air quality managers who had not been involved ("non- participants," with survey invitations sent through e-mails of major air quality agency organizations). They found the largest difference in opinion between AQAST participants and non-participants on the view that it is "hard to find out what data are available or potentially useful," with ~ 75% of non-participants agreeing with that statement, compared to just 50% of AQAST participants. In contrast, AQAST participants ranked higher than non-participants in their doubt about the data products, including that "available data are not relevant to air quality management," "data are too uncertain for applications of interest," and "inadequate coverage or frequency."

These survey results align with anecdotal experience shared at the 2024 HAQAST Massachusetts Meeting (NASA HAQAST 2024), where a presenter from a national environmental nonprofit shared her experience learning to use satellite data. She reported an initial burst of enthusiasm, which then "tanked" as she learned about limitations in comparing with surface data, resolution, and other complicating factors. This period of disenchantment may also explain the doubts about data products reported by AQAST participants (Milford and Knight 2017). While there has not been a follow-up study to Milford and Knight (2017), a variety of informal indicators, like growing attendance at HAQAST meetings (online and in-person), and the widening scope of applications (discussed in "Major air quality applications"), suggest that interest in satellite data is growing across the air quality community, despite data limitations. Similarly, the nonprofit professional reported that her own use began to steadily grow as she learned about appropriate applications relevant to her needs. While not definitive, the evidence suggests that satellite data usage by air quality professionals may follow a pattern that is well-established in other learning domains: beginners exhibit a rise in confidence, followed by a decline, leading to a gradual growth in both knowledge and confidence (Sanchez and Dunning 2018).

There can be a tradeoff between ease-of-use, typical of web-based interfaces like NASA Worldview (Earthdata 2025), and flexibility, typical of specialized data analysis software. Some web-based tools allow more flexibility, including NASA's Geospatial Interactive Online Visualization and Analysis

Infrastructure (Giovanni, Disc 2024), EPA's Remote Sensing Information Gateway (RSIG; Hoff et al. 2012), and Google Earth Engine (GEE, McGinnis et al. 2023). More advanced data users may choose to download satellite data directly for manipulation with a data analysis software like Python, but they should be aware of large data sizes and specialized formats (e.g., the network common data format, or netCDF, Rew and Davis 1990). Many Python users handle large datasets using the Xarray (Hoyer and Hamman 2017), netCDF4 (Unidata 2025), numPy (Harris et al. 2020), or pandas (McKinney 2010) Python packages. The NASA Applied Remote Sensing Education and Training program (ARSET, launched in 2009, Prados et al. 2019) provides training across many of these platforms. Informed by a growing understanding of the data preferences of air quality and health users, data products are increasingly available in formats for geospatial software (e.g., shapefiles).

A flow-chart has been developed to help users move from information needs to available resources (McGinnis, Holloway, and Bratburd 2023). Users interested in tracking smoke plumes on a particular day may be pointed to NASA Worldview, an easy-to-use web- based tool appropriate for qualitative imagery of individual days, or they may be directed toward resources to support data downloading and analysis of for more quantitative evaluation (Figure 5).

Inferring near-surface concentrations from satellite columns

In the following subsections, we focus on how satellite data can be used to infer surface-level concentrations of PM2.5 and NO2.

Inferring surface PM2.5 from satellite AOD

PM2.5 is not directly observable from space (more background on PM2.5 in Supplementary Material). While AOD has been used directly as an air quality indicator (Zhang and Kondragunta 2021), it is more commonly used to estimate PM2.5 using various methods. The methods to infer PM2.5 have evolved from statistical approaches, through model-based calculations, to machine learning techniques. As AOD is a column quantity, relating AOD to dry surface PM2.5 mass is dependent on boundary layer height, mass extinction efficiency, aerosol hygroscopicity, aerosol mass density and effective radius (Koelemeijer, Homan, and Matthijsen 2006), further discussed in the recent review by Ma et al. (2021). It should also be pointed out that statistical methods rely heavily on surface measurements, so they may exhibit poor performance in regions with sparse ground measurements (Martin et al. 2019).

Hoff and Christopher (2009) concluded that the promise of satellite data for PM2.5 had "limited utility" for informing estimates of surface-level concentrations due to the ~ 20% error in AOD detection as well as the limited correlation (R2 < 0.25) between satellite-measured AOD and surface-level PM2.5, even when controlling for atmospheric characteristics like aerosol type and boundary layer structure. Early studies estimated PM2.5 from AOD at 550 nm through simple linear regressions between surface measurements and satellite data (Gupta et al. 2006; J. Wang and Christopher 2003). These relationships were then refined by meteorological variables including wind speed, temperature, planetary boundary layer height, surface pressure, relative humidity, and visibility (Gupta and Christopher 2009; Gupta et al. 2006; Liu et al. 2005).

