

Satellite Monitoring for Air Quality and Public Health Research in Africa: A Scoping Review

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Systematic Review

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Satellite Monitoring for Air Quality and Public Health Research in Africa: A Scoping Review

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Abstract

Background

Satellite remote sensing is an important approach for estimating air pollution exposure in regions with limited ground-based monitoring, yet its application in environmental health research across Africa has not been synthesised. This scoping review mapped the use of satellite-derived air quality products to investigate relationships between air pollution and human health in Africa.

Methods:

A scoping review was conducted following the Joanna Briggs Institute (JBI) methodology and reported according to the Preferred Reporting Items for Systematic Reviews and Meta-Analysis extension for Scoping Reviews (PRISMA-ScR) guidelines. Five electronic databases and grey literature sources were searched for studies published until May 2026. Eligible studies used satellite-derived air quality data to investigate associations with human health outcomes in Africa. Data were extracted using a standardised form and synthesized descriptively.

Results:

Twenty-six records met the inclusion criteria. Most studies were published after 2015 and employed ecological time-series or cross-sectional designs. Research was concentrated in West Africa and fine particulate matter (PM_{2.5}) was the most frequently investigated pollutant, followed by desert dust and nitrogen dioxide (NO₂). Respiratory diseases, meningitis, adverse birth outcomes, and child mortality were the predominant health outcomes, with most studies reporting positive associations between air pollution exposure and adverse health outcomes. Hybrid exposure assessment approaches combining satellite observations with atmospheric

models or ground-based monitoring were more common than satellite-only approaches. Geographical, methodological, and research leadership gaps were identified.

Conclusions

Satellite remote sensing is a valuable approach for investigating air pollution and health in Africa. Future research should expand geographical coverage, improve methodological reporting and validation, investigate a broader range of pollutants, include chronic health outcomes and strengthen African research leadership and capacity.

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Background

Air pollution is one of the leading environmental risk factors, contributing substantially to the global burden of premature mortality and disease (1). This burden falls disproportionately on low- and middle-income countries (LMICs), where ambient air pollution concentrations frequently exceed the World Health Organization (WHO) Air Quality Guidelines (AQG) (2). Higher exposure levels in LMICs are compounded by the limited capacity to monitor and manage air quality effectively, constraining efforts to quantify health risks and implement evidence-based interventions (3, 4). In Africa, an estimated 1.1 million deaths were attributed to air pollution exposure in 2019, including approximately 394,000 from ambient (outdoor) air pollution (1). Continued urbanisation, industrialisation, and population growth are expected to further increase air pollution and its associated health burden across the continent (4).

Ground-based monitoring stations remain the reference standard for measuring ambient air pollutants because they provide accurate and continuous observations (5). However, monitoring networks are typically concentrated in urban and industrial centres and provide limited spatial coverage in many areas where vulnerable populations reside, including informal settlements, rural communities, communities living near waste and landfill sites, mountainous areas, and regions frequently exposed to wildfire smoke (6-8). Even in urban environments, sparse monitoring networks may inadequately capture fine-scaled spatial variability in pollutant concentrations, particularly for particulate matter (PM) and nitrogen dioxide (NO₂) (9). These challenges are especially pronounced in LMICs, where the financial and technical requirements associated with establishing and maintaining regulatory networks often result in limited observation data for air quality surveillance and epidemiological research (4, 10). In Africa, these gaps leave policymakers and environmental and health authorities with an incomplete picture of pollution patterns and related health effects.

Satellite remote sensing has emerged as an important complementary approach for addressing these monitoring limitations by providing consistent, spatially continuous observations of air pollutants over large geographic areas (11). Satellite-derived air quality products have been used internationally to support environmental monitoring, exposure assessment and epidemiological studies (12), with applications dating back to the late 1990s, including their incorporation into global assessments by the WHO and Greenpeace (5). More recently, satellite observations have been increasingly important for estimating population exposure particularly in areas with sparse ground monitoring (13, 14) for characterising spatial gradients in pollutants such as NO₂ that are relevant to respiratory and cardiovascular health (15) and satellite-derived Particulate Matter with diameters of 2.5 micrometres or smaller (PM_{2.5}) used in Global Burden of Disease study (4). As advances in remote sensing technologies continue, satellite data are expected to play an increasingly important role in supporting interdisciplinary research at the

interface of atmospheric science, remote sensing, epidemiology and public health (12, 15). However, region-specific research remains limited, highlighting the need to improve exposure assessment approaches that account for the environmental and socio-economic contexts of African countries (16, 17).

Despite the growing application of satellite-derived air pollution data, existing evidence synthesis provides limited guidance for African contexts. Existing reviews have focused primarily on high income settings, particularly the United States (9, 15, 18), or global reviews that have addressed only selected health outcomes (19), or lacked systematic and reproducible review methods and comprehensive summaries of satellite datasets and analytical approaches (12, 20). To our knowledge, no review has comprehensively mapped the use of satellite observations to investigate air pollution and human health across Africa. This scoping review therefore aims to systematically map and synthesise the available evidence by characterising the pollutants, satellite datasets, health outcomes, geographic coverage, study designs and analytical approaches reported in the literature, while identifying evidence gaps and future research priorities to support the application of satellite remote sensing for air pollution and public health in across Africa.

