Satellite-derived air quality data can effectively support health needs when use cases, Earth observing capabilities, and capacities align

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Abstract

Advances in Earth observation (EO) remote sensing technologies have delivered a range of aerosol and trace gas pollution data with ever-improving spatial and temporal resolution, significantly benefitting assessments of global air quality (AQ). Furthermore, the application of data synthesis techniques incorporating satellite EO with other information sources has improved the availability of satellite-derived estimates of pollutant exposure at local to global scales. These data have been applied to address a diversity of use cases in AQ monitoring and public health, from long-term trend tracking, exposure assessment, and epidemiological analysis to short-term emissions identification and early warning. Successful application of satellite EO to address AQ and AQ-related health problems requires an alignment between (1) the technical capabilities of satellite data to provide relevant information, (2) a defined case for using this information to address a particular need, and (3) the human capacity, computational resources, operational plans, and policy and governance frameworks to implement a solution and take action, and to sustain the solution for as long as the need remains. Only when there is substantial alignment across all these factors can satellite EO information be effectively translated into public health benefits. This paper surveys applications of satellite EO to AQ assessment and AQ-related health management globally, synthesizing key commonalities into recommendations for how satellite EO can effectively support health needs. We also identify gaps in current satellite EO capabilities, use case applications, and feasibility factors where future research and investment could reduce barriers to increased application of satellite EO to address pressing public health concerns related to AQ worldwide.

Keywords

- Air Quality
- Public Health
- Remote Sensing
- Respiratory Health

Introduction

Poor air quality (AQ) is estimated to be responsible for nearly 8 million premature deaths worldwide annually, making it one of the leading public health challenges today (Murray et al., 2020; HEI, 2025). Management of AQ and its associated impacts on human and environmental health requires detailed data, especially on the concentrations of key air pollutants such as particulate matter (PM) and trace gases such as nitrogen dioxide (NO_2), sulfur dioxide (SO_2) and ozone (O_3), as well as supporting information such as the identification of emission sources of these pollutants or their precursors (Vahlsing and Smith, 2012; WHO, 2021, 2025; Taha et al., 2025). Unfortunately, such information is not systematically available on a global scale, leading to gaps in understanding the status and impacts of AQ and limitations on making effective decisions regarding its management and mitigation (Hasenkopf et al., 2023; Shairsingh et al., 2023). In the 21st century, satellite-derived information has emerged as a key tool in addressing this limitation.

This paper builds upon previous work which has assessed the current state and future outlook of the use of satellite remote sensing data for AQ and related health applications. Engel-Cox et al. (2004) present some of the earliest assessments of use cases for satellite data in supporting air quality management decisions, identifying several promising missions and applications, while identifying barriers such as a need for cross-disciplinary expertise and dedicated resources and funding to promote the needed collaborations developing such expertise. The US National Aeronautics and Space Administration (NASA) Air Quality Applied Sciences Team (AQAST) undertook dedicated projects to develop such cross-disciplinary capacity; the impacts of this team on facilitating the use of remote sensing in air quality management are summarized by Milford & Knight (2017). Despite such efforts, Potts et al. (2024) still identified the lack of cross-disciplinary expertise and constraints on time and funding to develop such expertise as key barriers to the use of satellite data for air quality regulation in the UK context. Technical limitations of satellite data, especially low spatial resolution, were also perceived as key barriers. Related to such satellite capabilities, Hoff & Christopher (2009) provide a survey of early work in the application of satellite remote sensing to study AQ, with a particular focus on the estimation of fine particulate matter concentration ($PM_{2.5}$) from satellite-derived Aerosol Optical Depth (AOD) and the applicability of such measurements. They also emphasize that remote sensing should be considered as one element of an Earth observation (EO) system combining these with in-situ measurements and modeling efforts. Duncan et al. (2021) discuss how satellite data and related information (e.g., satellite-informed AQ forecasting models) can be integrated into the operational work of AQ managers and forecasters. He et al. (2025) provide an overview of the technical capabilities of satellite remote sensing and its implications for modeling and data assimilation of air-quality-relevant atmospheric constituents, with a focus on new geostationary satellite capabilities. Holloway et al. (2025) focus on the use of satellite data in the USA in support of the country's Clean Air Act, mainly for conducting health risk assessments, assessing emissions, and tracking AQ trends. We integrate insights from these previous surveys with additional evidence from a global context and assess both the factors leading to success in these AQ and related health applications of satellite EO, as well as outstanding issues and challenges which have hindered success, and thus provide opportunities for future effort.

In this paper, we seek to summarize not only what is possible (or not) in the application of satellite-derived data to health needs and decision-making, but to identify the fundamental elements which are necessary in such a successful application. Our assertion, as illustrated in Figure 1, is that this success derives from an alignment of three basic elements: (1) the technical capabilities of satellites and satellite-derived data, including scientists producing these data, to provide certain information; (2) a defined case for the use of this information to address a particular need; and (3) the financial, institutional, and human capacity to implement a solution, to take action based on that solution, and to sustain the solution for as long as the need remains. Only when these elements are aligned is it possible for satellite-derived AQ data to effectively support health needs. Throughout this paper, we include sets of guiding questions to help the reader assess whether their AQ and related health question or application might be amenable to a solution involving satellite EO data. We also revisit these guiding questions in the supplemental material for this paper, which includes responses to the questions related to each of the paper's three featured case studies.

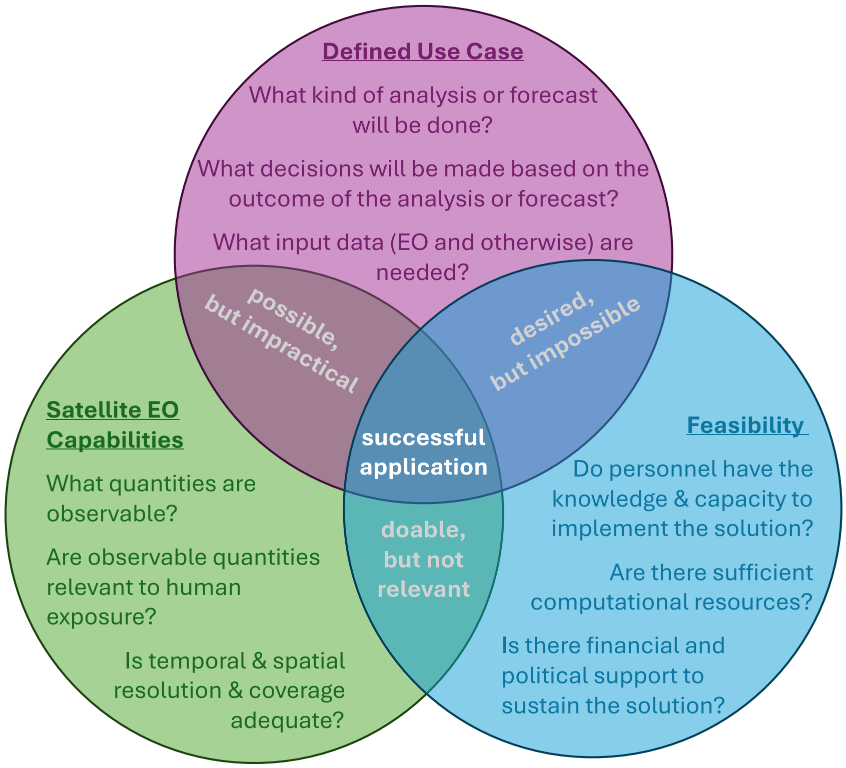

Figure 1. When technical capabilities, defined use cases, and feasibility considerations are aligned, satellite EO data can be successfully applied to health and AQ decision-making needs.

Satellite Earth Observation Capabilities to Support Air Quality & Health Decision-Making

Several remote sensing instruments aboard Earth-orbiting satellites have the capacity to measure the abundance and properties of atmospheric pollutants, including aerosols and certain trace gases. This section summarizes current capabilities in this area, emphasizing commonly used instruments and datasets, though it does not represent an exhaustive list.

Basic Features of Satellite EO

Satellite EO of air-quality-relevant quantities involves measurements of the electromagnetic (EM) spectrum and the inference of the presence and concentration of air pollutants based on their spectral characteristics. A retrieval algorithm translates this spectral data into physical quantities, e.g., the concentration of a certain gas. Satellites measuring in different realms of the EM spectrum allow retrieval of different atmospheric constituents. Satellite orbits influence where and when observations can be made. Polar-orbiting satellites in low Earth orbit (LEO) typically provide full global coverage, revisiting a given location every 1-2 days (around the same local time); these platforms thus provide wide spatial coverage at the expense of less frequent observations. Conversely, satellites in geostationary Earth orbit (GEO) occupy a fixed position relative to the Earth's surface, offering more frequent observations (e.g., every hour during the day). For a summary of satellite missions based on their temporal and spatial resolutions and spectral ranges (determining their ability to remotely sense aerosols and/or trace gases), see Figure 1 of Kim et al. (2020), with an update in Figure 1 of He et al. (2025).

A key determinant of satellite sampling is whether instruments are passive or active. Passive remote sensing instruments rely on illumination by the sun to make measurements, and therefore provide daytime-only information in most cases. Clear-sky conditions (i.e., with minimal cloud or smoke cover) may also be required. Active remote sensing instruments provide their own illumination, widening the range of conditions under which observation is possible, but power limitations typically restrict these observations to small spatial footprints at nadir (i.e., directly below the sensor). This small spatial coverage increases the time between observations for any given location, as the satellite must complete many orbits before passing over the location again.

Passive satellite data are retrieved as either slant (or nadir) columns rather than direct near-surface concentrations. Slant column densities are dependent on the satellite instrument's viewing angle, i.e., its orientation relative to the sun and surface at the time of retrieval. Slant columns differ from vertical columns as the vertical column is the nominal amount of the target pollutant above a point on the surface whereas the slant column is the entire path through the atmosphere. Slant column densities are converted to vertical column densities using air mass factors during the satellite data retrieval process. Assumptions about the air mass factor can introduce uncertainties in reported vertical column values. Limb sounding is an important area of research where this difference in optical path length is used to generate high resolution vertical profiles which allow some disaggregation by altitude. Retrieval accuracy and near-surface sensitivity depend on a number of factors (see Bormann, 2017 for an overview). As a result, translating satellite-derived column quantities to surface concentrations or exposure metrics typically requires models and/or data fusion with ground observations (see below).