To better address spatial variability, a number of land use parameters have been added for analysis, including norrmalized difference vegetation index (NDVI), urban cover, distance to a major road, forest cover, fire location, elevation, and emissions (Liu 2013; Ma et al. 2021). Statistical models have also advanced, such as generalized linear regression, generalized additive, geographically weighted regression, and land use regression models, resulting in contiguous spatial estimates of PM2.5 from AOD data on a regional scale (Hu et al. 2013; Ma et al. 2014; Van Donkelaar et al. 2016; Zhang and Kondragunta 2021). With the availability of 1 km AOD data and geostationary satellites, these statistical methods are used for estimating both daily and hourly PM2.5 values (Pruthi et al. 2024; Zhang and Kondragunta 2021; Zhang et al. 2023).

Machine learning techniques, such as artificial neural networks (Gupta and Christopher 2009), random forest (Chen et al. 2018; Hu et al. 2017; Wei et al. 2019), and convolutional neural networks (Park et al. 2020; Shen et al. 2024), have been developed to manage complex nonlinear relationships between AOD and PM2.5 and yield more precise and spatially resolved PM2.5. A future direction is to include recent aerosol products, such as aerosol layer height.

Chemical transport models may also be used to infer AOD-PM2.5 relationships. Chemical transport models take meteorology, emissions, and land cover as inputs, as well as boundary conditions depending on the model domain. Then, the models calculate the distribution of atmospheric constituents based on chemical processes, atmospheric transport, and removal processes; the three-dimensional output fields from atmospheric models may be used to calculate the ratio of the column-to-surface chemical abundance. In this role, chemical transport models are used to scale satellite-measured AOD to surface-level PM2.5 estimates, as illustrated in Figure 6. First proposed by Liu et al. (2004), this scaling method does not require surface PM2.5 measurements as input, so it can provide AOD-PM2.5 relationships in both space and time (we note that chemical transport models may be combined with ground measurements and AOD in other ways, such as through chemical data assimilation). These model-scaling methods rely on model representation of resolved vertical distributions, aerosol compositions, particle size distributions, and water content to capture the spatial and temporal variability in AOD-PM2.5 relationships (Van Donkelaar, Martin, and Park 2006; Schaap et al. 2009), but may underestimate surface PM2.5 in areas with high aerosol loading (Pan et al. 2015). This approach has been expanded to generate monthly or annual average PM2.5 concentrations globally, improving large- scale surface PM2.5 estimates (Van Donkelaar et al. 2010, 2015). As chemical transport models are limited by uncertainties in meteorology, emissions, and chemical processes (Carter et al. 2020; Eastham and Jacob 2017), the error associated with model-scaling methods is expected to be higher than statistical methods that include information on observed PM2.5. Modeled AOD-PM2.5 relationships dominate the uncertainty at the daily scale, with simulated column mass, speciation, vertical distribution, and relative humidity contributing most to systematic biases (Zhao et al. 2024); optical properties also contribute to random uncertainties (Jin et al. 2019).

To combine the strengths of statistical approaches and model scaling, a hybrid method (Van Donkelaar et al. 2016) combines model information and surface measurements. This approach derives surface PM2.5 based on a model-scaling method, then compares calculated surface PM2.5 to ground-based measurements through a statistical model as a function of driving factors. The corrected PM2.5 is then integrated with both model and ground-based measurements, resulting in improvements on both annual and monthly estimates (Hammer et al. 2020; Van Donkelaar et al. 2021). Notable examples of these model-satellite fusion datasets include a 0.01° x 0.01° global dataset that ingests AOD from several Earth-observing satellites to predict PM2.5 concentrations at monthly and annual timescales (Shen et al. 2024; Van Donkelaar et al. 2021), with an example shown in Figure 7.

The episodic and intense nature of wildfires, coupled with the impact of fire intensity on the vertical distribution of aerosols, adds complexity to the AOD-PM2.5 relationship (Cheeseman et al. 2020; Zhao et al. 2024). Current models may fall short in capturing the fine- scale, hourly PM2.5 variations during these events (Ye et al. 2021). Addressing this issue requires an integrated approach, combining satellite observations, surface network data, models, and machine learning techniques to improve estimates (Zhang et al. 2023; Zhao et al. 2024). Achieving accuracy in hourly PM2.5 estimates remains a challenge (Zhang et al. 2022).

Aerosol composition and vertical distribution play a critical role in determining aerosol optical properties, yet current AOD-PM2.5 relationships often lack explicit incorporation of these variables. While modeled relationships may implicitly account for some aspects of aerosol composition, the accuracy of modeled aerosol properties remains limited. The expansion of emerging ground-based networks (Snider et al. 2015) offer opportunities to enhance AOD-PM2.5 relationships, including the development of hourly PM2.5 products. The vertical distribution of aerosols is another essential factor affecting the AOD-PM2.5 relationship. Previous studies have utilized CALIOP to better understand aerosol vertical profiles (Van Donkelaar et al. 2016; Zhao et al. 2024). However, this use is limited by its frequency of global coverage at every 16 days. Recently developed aerosol optical centroid layer height products for instruments like TROPOMI and TEMPO offer new insights into aerosol vertical distribution and have the potential to improve real-time AOD-PM2.5 estimates (Chen et al. 2021; E.J. Kim et al. 2024).

Improvements in the quality and deployment of low cost sensors hold the potential to complement satellite data and improve characterization of the AOD-PM2.5 relationship (deSouza et al. 2020; Li et al. 2020). Advancing integrated analyses, with satellite observations, surface-level measurements, models, and machine learning techniques also offer opportunities to improve daily PM2.5 (Pruthi et al. 2024; Zhang et al. 2023; Zhao et al. 2024). Reliable hourly PM2.5 estimates remain a future goal, necessitating further mechanistic improvements in model representation and data integration (Zhang et al. 2022).

Inferring surface NO2 from satellite VCDs

With its strong spectral absorption in the visible range and more established retrieval algorithms (Lange, Richter, and Burrows 2022; Y. Liu et al. 2021; Seo et al. 2024; Y. Wang et al. 2020), NO2 is one of the most robust data products available for atmospheric composition. Because stratospheric NO2 can be responsible for over 90% of the total columnar NO2 (Bucsela et al. 2013; Martin et al. 2002), researchers and practitioners typically focus on tropospheric VCD alone, distributed as a standard product by subtracting model-calculated stratospheric NO2 from the total column. Spatial patterns in tropospheric NO2 VCD closely align with emission sources and with annual average surface concentrations from monitors, due to the short atmospheric lifetime of NO2 (Bechle, Millet, and Marshall 2013; Goldberg et al. 2021; Lamsal et al. 2015). Similarly, temporal patterns in tropospheric NO2 VCD align with temporal variability in surface concentrations from monitors (Harkey and Holloway 2024; Lamsal et al. 2014; Zhang et al. 2018).

Much like the AOD-PM2.5 relationship, research has focused on translating satellite-derived NO2 VCD measured by instruments like GOME, SCIAMACHY, OMI, TROPOMI, and others into surface concentrations (e.g., Ahmad et al. 2024; M. Kim, Brunner, and Kuhlmann 2021; Shetty et al. 2024; Virta et al. 2023). In many studies, the NO2 column itself is used directly to assess emission patterns and trends (Bechle, Millet, and Marshall 2013; Goldberg et al. 2024; Kerr, Meyer et al. 2024; Lamsal et al. 2015). Various approaches – including statistical, modeling, and machine learning techniques – are employed to establish these connections, sometimes accounting for monitor locations, roadway proximity, and land use type (Griffin et al. 2019; Hoek et al. 2008; E.J. Kim et al. 2024; Novotny et al. 2011; Young et al. 2016). Land Use Regression (LUR) explicitly uses land use and other geographical variables to estimate NO2 concentrations. LUR models are particularly useful in urban settings, where spatial heterogeneity in NO2 is high, and they have been applied at fine spatial scales (Anenberg et al. 2022; Demetillo et al. 2020; Larkin et al. 2023). As with the AOD-PM2.5 connection, chemical transport models are used to convert tropospheric NO2 columns to surface-level concentrations through a model-simulated surface-to-column conversion factor (Bechle, Millet, and Marshall 2013; Cooper et al. 2020; Gu et al. 2017; Lamsal et al. 2008). Chemical transport models provide spatially resolved NO2 data, with resolutions improving from 10 km (Geddes et al. 2016) down to 1 km (Cooper et al. 2020), enabling detailed estimates of surface NO2 levels at the neighborhood scale. Machine learning algorithms, including neural networks, random forests, and ensemble methods, can capture complex, nonlinear relationships between satellite NO2 columns and surface-level concentrations (Chi et al. 2022; Shetty et al. 2024; Sun et al. 2024).

Comparisons between satellite-derived NO2 and ground-based measurements have shown some discrepancies, with satellite instruments often underestimating surface-level NO2 in urban areas and near roadways (Dressel et al. 2022; Goldberg et al. 2024; Ialongo et al. 2020, see also Figure 2 and related discussion). This underestimation arises partly from the coarse spatial resolution of satellite sensors (~5 km2), which may fail to resolve some localized NO2 hotspots, as well as from the fundamental difference in vertical column of NO2 versus near-surface concentrations. Satellite-derived VCDs may not reflect rapid changes in surface-level NO2, particularly when the boundary layer is shallow, causing a lag between surface pollution levels and satellite observations (Harkey and Holloway 2024).