Each satellite mission undergoes a process of spectral calibration for its instruments, development of retrieval algorithms for extracting observable quantities (e.g., concentrations and properties of aerosols and trace gases) from the spectral data, and validation of these retrieved quantities with independent data from other satellites, ground-based measurement, and-or airborne instruments. Assessments of uncertainties in retrieved quantities, along with recommendations for quality control and quality assurance of the data (e.g., filtering out cloud-contaminated pixels or other anomalous data), are generated as part of this quality control process, and published in guidance documentation accompanying the datasets. Further processed or derived products are also produced from the basic satellite information, e.g., aligning data to a common latitude-longitude grid or averaging data across days or months. The capabilities and uncertainties in satellite-derived datasets result from the instruments' technical capabilities and the retrieval algorithms applied to data collected by the instruments, both of which involve the expertise of large groups of scientists and engineers working together. In the following sections, we describe common attributes and challenges of the retrieval of aerosol and trace gas information from satellite data and list commonly used instruments and retrieval products.

Aerosols

The optical properties of aerosols make them amenable to remote detection by satellite instruments (Hsu et al., 2012; Zhang et al., 2025). Typical remotely sensed aerosol optical properties include: Aerosol Optical Depth (AOD), a measure of the total amount of light blocked by aerosols; Angstrom Exponent (AE), a measure of how this light blocking varies as a function of wavelength; and UV aerosol absorption index (UVAI), a measurement of how much UV light is absorbed versus reflected by the aerosols (Kahn and Samset, 2022). From these remotely sensed quantities, methods have been developed to estimate air-quality-relevant parameters, such as PM surface concentration, relative abundance of finer or coarser particles, and likely classification of aerosols into broad types, e.g., smoke versus dust (e.g., Scagliotti et al., 2024).

Remote sensors on LEO satellites facilitate global aerosol studies and can achieve insights in otherwise data-sparse regions. Common LEO sensors used for these purposes include the NASA Moderate Resolution Imaging Spectroradiometer (MODIS), Multi-angle Imaging Spectro-Radiometer (MISR), and the USA National Oceanic and Atmospheric Administration (NOAA) Visible Infrared Imaging Radiometer Suite (VIIRS). It should be noted that the satellites mounting MODIS and MISR are nearing the ends of their operational lives and will be decommissioned. GEO satellites used for regional aerosol tracking include the NOAA Advanced Baseline Imager (ABI), Japan Meteorological Agency (JMA) Advanced Himawari Imager (AHI), and European Space Agency (ESA) Flexible Combined Imager (FCI), covering the Americas, East Asia, and Europe/Africa respectively (Choi et al., 2019). These allow for near-continuous observation of rapidly evolving aerosol plumes, such as wildland fire smoke and wind-blown dust.

The passive sensors discussed above provide minimal information about the vertical distribution of aerosols. Furthermore, although recent efforts have enabled nighttime AOD retrieval from passive sensors under certain conditions, the use of nighttime AOD is far less prevalent than daytime-only AOD products (Zhou et al., 2021). Active remote sensors, such as NASA and the French Space Agency's CALIPSO mission and the ESA/Japan Aerospace Exploration Agency (JAXA)/ National Institute of Information and Communications Technology's Earth Cloud, Aerosol and Radiation Explorer (EarthCARE) satellite mission (Wehr et al., 2023), launched in 2024, can probe this vertical distribution of aerosols, day or night, assessing whether or not they impact near-surface AQ (Toth et al., 2019).

Biological aerosols (or bioaerosols) are a class of particulate matter derived from animals, plants, fungi, or bacteria (both live and dead). Examples such as pollen and mold are especially relevant for public health. Yet, they remain difficult to track across large spatial domains since surface measurements of bioaerosols are extremely limited and it is difficult to disentangle bioaerosols from other aerosol types using observed properties (e.g., AOD). Limited studies have used optical properties (which might be satellite derived) to infer pollen concentrations with varied success (e.g., Bohlmann et al., 2019, 2021; Renard et al., 2022). For example, pollen is often irregularly shaped, and so, like dust, the particulate depolarization ratio (PDR) can be used to identify pollen (e.g., Sicard et al., 2016, 2021). For example, satellite aerosol optical properties including the PDR from the CALIPSO CALIOP instrument have been used to improve pollen emissions estimates in models (Subba et al., 2021). Paired with a machine learning (ML) algorithm and surface lidar measurements, Zhang et al. (2026) used CALIPSO to estimate pollen concentrations across the United States. The CALIPSO mission ended in 2023, though NASA's Plankton, Aerosol, Cloud, Ocean Ecosystem (PACE) satellite launched in 2024 and provides aerosol depolarization properties (Werdell et al., 2019). However, unlike CALIPSO, PACE does not provide vertically resolved information. EarthCARE could help to fill in this information alongside surface lidars or other ML algorithms.

Satellite detections of fires and measurements of fire radiative power (FRP) are an important piece of information to inform smoke transport forecasting, risk assessment and early warning. Operational wildland fire forecasting models heavily rely on FRP detections from MODIS, VIIRS, ABI, AHI, FCI, or other comparable instruments as input for plume injection models and emission estimates. However, localized events, such as small prescribed burns (<0.04 km^2), often go undetected due to coarse satellite resolution or viewing angle constraints. While some methods such as fire plume height modeling expand capabilities, gaps in observational thresholds remain (Singh et al., 2025), and reliance on localized ground-based systems, fire reports and permits, or regional modeling frameworks continues to be necessary.

Trace Gas Pollutants and Ozone Precursors

Satellite instruments making measurements in the UV, Visible, and Near-Infrared portions of the EM spectrum can be used to retrieve atmospheric column concentrations of several trace gases relevant to AQ, such as NO_2, SO_2, CO, and ammonia (NH_3), as well as formaldehyde (HCHO) and glyoxal (CHOCHO) which can provide supporting evidence for recent volatile organic compound (VOC) releases. Across all gases, retrievals make use of prior information about the vertical distribution of gases in the atmospheric column, captured in the air mass factor used. Uncertainties in these air mass factors translate into uncertainties in the retrieved products and can make the separation of stratospheric and tropospheric contributions challenging for certain gases. LEO satellites commonly used for studying trace gases include the NASA Ozone Monitoring Instrument (OMI; Levelt et al., 2006), the NOAA Ozone Mapping and Profiler Suite (OMPS; Flynn et al., 2014), the ESA TROPOspheric Monitoring Instrument (TROPOMI; Veefkind et al., 2012), and more recently PACE (NASA Ocean Biology Processing Group, 2026). It should be noted that the satellite mounting OMI is nearing the end of its operational life and will be decommissioned. Recently-launched GEO instruments such as NASA's Tropospheric Emissions: Monitoring of Pollution (TEMPO; Chance, K. et al., 2025) over North America, the South Korean National Institute of Environmental Research's Geostationary Environment Monitoring Spectrometer (GEMS; Kim et al., 2020) over East Asia, and ESA's Sentinel-4 (Kolm et al., 2017) over Europe and North Africa provide hourly atmospheric composition measurements throughout the daytime. At present, dedicated geostationary air-quality missions are concentrated in the Northern Hemisphere, leaving most of the Southern Hemisphere without GEO coverage for trace gases.

The short chemical lifetime of NO_2 leads to it being more concentrated near its sources in the lower atmosphere, making satellite NO_2 columns more informative for diagnosing near-surface pollution patterns in urban areas. Thus, NO_2 columns from satellites, together with modeling tools, simultaneous aircraft measurements, surface observations including lidar (light detection and ranging), have been applied to study NO_2 concentrations and fluxes as well as their spatial, interannual, (intra)seasonal, and day-to-day variability (e.g., Boersma et al., 2009; Russell et al., 2012; Bechle et al., 2013; Geddes et al., 2016). Satellite NO_2 has further been used to identify urban pollution due to fossil fuel combustion, such as truck idling and activity near warehouses (Kerr et al., 2024) and to quantify urban fossil-fuel-related emissions (Liu et al., 2024).

There is a higher concentration of O_3 in the upper compared to the lower atmosphere due to continuous O_3 production in the stratosphere (known as the Chapman cycle). Due to these high concentrations in the upper atmosphere, satellite observations of the total O_3 column are rarely sensitive to changes in near-surface concentrations, which is the most relevant altitude for AQ impacts. Thus, studies of O_3 pollution using satellite data have pursued other avenues, especially using satellite data on NO_2 and HCHO to categorize the chemical regimes which influence O_3 production as a secondary pollutant (e.g., Martin et al., 2004; Duncan et al., 2010; Jin et al., 2017, 2025; Jang et al., 2020; Souri et al., 2023, 2025). Such information can inform decisions about which pollutant control strategies are most likely to reduce O_3 pollution formation. A product for near-surface O_3 from TEMPO is under development and shows promise in overcoming O_3 measurement challenges, but is still at a "beta" stage (Liu, 2025).

Satellite retrievals of CO, with its longer lifetime, can be used to trace long-range pollutant transport (Marey et al., 2024). As the signature of CO extends into the infrared portion of the EM spectrum, which is emitted by Earth at night, retrieval of CO during nighttime satellite passes is also possible, though these are less sensitive to lower tropospheric CO than daytime data (Deeter et al., 2007; Ho et al., 2009). SO_2 is also measurable by satellite data, and has been applied to identify and quantify large emission sources such as volcanoes, coal power plants, and smelters (Fioletov et al., 2023); hyperspectral GEO instruments such as TEMPO show promise for more frequent volcanic plume monitoring (C. Li et al., 2025).

Besides these, instruments like the ESA Infrared Atmospheric Sounding Interferometer (IASI), NOAA Cross-track Infrared Sounder (CrIS), and NASA Tropospheric Emissions Spectrometer (TES) provide detections of NH_3, a key aerosol precursor. Significant recent progress has been made in quantifying NH_3 point-source emissions using satellite & aircraft remote sensing data (Van Damme et al., 2018; Clarisse et al., 2019; Noppen et al., 2023; Balasus et al., 2026). Anthropogenic and biogenic VOC emissions, an important driver of O_3 and aerosol formation, are largely under-monitored by current satellite EO systems, with only HCHO being routinely available from several sensor retrievals (Cady-Pereira et al., 2017; Huang et al., 2017; Nair and Yu, 2020).

Understanding Column vs. Surface Relationships with Modeling and Data Fusion

A key challenge to actionable insights from satellite data lies in the translation of retrieved column quantities to near-surface concentrations. At one extreme, an erroneous assumption that satellite column measurements (e.g., tropospheric integrated values) can be used as a direct proxy for human exposure will lead to incorrect conclusions. At the other extreme, users may dismiss potentially valuable satellite-derived information because of this discrepancy.

Near-surface AQ information is typically derived from satellite information using data assimilation and/or data fusion techniques. Data assimilation refers to the incorporation of observational data from satellites and other sources (such as in-situ monitors) into a chemical transport model (CTM) to correct the model's biases and constrain its outputs. The resulting product, known as a reanalysis, offers a spatially and temporally complete dataset for the simulated parameters at the original CTM resolution. Global reanalyses including NASA's MERRA-2 (Gelaro et al., 2017) or the European Centre for Midrange Weather Forecasting's Copernicus Atmosphere Monitoring Service, CAMS (Inness et al., 2019) have been used to assess AQ (e.g., Ali et al., 2022). Data fusion refers to the combination of multiple data sources to generate additional derived products. For AQ, this typically involves combining CTMs, reanalyses, satellites, in-situ monitoring data, and/or explanatory factors such as meteorology and land use information using statistical or ML techniques (e.g., Mhawish et al., 2020; Malings et al., 2024; Tang et al., 2024; Choi and Hummel, 2025). Data fusion often provides output at a higher spatio-temporal resolution than available from a reanalysis, but may be limited by the availability of inputs to provide only local or regional information. Furthermore, both data assimilation and fusion approaches may exhibit systematic biases. In data assimilation, the quality of analysis fields can depend on the observation sampling strategy, the assimilation algorithm, and error specification (i.e., assumptions on relative error between the model and observing system). In data fusion, regional biases may arise from uneven distributions of calibration data, often better representing AQ in regions with extensive ground-based AQ networks, e.g., high income countries (HICs), where these techniques were developed and validated (Seo et al., 2025). This is a particular issue when trying to transfer approaches to assess AQ issues in low and middle-income countries (LMICs), especially at finer spatial scales.

A representative case is that of the estimation of $PM_{2.5}$ from remotely sensed AOD. Retrieval of AOD can be complicated over certain land covers, including urban areas. Further, deriving $PM_{2.5}$ from AOD relies on assumptions about aerosol typology and mixing heights, which in practice vary spatially and temporally (Gui et al., 2021; Zhu et al., 2023, 2024). Past research has used historical datasets of ground-level $PM_{2.5}$ and AOD and other covariates to derive a statistical relationship between the two (e.g., Gupta and Christopher, 2009). Other research has used CTMs to derive the relationship between surface $PM_{2.5}$ and AOD (e.g., van Donkelaar et al., 2015). Both approaches have been used at local to global scales, with promising results (Gupta et al., 2018; van Donkelaar et al., 2021; Park et al., 2025). However, most research validating the use of satellite-derived $PM_{2.5}$ has been conducted in HICs with a well-calibrated, extensive surface network. Bechle et al. (2023) have investigated discrepancies in different satellite-derived $PM_{2.5}$ products and have found generally good agreement. Other research in countries like India, with a limited ground-based network, has found significant differences between different products, especially in rural locations; in spite of these differences, however, research demonstrated significant associations between $PM_{2.5}$ and infant mortality in India regardless of the exposure product used (Dey et al., 2020; deSouza et al., 2022). A study across nine cities in LMICs found that a daily-averaged satellite-derived $PM_{2.5}$ product for the cities exhibited errors of 21% to 77% and could not reliably capture intraurban $PM_{2.5}$ variation (Alvarado et al., 2019). Promising work has attempted to combine data from low-cost sensors with satellite data to improve satellite-derived $PM_{2.5}$ estimates. Specifically, Malings et al. (2020) found that combining low-cost $PM_{2.5}$ concentrations in Kigali, Rwanda, with AOD from NASA's MODIS instrument reduced the mean absolute error in surface $PM_{2.5}$ estimates. deSouza et al. (2020) combined measurements from low-cost sensors in Nairobi, Kenya, with those from NASA's MISR and MODIS instruments to improve estimates of $PM_{2.5}$, and Kassandros et al. (2026) combined reference-grade monitors, low-cost sensors, and satellite data using ML methods to establish $PM_{2.5}$ burdens for Kampala, Uganda. Though more work is needed to validate satellite-derived $PM_{2.5}$ estimates for cities in LMICs, these products represent a readily available data source, and analyses involving multiple products can establish conclusions which are robust in the face of uncertainties across product methodologies.

Trace gas retrievals face similar challenges, requiring accounting for vertical mixing, atmospheric chemistry, meteorology, and boundary layer dynamics. CTMs are often used to provide such information, but even then, there can be highly non-linear interactions which complicate near-surface concentration estimations. Co-located surface and aircraft observations can be used for calibration and validation, as demonstrated in field campaigns such as DISCOVER-AQ and KORUS-AQ (Jassim Al-Saadi et al., 2022; DISCOVER-AQ, 2022). NO_2 columns tend to be relatively well-correlated with surface-level concentrations, which has facilitated deriving surface NO_2 concentrations and emissions from satellite data (e.g., Huang et al., 2014; Cooper et al., 2020). Conversely, the highly non-linear relationship between column and surface O_3 makes estimating surface O_3 from satellites more challenging; ML techniques are being increasingly applied to address these challenges (T. Li et al., 2025).

Overall, the estimation of surface-level AQ from satellite-derived data involves several sources of uncertainty. Satellite products come with retrieval uncertainties that must be carefully incorporated into downstream analyses, and the downstream analyses often involve assumptions or bringing in additional data sources which introduce further uncertainties. Robust quantification of these uncertainties is necessary to understand which use cases these satellite EO data may be suitable for. Finally, multiple derived products may be developed based on different input datasets, integration methodologies, and product use goals, leading to potential confusion about which products may be suitable for which regions, pollutants, or applications. All these factors mean that subject-matter expertise continues to be necessary for appropriate application of satellite-derived AQ data products. Improving standardization, documentation, and user familiarization with these products and their nuances is thus a promising area for future work.

Guiding Questions for Identifying Suitable Satellite EO Capabilities - answering these questions can guide identifying suitable satellite EO capabilities for a particular application.

- What are the pollutant(s) of interest to be observed? If the pollutant is not (yet) observable, is there an observable proxy for exposure?
- What is the domain of interest (e.g., global, national, province, city)?
- What is the necessary spatial resolution (e.g., national or regional gradients, city-scale patterns, neighborhood hotspots)?
- What is the time period of interest (e.g., range of days, weeks, months, years)?
- What is the necessary temporal frequency of the data (e.g., annual, monthly, daily, hourly)?
- What is the required latency, i.e., how rapidly after-the-fact are the data needed?
- Is spatially and/or temporally complete information required (which may necessitate gap-filling satellite data or using derived products), or are intermittent observations sufficient?
- What is the acceptable level of uncertainty in the data? Are absolute concentration values (e.g., $\mu g/m^3$, ppm) needed or is relative information (e.g., patterns, trends, anomalies) sufficient? What specific decisions will inform the acceptable uncertainty (e.g., is concentration above or below an exposure threshold)?

Use Cases for Earth Observations in Air Quality & Health Decision-Making

The applications of satellite EO to AQ and health decision-making typically fall into two broad categories. The first category is strategic, where decisions are made across multiple years or decades, usually involving policy changes. The second is operational, where decisions are made closer to near real time in reaction to specific situations. The strategic category encompasses long-term planning and mitigation decisions, and includes use cases such as quantification of pollutant-health relationships, prioritizing AQ management strategies and assessing their efficacy, or mapping population exposures to air pollutants to support epidemiological analysis and health impact assessment. The operational category encompasses short-term response and adaptation decisions, and usually includes forecasting or "nowcasting" of pollutant concentrations and their potential health impacts to support public awareness, early warning, short-term management activities such as issuing no-burn advisories, and individual choices about how to respond to potentially unhealthy AQ. The following sections present a survey of applications across these use case categories, though they do not represent an exhaustive list.

Strategic Use Cases: exposure, epidemiology, health impact, emissions, policy

There is a long history and a growing body of literature exploring the relationship between AQ and human health, utilizing satellite-derived AQ products (Holloway et al., 2021). Here, we summarize 34 peer-reviewed articles, reports, and tools since 2010, collected by members of the GEO Health Community of Practice Air Quality Work Group. Work group members were asked to nominate papers for inclusion in the review based on geographic diversity and relevance to respiratory health or air quality management decision-making. Some work group members made use of AI search and summary tools to suggest relevant materials; these references were independently evaluated by other work group members to ensure accuracy of AI-generated summaries. Together, the materials reviewed here highlight an applied pipeline from satellite EO data to epidemiological evidence and health-impact insights. Geographically, these cases span multiple world regions, including the Americas (e.g., USA, Peru, Brazil), Africa, Asia (e.g., China, India), and Europe (Figure 2). Air pollutants studied range from $PM_{2.5}$, PM_{10}, NO_2, SO_2, CH_4, CO, to O_3, with $PM_{2.5}$ being the most referenced (Figure 3). The health outcomes examined include all-cause mortality (including mortality in infants and older adults), stroke, emergency room visits, etc. (Figure 4). They used satellite sensors, including MODIS, VIIRS, OMI, and TROPOMI (Figure 5). Please note that Figures 2–5 reflect only the studies included in this review and are intended to illustrate the diversity of satellite EO applications in air quality and health research. The distributions shown in these figures should not be interpreted as representative of the global EO–air quality–health literature, which is substantially larger and may exhibit different magnitudes in terms of geographic, thematic, and methodological patterns. Nevertheless, the major categories represented in these figures, including geographic regions, air pollutants, health outcomes, and satellite sensors, are broadly consistent with those reported in the wider EO–air quality–health literature.