Major air quality applications

In the context of air quality management, we consider satellite data and low-cost sensor networks as newer data sources joining regulatory monitors and air quality models to support decision-making processes. We describe past and future applications of satellite data to air quality through the lens of the Air Quality Management Cycle, defined by the National Research Council (National Research Council 2004). While not specific to satellite data, we present the cycle as a framework to outline the scope of satellite data applications. The specific steps are to: set standards and objectives, “Setting standards and objectives to protect public health” and implement control strategies “Designing and implementing control strategies,” and assess status and monitor progress “Assessing status and monitoring progress.” Within each of these areas, we focus on proven or emerging applications of satellite data to health and air quality management.

Setting standards and objectives to protect public health

Satellite data applications relevant to setting standards including the use of satellite data in epidemiological studies and health impacts assessments (discussed in “Satellite data application: Epidemiological studies and health impact assessments”), as well as the evaluation of community health and equity (discussed in “Satellite data application: Community health and environmental justice”).

Satellite data application: Epidemiological studies and health impact assessments

Satellite-derived surface PM2.5 has been used to assess health impacts through studies cited in the 2022 EPA PM2.5 Regulatory Impact Assessment (EPA 2022), including Di et al. (2017) and Wu et al. (2020) where satellite-derived PM2.5 concentrations were used to quantify PM-attributable mortality across the Medicare population. For the more recent of these studies, satellite data were used along with other data sources to estimate PM2.5 concentrations at a high spatial resolution (1-km2) and apply this dataset to estimate the exposure of 68.5 million Medicare enrollees, representing the largest air pollution exposure study up to that time (Wu et al. 2020). While this critical review primarily focuses on the use of satellite data to support air quality assessment and management in the U.S., satellite-derived estimates of PM2.5 have been used to support global assessments, including the Global Burden of Disease study, the most comprehensive worldwide epidemiological study to date (Brauer et al. 2024), as well as in regional epidemiological studies in low and middle income countries where lack of in-situ monitoring would likely make such studies impossible without satellite-derived estimates (e.g., Bachwenkizi et al. 2022; Odo et al. 2023).

When discussing methods to estimate NO2 exposure for epidemiological studies, EPA included remote sensing as a valid method for exposure estimation, along with fixed-site monitors, personal monitoring, models and biomarkers, noting that, “[r]emote sensing approaches should be calibrated using ground-level monitoring networks and their accuracy, precision, and any interferences should be clearly documented" (EPA 2024).

Epidemiological studies generally develop measures of association (e.g., risk ratios, odds ratios, etc.) between an exposure and a health outcome. Health impact assessments can then use these measures together with exposure, population, and health datasets to estimate the health impacts of ambient pollution; to consider potential policy or technology interventions before they are implemented; and/or to evaluate health impacts across different demographic subgroups to understand potential confounding factors and/or environmental inequities. Satellite-derived NO2 and PM2.5 have been incorporated into health and equity impact assessments, which have uncovered higher rates of attributable premature deaths (linked to NO2 and PM2.5) and pediatric asthma (linked to NO2; Achakulwisut et al. 2019) in Black and Brown communities (Camilleri et al. 2023; Kerr, van Donkelaar et al. 2024).

Satellite data application: Community health and environmental justice

In recent years, one objective of air quality management has been to advance environmental equity and justice in tandem with local stakeholders. Satellite data have been applied to evaluate the impact of discriminatory practices in the U.S., such as redlining (Aaronson, Hartley, and Mazumder 2021), and the impact of emission sources concentrated in communities of color and communities of low wealth (Cushing et al. 2022; Mohai and Saha 2015).

Satellite applications to environmental justice have focused on PM2.5 and NO2, and community exposure to major precursor emissions, including on-road transportation and heavy-duty traffic in particular (Demetillo et al. 2021; Kerr, Goldberg, and Anenberg 2021), ports and railyards (Thind, Tessum, and Marshall 2023), and warehousing facilities (Kerr, Meyer et al. 2024). In multiple studies, TROPOMI NO2 VCD have been compared with demographic data to show that majority-Black and -Hispanic communities and communities with low wealth experience NO2 levels that are significantly higher, across the U.S. and in specific urban areas (Bradley et al. 2024; Demetillo et al. 2020; Dressel et al. 2022; Hrycyna et al. 2022; Kerr et al. 2023). The contiguous spatial coverage of satellite data allows for neighborhood-to-neighborhood comparisons, as shown in Figure 8, which capture inequities more clearly than limited point monitors (Kerr et al. 2023).