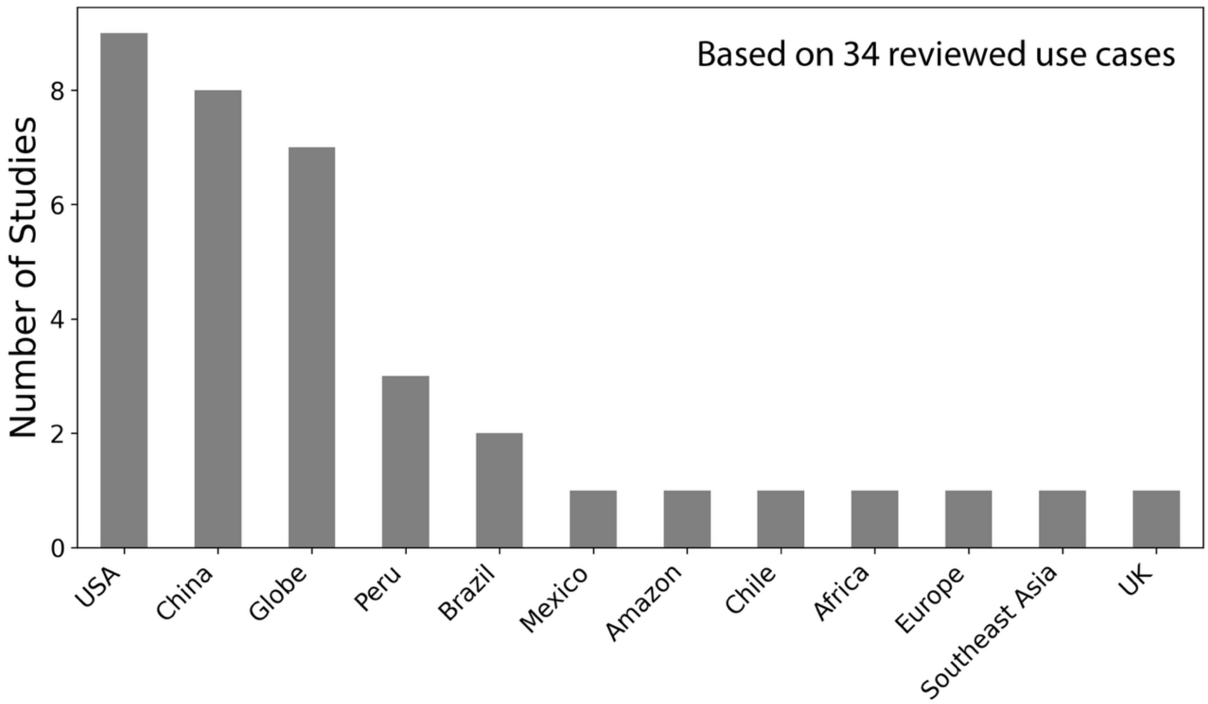

Figure 2. Countries/regions in the 34 selected satellite EO AQ and health use cases.

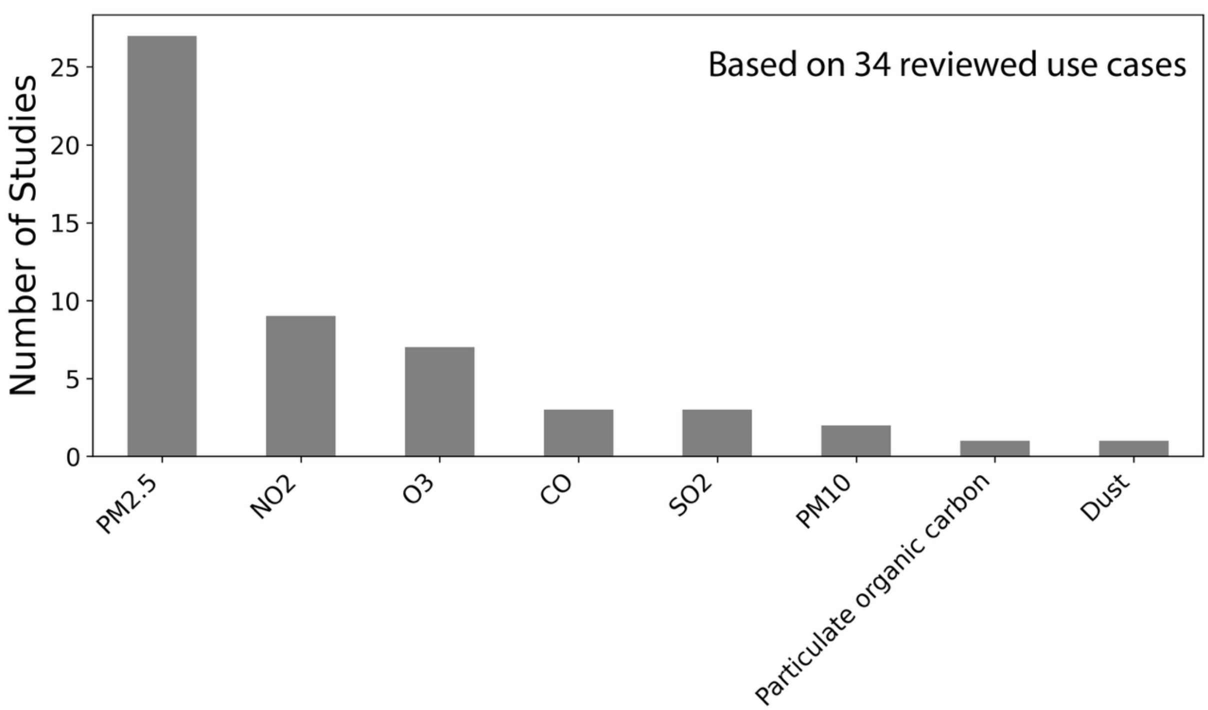

Figure 3. Air pollutants used in the 34 selected satellite EO AQ and health use cases.

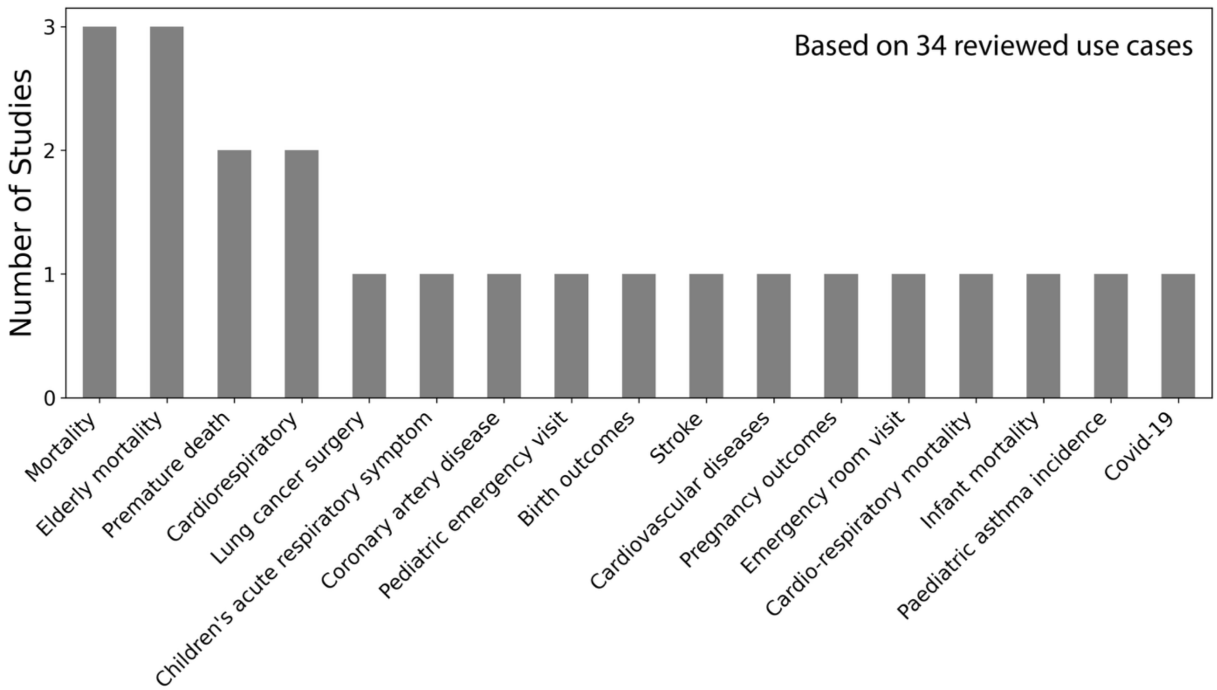

Figure 4. Health outcomes studied in the 34 selected satellite EO AQ and health use cases.

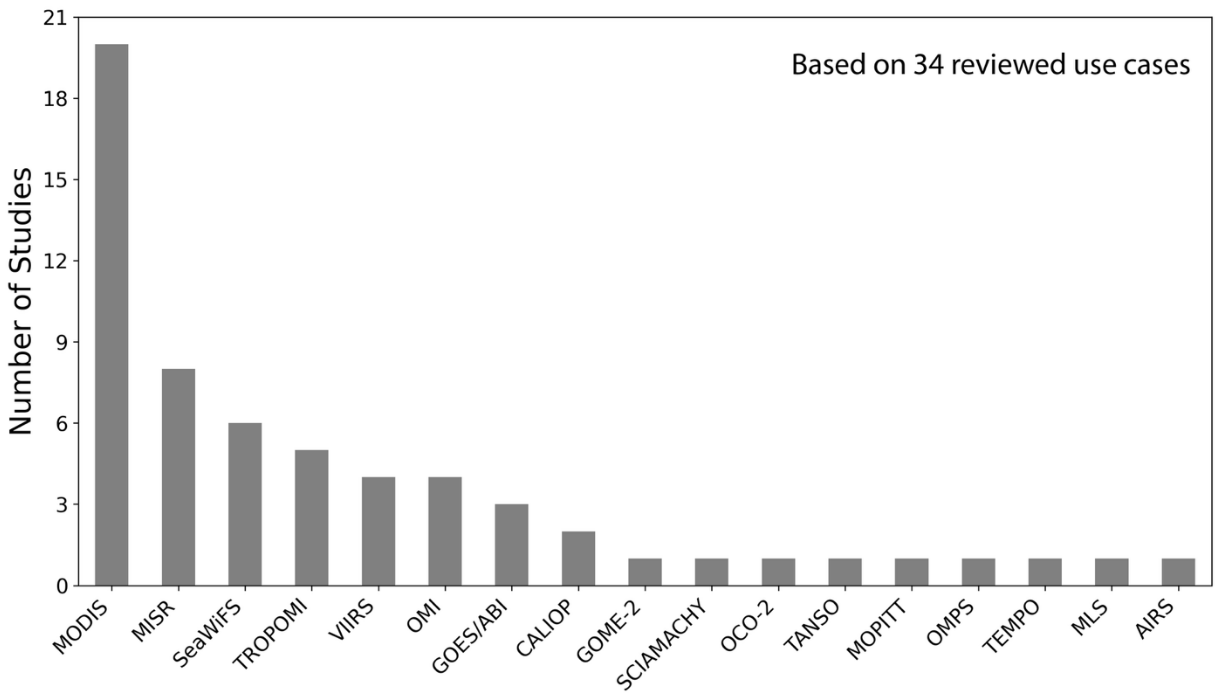

Figure 5. Satellite sensors used in the 34 selected satellite EO AQ and health use cases.

Exposure studies and findings depend on projects that fuse satellite products, e.g., AOD from MODIS via the Multi-Angle Implementation of Atmospheric Correction (MAIAC) algorithm, with CTMs (e.g., Goddard Earth Observing System and Chemistry, GEOS-Chem), and surface observations to generate spatially continuous estimates of $PM_{2.5}$ and other pollutants at sub-city to national scales. Shen et al. (2024) developed global, 1 km, monthly $PM_{2.5}$ exposure surfaces used in long-term epidemiologic and burden-of-disease analyses; daily products have also been developed using ML gap-filling techniques (Wei et al., 2023). Similarly, integrating MISR data with other information, Hang et al. (2025) produced daily particulate organic carbon concentrations across China at a spatial resolution of 10 km. Sablan et al. (2024) combined NOAA Hazard Mapping System (HMS) smoke plumes and fire hotspots with low-cost sensors in Kansas and Florida.

For epidemiological analyses, long-term studies leverage multi-year satellite-derived $PM_{2.5}$ to examine mortality, chronic disease, at regional, national, and global scales (Evans et al., 2013; Huang et al., 2019; Tapia et al., 2020). Requia et al. (2021) quantified cardiorespiratory admissions from wildfire $PM_{2.5}$ across Brazil 2008-2018 using MODIS and VIIRS fires detections and CAMS reanalysis $PM_{2.5}$, and found wildfire waves were associated with an increase of 23% in respiratory hospital admissions and an increase of 21% in circulatory hospital admissions. In studies of specific wildfires and prescribed fires, where events produce sharp $PM_{2.5}$ spikes, satellite EO data have been paired with time-series or case-crossover designs to estimate respiratory symptoms, emergency room (ER) visits, and other acute outcomes (Stowell et al., 2019; Requia et al., 2021; Zhang et al., 2023). Collectively, these studies illustrate a developing global exposure-to-health outcome pipeline for both acute and chronic research, with satellite EO essential for spatial completeness and temporal coverage.

Health impact assessments translate satellite-derived exposures into estimates of attributable disease burden, providing metrics that are directly relevant to decision-making (Ciarelli et al., 2019). A number of studies translated exposure and risk into estimates of mortality, especially for long-term $PM_{2.5}$ burdens (Evans et al., 2013; Li et al., 2018). The Global Burden of Disease project is a comprehensive effort to quantify health burdens of diseases, including non-communicable diseases such as those resulting from air pollutant exposures; the latest 2023 study makes extensive use of satellite EO data for assessing the health impacts of outdoor air pollution (IHME, 2025). A few studies explored the mortality and symptom burdens due to NO_2 (Achakulwisut et al., 2019; Huang et al., 2023). Some studies go beyond quantification to focus on risk communication. Gladson et al. (2022) developed a Children's Respiratory Health Index integrating satellite-based pollutant fields with pediatric epidemiologic data, producing an index that translates pollution into child-specific health risk messages for parents, schools, and public health agencies.

To further improve exposure and health outcomes, satellite EO data also can play a central role in improving emissions inventories of the pollutants that contribute to poor AQ (Streets et al., 2013; Holloway et al., 2025). TROPOMI data have been used to derive top-down NO_X emissions for two large power plants and three megacities in North America (Goldberg et al., 2024), and more recently for multiple US cities (Liu et al., 2024). Satellite data have similarly been used to develop emissions inventories for biomass burning CO (Griffin et al., 2024) and NO_2 (Griffin et al., 2021) and anthropogenic and volcanic SO_2 (Fioletov et al., 2023). These "top-down" emissions assessments complement "bottom-up" efforts, help fill spatial and temporal gaps, and support pollution control policy development and evaluation.

Finally, satellite EO data can play a part in the development and assessment of AQ management policy (Potts et al., 2021, 2024; Holloway et al., 2025). Satellite EO data can contribute corroborating evidence to establish trends (e.g., Dey and Chowdhury, 2022), global and regional disparities (van Donkelaar et al., 2010), identify emerging sources (Potts et al., 2021), site ground-based regulatory monitors (Puchalski et al., 2019), and assess the effectiveness of existing policies at regional scales (Lacey et al., 2017; Anenberg et al., 2020). While direct use of satellite EO data for regulation enforcement has not yet been applied, to the authors' knowledge, increasing satellite EO capabilities may make this a technically feasible option in the future, though political & legal considerations will be the deciding factor for this use case.

Operational Use Cases: near-real-time tracking, forecasting, public awareness

Operational satellite-based applications focus on near-real-time tracking, forecasting, and communication of AQ conditions to support rapid decisions by governments, health agencies, and the public.

During the COVID-19 pandemic, the Earth Observation Dashboard documented substantial NO_2 reductions across major cities through a multi-agency collaboration (NASA, ESA, JAXA), validating mobility restriction efficacy and demonstrating rapid AQ improvement potential when emission sources are reduced. NO_2 monitoring served as a proxy for adherence to social distancing measures, helping governments assess lockdown effectiveness in near real-time. The Tracking Air Pollution (TAP) project, based in China, is a regional dashboard that provides daily nationwide $PM_{2.5}$ maps at 10 km resolution by combining satellite data, ground-based observations, and CTMs. This system allows continuous tracking of $PM_{2.5}$ and supports epidemiological studies, long-term exposure assessments, and evidence-based policy interventions.

Public access to near-real-time information is usually supported by government and intergovernmental organizations. The World Health Organization (WHO)'s Air Pollution Portal synthesizes global observations for international health guidance, serving all WHO member states, with effectiveness establishing exposure thresholds and adoption among national governments. By integrating multiple data sources, the platform supports the establishment of exposure thresholds and encourages the adoption of evidence-based AQ policies.

The NASA Worldview platform provides open access to near-real-time satellite imagery and derived atmospheric products. It primarily serves users already familiar with satellite remote sensing data and available products, supporting near-real-time assessment and short-term forecasting of AQ. While it does not currently provide tailored health-risk messaging or structured outreach to vulnerable populations, the platform is well maintained and frequently updated with new datasets that could support health-focused applications.

Satellite-informed air quality forecasts are routinely available from global modeling and data assimilation systems such as the CAMS global atmospheric composition forecast or the NASA Goddard Earth Observing System Composition Forecast (GEOS-CF). While these forecasts can be used directly, there are also third-party forecast post-processing systems and user interfaces developed for these forecasting products to serve different user communities and use cases. A survey of such user-specific interfaces for GEOS-CF forecasts is provided by Malings et al. (2026).

The United Kingdom (UK) Department for Environment Food & Rural Affairs (DEFRA) Air Quality System integrates satellite data with ground monitoring to support over 300 local authorities, covering 67 million people, including well-defined vulnerable groups, with strong evidence for integration with the UK National Health Service. This includes a statutory mandate for adoption with extensive user engagement, robust expertise and validated products, and 30 years sustained future government funding.

The Destination Earth (DestinE) Air Quality project addresses rapid AQ fluctuations associated with extreme weather. The platform integrates ML with EURopean Air pollution Dispersion-Inverse Model (EURAD-IM) chemistry transport modeling, enabling emission scenario testing. Demonstrator applications analyzed 2016-2018 episodes, providing agencies evidence-based intervention protocols. DestinE dust forecasting for the Barcelona area provides 72-hour forecasts of dust and particulate pollutants. Saharan dust intrusions contribute to PM_{10} exceedances exacerbating respiratory conditions. Forecasts enable 24-48 hour advance warnings for targeted health advisories and differentiation between controllable local sources and unavoidable natural dust transport.

Guiding Questions for Defining a Satellite EO Use Case - answering these questions can define the scope of a use case, helping clarify the satellite EO capabilities necessary to support it.

- What is the process or mechanism being investigated (e.g., respiratory health impacts of pollutant exposure, impacts of pollution control policies on emissions)? Over what spatial domain and timeframe is this process operating?
- Besides satellite EO information, what other input data are required (e.g., health records, demographic data)?
- Who is the output information being provided to? In what format will they need it? What will they be doing based on the information?