Researchers have evaluated equity in the context of multi-year trends in satellite-derived NO2 and PM2.5, finding that, despite overall air quality improvements in the U.S., relative disparities in exposures have overall remained relatively static with time, considering differences between non-Hispanic white communities and Black and Brown communities, and differences between communities of higher and lower wealth (Colmer et al. 2020; Jbaily et al. 2022).

Designing and implementing control strategies

Control strategies connect with satellite data in multiple ways, including assessment of photochemical models used for policy design (discussed in "Satellite data application: Model evaluation"), improving emission inventories (discussed in "Satellite data application: Improved emission inventories"), diagnosing sources of pollution through Exceptional Event Demonstrations (discussed in "Satellite data application: Exceptional event demonstrations"), and informing ozone sensitivity to precursors (discussed in "Satellite data application: Ozone sensitivity to precursors"). Each of these proven applications can play a role in the development of State Implementation Plans (SIPs) (Fiore, Bratburd, and Miller 2021), supported by new tools like the Urban Increment Calculator developed by the Lake Michigan Air Directors Consortium (LADCO), where satellite-derived data like that shown in Figure 7, can estimate the difference between urban and rural annual average PM2.5 (Adelman 2024).

Satellite data application: Model evaluation

Global chemical transport models have a long history of evaluation with satellite data (e.g., Velders et al. 2001). Evaluation of regional photochemical models such as the Community Multiscale Air Quality (CMAQ) began with AOD (Roy et al. 2007) and has since extended to trace gases (S. Wang et al. 2011; Zhang et al. 2009), with an extensive analysis of NO2 to inform emission inventories (e.g., Canty et al. 2015; Harkey et al. 2015; Goldberg, Saide et al. 2019).

In the context of model evaluation, the column- based satellite measurements are not a limitation of satellite data, as model layers may be integrated to calculate vertical metrics comparable to the satellite retrieval. Most major satellite retrievals are provided at the native resolution of the instrument ("Level-2") or transformed to a structured grid ("Level-3"), so the comparison of satellite data with a model is facilitated by spatially allocating or interpolating the satellite measurements to the same horizontal grid as the model. Various techniques have been developed for this allocation, which lead to broadly similar results (Goldberg et al. 2022). The vertical aggregation of model data to calculate column-integrated values involves uncertainties associated with AMF (discussed above in "Trace gas instruments and retrievals"), such that different integration approaches can affect the model-calculated VCD (Harkey and Holloway 2024). Models and satellites can also have different treatments of the stratosphere, relevant for species like NO2 and O3 (e.g., Chatterjee et al. 2024; Fishman et al. 1990).

Satellite data application: Improved emission inventories

Emission inventories connect across the air quality management cycle, informing risk factors, regulatory models, and opportunities for control. Satellites have been widely used in emission inventories, as reviewed by Streets et al. (2013), with newer studies for NOx (East et al. 2022; Goldberg et al. 2022, 2024; Kemball-Cook et al. 2015), SO2 (Qu et al. 2019), dust (Chappell et al. 2023), fire (Bray et al. 2018; Stockwell et al. 2022; Wiggins et al. 2021; Zhao et al. 2022), CO2 from coal plants by way of NOx (Goldberg, Lu et al. 2019; Liu et al. 2020), soil NOx emissions (Huber, Steiner, and Kort 2020; Vinken et al. 2014; Y. Wang, Faloona, andHoulton 2023), and point-source methane emissions (e.g., Varon et al. 2018).

Satellite data to inform bottom-up emissions inventories includes fire detection products, such as those from MODIS and VIIRS, which are now standard for driving emissions in air quality models. Recent advancements, including VIIRS fire detection at 375 m resolution, have facilitated the development of near-real time daily wildfire emission inventories.

HCHO from space may be used to infer biogenic VOC emissions (Li, Zhao, and Kleeman 2024; Millet et al. 2008; Palmer et al. 2006). Another active area of satellite application to emissions involves the detection of NH3 from the Cross-track Infrared Sounder (CrIS) and the Infrared Atmospheric Sounding Interferometer (IASI) as constraints on agricultural emissions (Ding et al. 2024; Luo et al. 2022; CrIS is part of the same payload as VIIRS, and IASI is part of the same payload as GOME-2). This new capacity to observe NH3 from space fills a major gap as surface measurements of NH3 are rare, especially with agricultural sources generally located in rural areas (Driscoll et al. 2024).

While many of the products used so far detect in the UV and visible wavelengths, new products detected in the IR, including for isoprene and other VOCs, show great promise and direct relevance to constraining biogenic emissions and large anthropogenic sources like oil and gas extraction (Fu et al. 2019; Tran et al. 2024; Wells et al. 2020). Hourly HCHO from TEMPO also holds promise for attribution of natural and anthropogenic VOCs through their temporal patterns, e.g., rush hour peaks due to traffic versus midday peaks due to biogenic emissions (P. Wang et al. 2022).