- Is this analysis only being performed once to inform a particular strategic decision, or will it need to be operationalized to support ongoing decision-making?
- Is there an existing tool or example for a similar use case which can be adapted?

Feasibility of Applying Earth Observations to Air Quality & Health Decision-Making Use Cases

Successful application of satellite EO to address AQ and health decision-making use cases requires that feasibility of the application be assessed to estimate what can plausibly be achieved. This requires consideration of available human capacity to understand satellite EO capabilities and interpret results, computational capacity to process EO data, institutional and financial sustainability to support the application long-term, and policy and governance for turning data into action (Kansakar and Hossain, 2016; Ifejika Speranza et al., 2023; KISS Continuity Study Team, 2024; Pabi, 2024).

Human Capacity Factors

Human capacity factors determine whether satellite EO data can be meaningfully applied to health-related decision-making (Kansakar and Hossain, 2016; Ifejika Speranza et al., 2023). While technical infrastructure and data access are essential, the feasibility of any use case ultimately depends on the skills, knowledge, and institutional continuity of the people involved. These capacities shape how data are interpreted, validated, and communicated to those who act on it.

Satellite EO data literacy represents the basic layer of capacity. It refers to the ability to understand what satellite instruments measure, how products are derived, and how their spatial, temporal, and algorithmic characteristics influence suitability for specific use cases. While awareness of satellite EO data availability and suitability is growing (e.g., Sorek-Hamer et al., 2016; Holloway et al., 2025), distinctions between platforms, sensors, and products remain opaque for many potential users. For health use cases, data literacy includes translating satellite indicators into forms that are compatible with exposure metrics, health risk assessment, and decision workflows. Without this interpretive capacity, satellite EO products may have limited relevance to operational health applications. This conceptual gap often leads to either overconfidence or undue skepticism. Strengthening literacy means building not only technical skills (such as accessing, preprocessing, and visualizing data) but also fit-for-purpose judgment: deciding when satellite EO products are adequate, when further validation is required, and what uncertainties must be communicated. Different capacities are needed by users who rely on derived tools or dashboards than from analysts who work directly with satellite data and validation workflows (Rosales et al., 2025).

In many LMICs, satellite EO analysis capacity currently resides mainly within academia or donor-funded projects. Government agencies often depend on short-term collaborations or external consultants, creating discontinuities once projects end. Conversely, some national agencies in HICs have technical teams where satellite EO processing is embedded into routine monitoring or policy assessment. A more systematic mapping of where such capacity exists, and where it is absent, remains an unmet need.

Initiatives such as NASA Applied Remote Sensing Training (ARSET), Copernicus Education, and GEO Knowledge Hub provide valuable training materials and open-access modules. Most of these resources are freely available online, including some multilingual resources (e.g., NASA ARSET Spanish-language material), but their reach remains uneven across languages, institutions, and professional sectors. For many potential users, English-only content and limited internet access remain barriers (Desservettaz et al., 2025). Locally adapted or translated materials, where they exist, are often project-specific or time-limited (Rosales et al., 2025). Establishing consistent, multilingual training pipelines would help close these gaps and facilitate equitable participation in health applications.

Furthermore, satellite EO products are predominantly developed, validated, and interpreted within atmospheric and remote sensing communities, while their potential users (e.g., epidemiologists, public health analysts, clinicians, etc.) operate within distinct domains. Interface capacity between science and policy refers to the ability to translate satellite-based insights into forms that are comprehensible and actionable for decision-makers. “Bridge” profiles (e.g., scientific translators, technical communicators, and data analysts) who interpret complex satellite EO outputs to policy frameworks or public communication formats, are often missing from institutional structures. Without such intermediaries, satellite EO applications remain confined to the research domain, with limited uptake in operational practice (Potts et al., 2024). Strengthening this interface requires institutional mechanisms for co-design and regular dialogue between data providers, scientists, and public-health authorities, such as targeted transdisciplinary training (Desservettaz et al., 2025).

Overall, sustained human capacity is not only a technical requirement but also a condition for the long-term sustainability of any initiative, ensuring that institutional knowledge, skills, and motivation persist beyond individual projects or funding cycles. High staff turnover and short-term funding cycles erode the institutional memory necessary to maintain EO-based processes (Yáñez-Serrano et al., 2022). Sustaining knowledge involves documenting workflows, providing mentorship for newcomers, and embedding satellite EO competencies into institutional mandates (for example, through national training programs, integration in university curricula, or long-term collaborations between agencies and academic centers). A motivated community of practice—spanning government agencies, academia, and civil society—can further reinforce this continuity, offering peer-to-peer learning and resilience as data sources, satellite EO capabilities, and health priorities evolve.

Computational Feasibility

A successful application of satellite EO to a health use case requires that the generation, processing and dissemination of outputs be computationally feasible. Feasibility hinges on three interconnected elements: access to input data, the software needed to transform those data into health-relevant products, and the hardware required to process, store, and distribute outputs (Ifejika Speranza et al., 2023). Furthermore, appropriate subject-matter expertise, as discussed in the previous section, is essential to bringing these elements together.

Access to input data is the starting point for computational feasibility, defining the required datasets (i.e., satellite data and supporting inputs, such as health, demographic, socioeconomic and meteorological data) and understanding how and where they can be obtained. This includes assessing whether data are freely accessible or subject to licensing or purchase costs, and requires domain knowledge of these datasets. Data accessibility can also change over time. The volume of the required data also affects feasibility, as larger datasets demand greater storage and processing capacity. In addition, satellite data are provided in a range of formats, making it important to assess in advance whether data will require preprocessing, reformatting, or conversion before use (Rosales et al., 2025).

For many applications, the core computational effort lies in the processing step to convert satellite EO data into health-relevant outputs. The complexity of this process can range from simple tasks such unit conversion, subsetting, or bias correction to workflows involving data assimilation or fusion, e.g., using CTMs, statistical interpolation, and/or ML. The required level of processing for a given application will depend on the characteristics of the specific satellite EO retrieval and the intended use. Developing custom workflows and code may require significant resources (including personnel with appropriate subject-matter expertise) to build and maintain. In addition to the main data processing pipeline, it is important to consider processes for ingesting and preprocessing of input data, including maintaining these pipelines over time as data sources change. Finally, outputs must be distributed to users, which can range from creating reports and graphics for a single decision-maker to interactive dashboards designed for broader public access. For public interfaces, it is also important to prepare for spikes in demand that may occur during air pollution events such as wildfires.

It is also necessary to consider the hardware required to run the proposed process, including processing power, memory and storage. A common decision-point is whether the workflow should be run on-premises (i.e., institutional servers managed locally) or "on the cloud" (i.e., remote computing services). The choice is highly dependent on institutional context, and may also be influenced by requirements for data availability and continuity of service (e.g., Chapter 10, WMO et al., 2024). In general, cloud platforms offer robust service-level agreements that reduce downtime associated with maintenance or unexpected outages. The frequency of analyses, the size of outputs and intermediate files, and the intended retention period for the outputs determine the storage requirements. Although not all details of the application may be fully defined at the outset, early clarification of key details is critical to plan computational requirements. These elements include the spatial and temporal domain and resolution, frequency of processing, number and type of input and output variables, algorithmic complexity, efficiency of software, and the intended mode of data distribution. Conducting an early test run using real input data, operational algorithms, and representative output formats can provide a practical baseline for processing time, memory needs, storage demands, and system stability.

Operational Sustainability, Policy, and Governance

For some strategic decisions, a one-time study may be sufficient — for example, using satellite observations to assess the impacts of a pollution control policy. However, other strategic decisions may require sustained data streams to support multi-year assessment and communication. For example, the American Lung Association has been analyzing AQ for over 26 years to support addressing air pollution, and recently explored the feasibility of adding satellite data to fill gaps for under-monitored counties (ALA, 2024). Most operational decision-making requires sustained data streams, analysis capacity and infrastructure that remain effective over longer periods. Often, transitioning from a pilot study or demonstration that proves value to an ongoing application or service requires hand off from an academic researcher or short-term contractor to government or other organization with the capacity or mandate to maintain a long-term service. Without a clear pathway for this handoff, promising pilot projects can wither (Pabi, 2024). Retaining human capacity can also facilitate the handoff (Gani et al., 2022).

For satellite EO to support AQ and health decisions, there needs to be a policy and governance framework through which these decisions are made and implemented. Ideally, products would be integrated with the institutions responsible for decision-making (KISS Continuity Study Team, 2024). In some jurisdictions, health decision-making may be separate from AQ decision-making, and either of these may be separate from data collection and analysis, which can complicate hand-off of data for decision-making. In the U.S., for example, NASA leads much of the research with satellite data, which in some cases is transitioned to operational agencies such as the CDC, EPA, and NOAA for longer-term management and to maintain public AQ data portals, such as AirNow (Bratburd et al., 2022). Many of these efforts have been led or coordinated through the Health and Air Quality Applied Sciences Team (HAQAST), a NASA-funded effort to transition satellite-derived products to support AQ applications in air quality management and public health, and a continuation of AQAST. Funding can often be a key representation of political support, and an enabling or limiting factor for maintenance of a service. One consideration is how funding models relate to the decision being made – if there is a specific source of funding, for example, through a tax on emitters, or if through a general fund for public health.

Changes in data availability impact sustainability. Data resources change, satellite products can be updated, and the satellites themselves may change as some missions end and new missions begin.

Likewise, ground-level data is often required to validate satellite data, which comes with their own operational costs.

Guiding Questions for Determining Feasibility - answers to these questions can help identify the necessary human capacity, computational resources, operational requirements, and governance structures to support a successful application of satellite EO data.

- Does your organization have personnel with the capabilities to implement the envisioned solution? If not, are there capability-building resources to draw upon, or can you call upon outside expertise?
- What is the accessibility, coverage, size, and format of required input data sets, including satellite EO data? Are there costs or restrictions for obtaining these (e.g., health data)?
- What computational processes will be conducted? What are the anticipated compute resource requirements for each run, and how frequently will the runs occur? What is the size of the output and corresponding storage needs, including need for long-term archiving?
- What sort of post-processing or user interface is required for the results? Will demands on the interface be stable or variable (e.g., many users needing access during a wildfire)?
- Who is responsible for performing the analysis and/or maintaining the data analysis system? Who will interpret the results? Who will take action based on the data output?
- What are the costs for set up and maintenance? How will the effort be funded, especially with long-term usage in mind?

Case Studies in the Application of Earth Observations to AQ-Related Health Decision-Making

This section presents three case studies illustrating how satellite EO capabilities were utilized to support specific AQ and health decision-making use cases, and assesses the feasibility factors that contributed to the implementation of each case. In the supplemental materials for this paper, the guiding questions presented in the preceding sections are addressed in the context of each of these case studies, illustrating how those key considerations influenced the approaches of each case study.

Case Study 1: Subcity Air Quality Forecasting Supported by Satellite Data

In this case, satellite EO data were used to improve AQ forecasts for Rio de Janeiro, Brazil. Forecasters in Rio have used data from several in-situ AQ monitors throughout the city, together with meteorological forecasts, to issue city-wide forecasts for the following day. Recently, additional location-specific AQ forecasts have been enabled by combining the in-situ measurement data with global CTM (GEOS-CF) AQ forecasts (Keller et al., 2021). However, these forecasts do not provide information needed to make decisions at smaller-than-city-scale, e.g., prioritizing hospital operations to anticipated health impacts in specific neighborhoods. Furthermore, siting of additional AQ monitors planned as part of Rio's sustainable development efforts requires understanding AQ patterns beyond the locations of existing monitors. These considerations motivated incorporating satellite EO data on pollutant spatial variability into local forecasts.

The specific requirement of this use case was to deliver intracity AQ forecasts for key pollutants (NO_2, O_3, $PM_{2.5}$, and PM_{10}) for the city of Rio and surrounding areas (about 9000 km^2) on an hourly basis. Low latency was essential; forecasts should be available at least one day in advance, but preferable 2 or 3 days out. Sufficient spatial resolution was needed to characterize intra-urban gradients; at minimum, this would be about 10 km, but ideally closer to 1 km. Key metrics such as spatial and temporal correlation and root mean square error would be used to assess forecast performance, verified using in-situ measurements. These metrics should meet or exceed the pre-existing baseline, i.e., the city-wide, daily forecasts based on the previous day's measurements.

While no operational forecast was identified which met these requirements, a method developed by Malings et al. (2021, 2024) could integrate multiple EO sources to provide the forecasts. For routine forecasting, this methodology would need to be integrated with live input data. Implementation was conducted using Google Earth Engine (GEE), which allowed using already established EO data streams and user interfaces, as well as accessing computational resources beyond those available locally. This facilitated relatively rapid implementation, testing, deployment and transfer of system operations to local users. One limitation encountered in terms of satellite EO data, however, was the lack of established methods for estimating PM_{10} concentrations from satellite data, leading to the desired PM_{10} forecasts not being implemented.

Regional technical capabilities and data availability also guided the implementation of this case. The forecast used globally available data from forecast models and polar-orbiting satellites; data from regional models and geostationary satellites, which might have improved performance, were not readily available for this region. Further, while in-situ data were available, certain measurements (particularly of $PM_{2.5}$) were limited, making evaluating key metrics like spatial correlation challenging. In terms of human capacity, this project combined foreign expertise (EO data integration and GEE implementation) with local expertise (Rio-specific data sources and AQ concerns). Local experience with diverse EO data was already relatively advanced, based on past institutional experiences, and was further developed through knowledge exchanges, especially transfer of the GEE system and associated technical guidance for ongoing operation by Rio personnel. This system has generated operational 3-day-ahead forecasts for Rio with an effective resolution of about 1 km^2 for $PM_{2.5}$ and 10 km^2 for NO_2 and O_3 since late 2025.

Overall, integration of satellite EO data allowed accounting for long-range pollutant transport and for forecasting AQ at locations without in-situ monitors, both of which would not have been possible with local data alone. Transition of this capability to sustained local operation was envisioned from the start of the effort, with GEE selected as the development environment to facilitate this transition. This has several advantages, noted above, but also incurs long-term service costs, which can be difficult to anticipate and may hinder long-term sustainability.

Case Study 2: A Multi-Source Earth Observation Framework for Air Quality Decision Support in SERVIR-SEA

Seasonal biomass burning across northern Thailand, Laos, and Myanmar produces some of the highest $PM_{2.5}$ concentrations observed globally. However, most of the affected population lives in rural or peri-urban areas where no ground-based AQ monitoring exists. Health agencies are therefore forced to respond to severe pollution episodes with limited situational awareness and minimal lead time, leaving outdoor workers, children, and elderly populations particularly vulnerable. The SERVIR Southeast Asia AQ Tracker was developed to address this health information gap by providing 5 km spatial resolution, near-real time $PM_{2.5}$ assessments and 3-day forecasts derived from satellite EO, global models, and ML. SERVIR was a US Government initiative designed to collaboratively develop EO-based decision support applications with international partners, which operated from 2005 to 2025.

Unlike existing city-level monitoring networks, a health-focused system had to capture cross-border smoke transport, valley-scale gradients, and rapid changes associated with new fires. To support health risk communication and risk reduction, forecasts needed to be spatially explicit (5-10 km), available with low latency (up to 3 hours), and validated against trusted reference measurements. These requirements were designed to enable early warning messages, guide decisions on school closures or advisories for sensitive groups, and reduce the burden on hospitals during extreme haze events.

Because no operational forecasting product met these spatial and temporal requirements, the AQ Tracker employed a combined EO–ML approach. A deep neural network corrected bias in CTM (GEOS-FP) $PM_{2.5}$ predictions using aerosol species, meteorology, and ground-level observations from Thailand's Pollution Control Department. A secondary convolutional neural network downscaled these corrected fields to 5 km, improving the representation of exposure patterns across rural communities, agricultural regions, and mountainous terrain where exposure varies dramatically over small distances. Atmospheric inputs from MODIS, VIIRS, and Himawari-8 AHI, along with GEOS-FP and MERRA-2 fields, provided the consistent regional information needed to characterize long-range smoke transport and day-to-day variability. The forecasts were operationalized through a cloud-based platform (https://aq-tracker-servir.adpc.net), ensuring accessibility for health agencies across Southeast Asia.

A major public health application of this system is its role in transboundary haze monitoring and forecasting across northern Thailand and Laos. The AQ Tracker provides a spatially consistent view of current conditions and short-term forecasts, allowing agencies to anticipate when pollution generated in one country will affect populations in another. By upscaling a Thailand-calibrated framework to data-sparse regions in Laos, the system supports early warning, coordinated communication, and regionally aligned health advisories, enabling a more effective response to transboundary haze.

Regional technical capabilities and data availability shaped potential applications. While Thailand has a robust $PM_{2.5}$ monitoring network, surrounding countries have few or no routine measurements, limiting the ability to quantify exposure and validate models in those regions. Satellite EO data played a particularly critical role in cross-border exposure assessment, enabling health officials to understand when pollution originating outside their jurisdiction would reach populated areas. Implementation required combining SERVIR's technical expertise in satellite EO data integration and ML with local expertise on haze season dynamics, health risk communication, and administrative procedures. Capacity building and code transfer ensured that partners at the Asian Disaster Preparedness Center (ADPC) and national health and environment agencies could maintain the system after deployment.

From a health perspective, the AQ Tracker provides clear benefits that would not be achievable with traditional approaches alone. It expands situational awareness into underserved regions, improves health advisory lead times, supports targeted protection of vulnerable populations, and reduces $PM_{2.5}$ exposure by informing burning restrictions. The system was deliberately designed to transition into routine use, leveraging cloud infrastructure for automation and scalability. While long-term sustainability will depend on reliable access to cloud compute resources and periodic model updates, the AQ Tracker demonstrates how EO-based AQ systems can become operational public health tools. It provides a concrete example of how satellite data, combined with local health priorities, can translate directly into reductions in human exposure and improved resilience to seasonal haze.

Case Study 3: Improving Outdoor Worker Health Using Earth Observation Data for $PM_{2.5}$ exposure risk

This study focuses on assessing $PM_{2.5}$ exposure risks for outdoor workers in Nebraska, USA, particularly during wildfire and prescribed burn events. These workers face heightened health risks from $PM_{2.5}$, which is linked to cardio-respiratory issues, especially for individuals with pre-existing conditions. The overarching goal is to enable timely operational decisions such as adjusting work shifts during poor AQ periods to reduce health risks and improve occupational safety.

To achieve this goal, specific requirements include high spatial resolution and a 1-6 hour temporal scale, capturing short-term exposure peaks aligned with work shifts and workplace locations. The requirements were informed by general and occupational health guidelines, as no specific $PM_{2.5}$ exposure limits currently exist for outdoor workers. This approach aimed to create shift-based exposure metrics that could guide scheduling strategies and health risk mitigation.

Regional infrastructure strongly shaped the application of satellite EO data here. Nebraska's limited ground monitoring network and reliance on low-cost Purple Air sensors primarily installed in urban centers, and the high cost to workplaces of fixed or personal $PM_{2.5}$ monitoring left rural workplaces under-monitored. This gap pushed the necessity of satellite EO integration for exposure assessment. The HAQAST MERRA-2 dataset, a data fusion post-processing of the MERRA-2 reanalysis, was selected because it provides hourly temporal resolution, gap-free coverage, and bias-corrected surface $PM_{2.5}$ estimates (Gupta and Sayeed, 2024). However, integration posed several challenges. The coarse spatial resolution (~50 km) hindered linking exposure metrics to workplace locations. It was found that accessing the full global-scale data to process and extract Nebraska-specific subsets required significant computational resources and relied on high-performance computing to efficiently accomplish. Finally, for such an interdisciplinary research study, GIS and remote sensing expertise is essential to integrate satellite EO data into the health workflow applications, which is often limited in occupational health settings. These challenges highlight that while satellite EO data offers powerful capabilities, feasibility barriers such as computational demands and need for remote sensing expertise must be addressed to enable broader adoption in occupational health decision-making. In future studies, improving spatial resolution to link satellite-derived exposure metrics to specific workplace locations and embedding EO-driven tools into routine occupational health assessments are key priorities. These efforts will be complemented by educational programs and awareness initiatives for workers and employers.