Satellite data application: Exceptional event demonstrations

Early satellite visual imagery of dust events crossing the Atlantic and Pacific helped raise awareness of a global dimension to air pollution (e.g., Husar et al. 2001; United States Geological Survey 2001), with trace gas retrievals of CO shaping a better understanding of intercontinental transport (Heald et al. 2003). Since then, numerous analyses have characterized local wildfire and dust events (Tong et al. 2012; Y. Li et al., 2021) and the long-range transport of both aerosol and ozone precursors (e.g., McMillan et al. 2008).

The Exceptional Events Rule allows states to submit documentation to identify pollution events meeting the criteria for exclusion from NAAQS attainment designations (Krupnick et al. 2025). Satellite data products are now a common feature of these Exceptional Event Demonstrations, used to track plumes of smoke across wide areas (Geigert 2018).

The NOAA Hazard Mapping System (HMS) is one of the most widely used smoke products for Exceptional Event Analysis (e.g., Georgia Department of Natural Resources, Air Protection Branch, Environmental Protection Division 2025), which combines data from multiple satellite instruments, interpreted by analysts (Brey et al. 2018). Additional resources include the data platforms discussed in "Navigating the landscape of satellite products"; satellite data integration in AirNowTech (Bratburd et al. 2022); and tools available through Google Earth Engine (Reddy 2025). Combining aerosol layer height and CO, along with HCHO and NO2, shows promise for improved tracking of transported wildfire plumes and their impacts on air quality (Jin, Fiore, and Cohen 2023).

Satellite data application: Ozone sensitivity to precursors

Satellite measurements of tropospheric column ozone have been analyzed to evaluate changes over time (Cooper, Ziemke, and Chang 2024; Gaudel et al. 2020; Ziemke et al. 2019). However, these patterns reveal little about ozone in surface air or even the lower troposphere, where trends can differ from those in the upper troposphere (e.g., Fiore et al. 2022; Szopa and Naik 2021; Yu et al. 2024). Aside from hotspots with high near-surface ozone, concentrations increase with altitude in the troposphere, and lower tropospheric ozone is generally not detectable from space (Xu et al. 2024). New tropospheric ozone profile data products from TEMPO (Zoogman et al. 2017) hold promise for retrieving lower tropospheric ozone based on methods developed earlier (Liu et al. 2010), but will require substantial work to validate and interpret. In tandem with data from chemical transport models and statistical models, satellite data have been used as predictor variables to provide estimates of near-surface ozone in unmonitored areas (Requia et al. 2020; Seltzer, Shindell, and Malley 2018; Y. Wang et al. 2024). In this way, satellites can inform the development of high-resolution surface ozone estimates, despite the limited ability of satellites to detect near-surface ozone directly.

The most direct application of satellite data to near-surface ozone has been to diagnose the local sensitivity of ozone formation to NOx versus VOC emissions (Jin, Fiore, and Geigert 2018). The potential for satellite-retrieved ratios of HCHO to NO2 (HCHO/NO2) to inform ozone sensitivity was first demonstrated for the GOME instrument (Martin, Fiore, and Van Donkelaar 2004) and later OMI (Duncan et al. 2010; Jin and Holloway 2015). At least qualitatively, satellite-retrieved HCHO/NO2 applications have diagnosed changing patterns of ground-level ozone to reflect shifts toward increased sensitivity to NOx emissions in several cities, as shown in Figure 9 (Jin et al. 2020; Koplitz et al. 2022; Zhu, Laughner, and Cohen 2022). The higher spatial resolution of TROPOMI has enabled additional insights into shifts along urban-rural gradients (Acdan et al. 2023; Johnson et al. 2023), and supported assessment of HCHO/NO2 on higher ozone days most relevant to air quality management (McGinnis et al. 2023; Tao et al. 2022).

The potential for HCHO/NO2 to support SIPs has been discussed by Fiore, Bratburd, and Miller (2021), with related guidance developed by Jin, Fiore, and Geigert (2018) and Duncan, Geigert, and Lamsal

(2018), and an example use case for Colorado described in Witman, Holloway, and Reddy (2014). Averaging is required to reduce noise, especially in the HCHO product, but careful compositing based on days with similar meteorological conditions enables process-oriented signals to be detected, including those associated with drought (Naimark et al. 2021). Several sources of uncertainty impede a more quantitative use of this metric, including uncertainty in the retrievals and in translating column measurements to surface-level concentrations (Jin et al. 2017; Schroeder et al. 2017; Souri et al. 2020, 2023).

In addition to HCHO/NO2, other indicators have been proposed for diagnosing local ozone production sensitivity to precursors. Given that HCHO is produced alongside ozone during the oxidation of VOCs, its columnar densities alone may be useful for understanding spatial distributions in ground-level oxidants, even in high-NOx regions where titration of O3 by NO occurs (Travis et al. 2022). The product of HCHO and NO2 has also been suggested for mapping ozone production rates (Souri et al. 2023). Combining satellite data with quantitative calculations using a chemical mechanism enables estimates of local ozone production rates (Souri et al. 2025).

Assessing status and monitoring progress

Satellite data have been used to track progress on meeting air quality and health goals, including forecasting on daily timescales (discussed in “Satellite data application: Air quality forecasting”) and analyzing trends on interannual scales (discussed in “Satellite data application: Trend analysis”). We also consider the possible future application of satellite data for NAAQS or related standards evaluations (discussed in “Potential satellite data application: Support for NAAQS evaluation”).

Satellite data application: Air quality forecasting

Satellite data have been used to evaluate the impacts of Canadian wildfire smoke on air quality in the eastern and midwestern United States (Yang et al. 2022), dust storms originating from Africa and reaching the southeastern United States (Yu et al. 2021), and volcanic emissions (Kahn et al. 2024). A key challenge remains in converting column-integrated AOD data into three-dimensional concentrations of aerosol species in model grids, leading to large uncertainties (O’Neill et al. 2023; Randles et al. 2017). With MODIS phasing out, VIIRS AOD is expected to take its place in operational data assimilation practices. We expect a future data assimilation system to include recent aerosol development such as aerosol types and aerosol layer height, which may improve model skills in air quality forecasting, particularly for exceptional events. In addition to direct assimilation and emission source characterization, machine learning has become a powerful tool to improve air quality forecasts (Lee et al. 2022).

Satellite data application: Trend analysis

With over 20 years of data from instruments such as GOME, OMI, GOME-2, and TROPOMI, the extensive satellite record provides an opportunity to evaluate the effectiveness of emission control measures as well as economic growth on a regional scale. For instance, Krotkov et al. (2016) utilized the first 11 years (2005–2015) of OMI data to analyze NO2 and SO2 trends globally, revealing significant trends in regions like the eastern United States (over a 40% decrease in NO2), eastern China (North China Plain had a 50% increase in NO2, then slight decrease), and India (50% increase in NO2), driven by economic, technological, and regulatory changes, while some regions such as Eastern Europe showed little to no change in NO2 levels. Some studies of long-term satellite trends averaged over the U.S. have shown stagnant trends due to the high background NO2 levels masking the steady decline in anthropogenic emissions (Dang et al. 2023; Jiang et al. 2022). Changes in satellite-derived NO2 over major U.S. and Canadian cities declined through the 1990s and 2010s by 1–7% per year depending on the time period analyzed and whether population-weighted or area-averaged metrics are selected (De Foy, Lu, and Streets 2016; Geddes et al. 2016), resulting in net decreases of up to nearly 50% over the multi-decadal period (Tong et al. 2015). Declines in these North American cities may be attributed to emissions reductions from power plants, vehicles, and industrial sources following regulations such as the Clean Air Act Amendments and stricter vehicle emission standards. On the other hand, satellite-derived NO2 and other trace gases (e.g., HCHO, NH3) have significantly increased in recent decades in urban areas outside North America and Europe, including in many parts of the Global South (Vohra et al. 2021, 2022). In these fast-growing urban areas, satellite measurements of air pollution have been used in tandem with source-sector-resolved emission inventories to highlight the role of anthropogenic versus natural activity in driving observed trends.

Trends of annual and monthly mean PM2.5 have also been informed by satellite data over the past two decades (Hammer et al. 2020; Van Donkelaar et al. 2021; Y. Li et al., 2023). Trends in AOD reflect reduced anthropogenic emissions in North America and Europe, and increased anthropogenic emissions in South Asia and the Middle East (Yu et al. 2020), consistent with the decreasing trend of PM2.5 in continental U.S. (Di et al. 2019) with the exception of the western U.S. showing increasing PM2.5 since 2010 due to wildfires (Wei et al. 2023). China and India show different trends: in China, surface PM2.5 increased until 2013 and significantly decreased thereafter (Wei et al. 2021), while PM2.5 in urban areas in India have steadily increased between 1998 and 2020 (Guttikunda and Ka 2022).

In addition to long-term trends, satellites have also been used to capture shorter-term variability in NO2 driven by human activity. One example is the weekday- weekend effect, where satellite observations show a 10% to 30% reduction in NOx emissions on Saturdays and a 20% to 50% reduction on Sundays in cities across the U.S. (Beirle et al. 2003; De Foy, Lu, and Streets 2016; Goldberg et al. 2021). Short-term variability in NO2 has also been observed in response to major events, such as the 2008 Beijing Olympics (Mijling et al. 2009; Witte et al. 2009).