This case study demonstrates the potential of satellite EO data to address critical gaps in occupational exposure assessment, but also highlights practical challenges and barriers. By leveraging hourly, gap-free $PM_{2.5}$ estimates, satellite EO enables more accurate and timely evaluations of AQ risks for outdoor workers in regions with limited monitoring capabilities. While challenges such as refining spatial resolution and integrating it into existing health management remain, the approach lays a strong foundation for scalable, data-driven strategies that protect worker health and support informed decision-making.

Conclusion

The current status of satellite EO for AQ and health decision-making is characterized by significant advancements as well as notable gaps. Satellite EO data fills a key niche, supplementing in-situ monitoring in data-sparse regions and providing valuable context, particularly for dynamic pollutants such as smoke or dust. Regional inequities in observational coverage, limitations in deriving surface-level concentrations from column measurements, and insufficient case-specific validation and uncertainty quantification remain primary barriers to actionable insights for AQ management. Modeling frameworks and data fusion techniques, while essential, still face uncertainties in integrating satellite-derived products across multiple scales, and a lack of ground-based data for training and validation remains an important barrier.

Nevertheless, application of satellite EO data to diverse use cases across spatial and temporal scales has proliferated. This encompasses both operational cases, such as forecasting and early warning, and strategic cases, such as epidemiological assessment and emissions quantification. Most use cases we identify have relied on purpose-built solutions, with limited evidence of adaptability and transferability of workflows and solutions between regions or application domains. This may be related to the numerous feasibility barriers we have identified, including the lack of a systematic global effort to build EO data literacy and analysis capacity for AQ & health applications. This is compounded by the high computational resource needs of satellite EO data analysis, fragmentary and limited support for sustained operations, and unclear or absent policy and governance structures underpinning the application of satellite EO data to AQ management and health decision-making.

Below are several opportunities we identify to address technical gaps in satellite EO capabilities, systematically assess the suitability of these capabilities to specific use cases, and enhance the feasibility of applying satellite EO data to these use cases.

Satellite EO Capability Gaps and Future Opportunities

Recent expansion of hyperspectral imaging with missions like TROPOMI, GEMS, TEMPO, Sentinel-4, and PACE represents a transformative capability for AQ monitoring. Upcoming instruments may further improve the ability to separate aerosol components, detect hazardous air pollutants, and monitor precursor emissions with greater accuracy. Especially relevant is the Multi-Angle Imager for Aerosols (MAIA), a joint mission of NASA and the Italian Space Agency with an explicit public health focus, anticipated to launch in 2027. MAIA aims to provide speciated PM datasets across several global target regions, contributing to global health studies linking outcomes with specific speciated PM exposures (Liu and Diner, 2017). Additionally, advances in combined use of multisensor EO data, such as the integration of soil moisture with precipitation and atmospheric composition datasets, could transform the monitoring of dust, pollen, biogenic VOCs, and other environmentally-driven pollutants (Huang et al., 2015, 2022, 2025). Small satellite (SmallSat) constellations also present new opportunities by enabling distributed, high-resolution monitoring at lower cost. These systems are potentially adaptable to track localized AQ issues, such as urban emissions or agricultural fires, which remain poorly resolved with larger satellite systems.

Accurate characterization of diurnal pollutant trends and their health impact remains an unmet need globally. Higher temporal resolution can be achieved with GEO satellites, but despite significant progress, regional inequities in their coverage remain a major challenge. For example, while GEMS, TEMPO, and Sentinel-4 are providing high temporal resolution monitoring of trace gas pollutants over East Asia, North America, and Europe, vast regions of the Global South, notably Sub-Saharan Africa and South America, lack similar capabilities. This absence restricts comprehensive tracking of dynamic AQ events, limiting the ability to identify and mitigate pollution sources in these regions. Proposals for future GEO satellites targeted at the Global South highlight the needs and current plans to expand satellite EO infrastructure to address these gaps (Omar et al., 2025).

Additionally, latency in delivering near-real-time satellite EO data can reduce their efficacy. Real-time observation is especially critical for high-impact events such as wildfires or industrial pollution episodes. Use of ML techniques to reduce data processing times, as well as improved space-to-earth communications, may reduce this latency in the future.

Finally, there is a persistent need to support and expand surface-based data collection and real-time reporting, considering their importance for calibrating and validating any application of EO data (e.g., Scagliotti et al., 2024). While satellite EO data cannot replace surface-based information in AQ applications, it can complement these data by expanding spatial coverage, as well as help indicate gaps where additional surface-based measurements are most urgently needed.

Gaps in Use Case Meta-Analysis

A key challenge across applications is matching use case requirements to "fit-for-purpose" satellite EO data, considering data uncertainties, availability, and limitations. While certain datasets and products have become widely used across similar use cases, this appears to have largely been the result of "momentum" behind particular datasets in specific user communities, rather than a systematic effort to match capabilities with requirements. This has become a concern for aging satellite missions; e.g., aerosol data based on the MODIS instruments continues to be widely used, despite these instruments nearing the end of their operations, while use of similar data from the successor VIIRS instruments remains less prevalent, even in recent studies. Thus, resources are needed to support users in transitioning their applications to use newer missions or data products. Potential resources include training materials such as the ARSET "MODIS to VIIRS Transition for Air Quality Applications" training, multi-mission continuity data products such as those produced through the NASA MEaSUREs program, and user support groups and communities of practice such as the HAQAST "Ensuring Continuity Across Satellite Transitions" 2026 tiger team activity. While no single comprehensive continuity plan or resource across all missions and data products is yet available, a systematic analysis of use case needs may allow for more pro-active identification of suitable EO datasets, including transitions from older to newer products where appropriate.

Significant opportunities exist for meta-analysis of satellite EO use cases in AQ and health decision-making. Such meta-analyses can supply quantitative evidence supporting the applicability of satellite EO for specific cases, to specific health or pollution control challenges, and in specific regions. We identify opportunities for (1) formal evaluations quantifying changes in health outcomes attributable to warning systems, demonstrating actual reductions in emergency visits or mortality due to the use of satellite EO data; (2) regionally specific health assessments examining the benefits of satellite EO-based health decision support systems; and (3) integration studies demonstrating how satellite monitoring complements ground networks. Future work by the authors will examine the application of public health intervention assessment frameworks such as Reach, Effectiveness Adoption, Implementation, Maintenance (RE-AIM) to assess case study examples of the application of satellite EO to health decision-making.

Overcoming Barriers to Feasibility

For human capacity factors, a key barrier remains the availability of regionally specific capacity-building resources in multiple languages which can build satellite EO literacy across a range of user groups. Capacity building resources supported by international organizations and global user communities for sharing knowledge and skills remain important tools for addressing this gap.

As the flexibility and trustworthiness of generative AI tools continue to improve, they may become increasingly useful for addressing challenges and reducing barriers to the application of satellite EO data for AQ and health applications. For example, AI tools assist with generating and updating EO data-processing code, developing user-oriented dashboards, identifying appropriate datasets for specific applications, and interpreting outputs, thereby lowering barriers to use in settings where local technical capacity is limited. However, this potential benefit comes with risks, particularly because hallucinated or inaccurate information may be difficult to identify without domain expertise. Furthermore, AI systems trained predominantly on data and literature from HIC contexts may reproduce the same regional biases that already constrain satellite EO applications in LMICs. AI tools should therefore be viewed as complements to, rather than substitutes for, local expertise and capacity, and their use in this domain will require rigorous validation and demonstrated trustworthiness by subject-matter experts. We suggest that near-term efforts to advance AI applications in this field should focus on AI-assisted code development and editing for EO data processing, translation of capacity-building materials into local languages, and identification of relevant examples, workflows, and templates for emerging use cases. We believe that concentrating on these applications, while maintaining expert oversight to ensure reliability and accuracy, offers the greatest potential to narrow—rather than exacerbate—existing disparities in satellite EO data access, literacy, and use.

Cloud computing platforms provide an important opportunity to expand access to the computational resources necessary to effectively use satellite EO data (e.g., WMO et al., 2024). However, user-friendly and open-source software optimized for cloud applications remain relatively underdeveloped for satellite EO applications in health and AQ. Long-term costs of these platforms can also be opaque, and data ownership and privacy issues, especially for sensitive health applications, remain a concern.

To promote operational sustainability, regionally focused meta-analysis to identify adoption facilitators and barriers across diverse contexts, as well as sustainability analyses examining funding models and governance structures can also yield important insights into effective strategies to transition satellite-derived data into operational use. These results can also inform policy recommendations to ensure satellite-derived data are appropriately used in decision-making.

AI Use Disclosure

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- Conducting searches as part of a literature review and identifying relevant case studies. In all instances, suggested references or examples were manually investigated to ensure their relevance and the accuracy of any AI summary.
- Creation of graphics, including assistance with generating code to create graphs. Underlying data were supplied by the authors, however.
- Correcting for spelling and grammar, as well as improving clarity and polishing language (especially for authors for whom English is not a first language). In all cases, outputs were examined to ensure the meaning of the text was not altered.

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Data Availability Statement

Sources of data included in this paper and listed in the included references. No additional data were gathered or generated in the preparation of this paper.

CREDIT Statement

All co-authors contributed to Writing - Original Draft, as well as Review & Editing. Additionally, Carl Malings, Nathan Pavlovic, Yaqian He, Rochelle Velho, Sebastian Diez, Jennifer Bratburd, Didier Davignon, and Siddhi Munde contributed to Conceptualization of the paper.

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Disclosure of Interest

The authors do not declare any competing interests.

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