Starting in 2020, COVID-19 outbreaks led to lockdowns in many regions worldwide. Satellites detected abrupt declines in NO2 levels in China (Le et al. 2020; Liu et al. 2020), Europe (Souri et al. 2021), and the United States (Berman and Ebisu 2020; Campbell et al. 2021; Goldberg et al. 2020), which persisted even after controlling for the confounding impact of meteorology (e.g., temperature, wind speed and direction) and other factors influencing the retrieval process such as solar zenith angle.

Satellite trends in other trace gases relevant to air quality were reviewed by Gonzalez Abad et al. (2019), with additional detail available for CO (Strode et al. 2016; Worden et al. 2013) and SO2 (Buchholz et al. 2021; Fioletov et al. 2017; Georgoulias et al. 2019; Li et al. 2017; McLinden et al. 2016).

Potential satellite data application: Support for NAAQS evaluation

The potential for remotely sensed data to inform NAAQS determinations is limited by the lack of direct surface observations from satellites. However, the advancement of methods to infer surface abundance (as discussed in “Inferring surface PM2.5 from satellite AOD”), opens the door to future regulatory applications, especially for annual average PM2.5 (Sullivan and Krupnick 2018). Satellite-derived PM2.5 from Van Donkelaar et al. (2021) was included in the EPA’s (2022) Regulatory Impact Analysis to showcase regional patterns in PM2.5, which in turn supported the 2024 decision to lower the annual average NAAQS for PM2.5 from 12 ug/m3 to 9 ug/m3 (Figure 8). The new lower standard may introduce a need for air quality estimates with greater spatial coverage (American Lung Association 2024).

Conclusion

Satellite data have moved beyond the research community to bring direct benefits and new challenges to air quality management. The two pollutants with the most proven success for satellite applications are

PM2.5 and NO2. The data have a range of applications relevant to air quality management, including epidemiological studies and health risk assessments used for reviewing and setting regulatory standards; evaluation of regulatory models; constraining emissions inventories; supporting Exceptional Event Demonstrations through tracking wildfire plumes and other sources; characterizing ozone-forming chemistry for State Implementation Plans; improving air quality forecasting; and both tracking long-term trends and shorter-term perturbations to evaluate regulatory impact.

In reviewing intended and actual use of air monitoring in North America, Demerjian (2000) noted a disconnect between the purposes for which monitoring networks were designed versus the historical applications for which they had been used. In the case of satellite data, such a disconnect is far more pronounced. In the U.S., NASA and NOAA are responsible for satellite operation, but these agencies do not have a regulatory mission. There is also a disconnect in perceptions of satellite data utility with the satellite community and the air quality management community: 87% of satellite-related scientists consider satellite data already useful for air quality end-users, versus only 32% of air quality and health professionals (Potts, Ferranti, and Hey 2024). While a few initiatives have helped to connect satellite capabilities and air quality management needs, a higher level of integration between these communities would almost certainly facilitate advances. Such advances could include higher spatial and temporal data resolution, coverage, and certainty; improved retrievals and develop methodologies to infer near-surface abundance; improved methodologies to constrain emissions based on satellite detection; and partnerships with air quality professionals who can help identify where and when research-based methods most effectively serve existing and emerging needs.

A number of applications appear on the horizon, especially to support health studies, ozone assessment, and increased relevance to regulatory decision-making. Health studies with satellite data are expected to benefit from hourly daytime data from TEMPO, and the launch of the health-focused MAIA instrument. Understanding of tropospheric ozone has been addressed through the lens of precursor sensitivities, using the ratio of satellite-detected HCHO to NO2. New data products for lower-tropospheric ozone from TEMPO offer the potential to better constrain local versus long-range contributions to ground-level ozone. Satellite-derived data to assess NAAQS attainment remains hypothetical, even for the relatively robust annual average PM2.5 data product.

With the growing contribution of wildfires to air quality, there is a need to consider both aerosols and gas molecules in plumes, which can be advanced by combining multiple retrieval products (e.g., Jin, Fiore, and Cohen 2023). One major obstacle to this approach is the interference of aerosols, both in terms of impact on AMF (discussed above in “Trace gas instruments and retrievals”) and in determining gas retrievals like NO2 and HCHO (Jung et al. 2019). Development of combined gas and aerosol retrievals holds the potential to inform air quality across pollutants, and to better reflect emissions and atmospheric processes affecting the chemical environment.

By continuing to explore and evaluate applications of satellite data, the air quality management community can better leverage the billions of dollars invested in space-based instruments and science. Two-way dialogue between researchers and practitioners offers a pathway to increase the value of satellite data to air quality management and to co-develop new solutions for monitoring, managing, and improving clean air around the world.

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