Methods

Research design

A scoping review was conducted to systematically map the current research on the use of satellite data to monitor air quality and health impacts in Africa. Due to satellite data for air quality being an emerging field, a scoping review was necessary to identify knowledge gaps, broadly identify concepts and key characteristics, understand how research in the field has been conducted and possibly serve as a precursor to a systematic review (21-23). This review systematically searched, identified, and catalogued the available evidence on satellite data

products, analytical techniques, and measures of air quality and health outcomes. It summarises the types of satellite products used, the analytical approaches applied, and the reported measures, and provides recommendations for future research on satellite-based air quality and health studies in Africa.

Based on the adopted framework by Arksey and O'Malley (2005) (23) and iterated by the Joanna Briggs Institute (JBI) (21), this review followed the five-stage methodological approach for a scoping review. Furthermore, we followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) checklist for reporting our findings (24). The protocol is registered with the Open Science Framework (<https://doi.org/10.17605/OSF.IO/U3MWV>) to ensure transparency and rigour (25).

Identifying relevant studies

This scoping review included primary quantitative studies conducted across the five regions (northern, southern, western, eastern, and central) of Africa with varied socio-economic status, sex, age and morbidity and mortality rates, and published in English through to 30 May 2026. The database search was conducted in 2024 and 2026, and search terms were drafted by the researchers with assistance from the University of Cape Town's experienced librarian. Boolean operators were used when searching databases Scopus, EBSCOhost, Environmental Science (via Proquest), PubMed and Web of Science. MeSH terms were also used in PubMed searches. Truncation (*) was used for relevant databases to broaden a search and allow for searching of multiple endings of a search term. Google Scholar and relevant organisations were searched for grey literature based on the identified keywords. The keyword search is provided in Table S1 in supplementary information. To ensure a comprehensive search of the available literature, forward and backward citation tracking was also used to identify studies and grey literature that were not included in the original search. Studies were excluded if they focused only

on ground monitoring data or on data extracted from other forms of remote sensing, such as aircraft or other moving objects, or low-cost sensors. Studies that did not focus on satellite remote sensing and air quality and health were also excluded. Articles were excluded for the following reasons: studies conducted in populations outside of Africa, studies that did not assess ambient air pollution, and any study not reporting on the impacts on human health. We did not include conference abstracts, books, book chapters, full-text, book reviews, protocols, animal studies, and studies without full-text availability.

Screening

Following the database search, identified studies were imported into EndNote (26) and were deduplicated. The included articles were then imported into Rayyan (27) for screening. The titles and abstracts of the included studies were screened according to the eligibility criteria, followed by the full texts of those articles that met the first-stage screening criteria. Thereafter, the authors identified the relevant studies to include in the review. In line with PRISMA-ScR guidelines, the data screening process was conducted by the first author. The second author independently screened 10% of records at both screen stages as part of a standard calibration exercise to ensure consistent application of the inclusion criteria, which is an accepted methodological approach when full dual review is not feasible due to time and resource constraints (28). Any uncertainties were discussed with the second reviewer, and a consensus was reached.

Data extraction and analysis

The authors developed a data extraction table to collect and summarise the key variables outlined in the study objectives, available in Table S2 in supplementary information. As the data extraction process was iterative, the authors updated the data charting table as new and emerging concepts were identified. The extracted data were analysed to identify satellite data

measures and techniques used to quantify air quality impacts on health in Africa and to understand the strengths and limitations thereof. Data were thematically categorised using qualitative thematic analysis based on Braun and Clarke's (2006) six steps to thematic analysis (29) and deductive reasoning. Identified themes included satellite data products and methodologies, associations between air quality parameters and health outcomes, and air quality measurement techniques and patterns. This study is reported in accordance with the PRISMA-ScR guidelines (24) (Supplemental material, Table S3).

Results

Study selection

This scoping review included 26 records after retrieving 1272 records following a database search pertaining to the review's research question (see Figure 1). Two hundred and eighty records were removed as duplicates, and 944 were excluded after the first screening stage of 992 records. Forty-eight records met the criteria for the second screening round, of which one could not be retrieved. Of the 47 records assessed for eligibility, 28 records were excluded due to several reasons: studies that were globally based ($n=14$), studies that did not have clear statistical results to investigate associations between satellite remote sensing and the impact on health ($n=1$), studies that focused on meteorological factors such as precipitation or humidity on health, rather than air quality ($n=6$), studies that were missing a health parameter in the analysis ($n=3$), studies that were not conducted in Africa ($n=3$), and studies that were qualitative ($n=1$). No records were identified through searches of relevant organisations and websites, but 32 records were identified through citation tracking, of which twenty-two records met the criteria for the second-stage screening. Of these, 15 were excluded due to the following reasons: studies that did not contain satellite data ($n=8$), studies that were not conducted in Africa ($n=3$), studies that did not contain a health component ($n=1$), studies that were globally

based (n=1), studies that focused on meteorological data (n=1), and studies where the results were unclear (n=1).

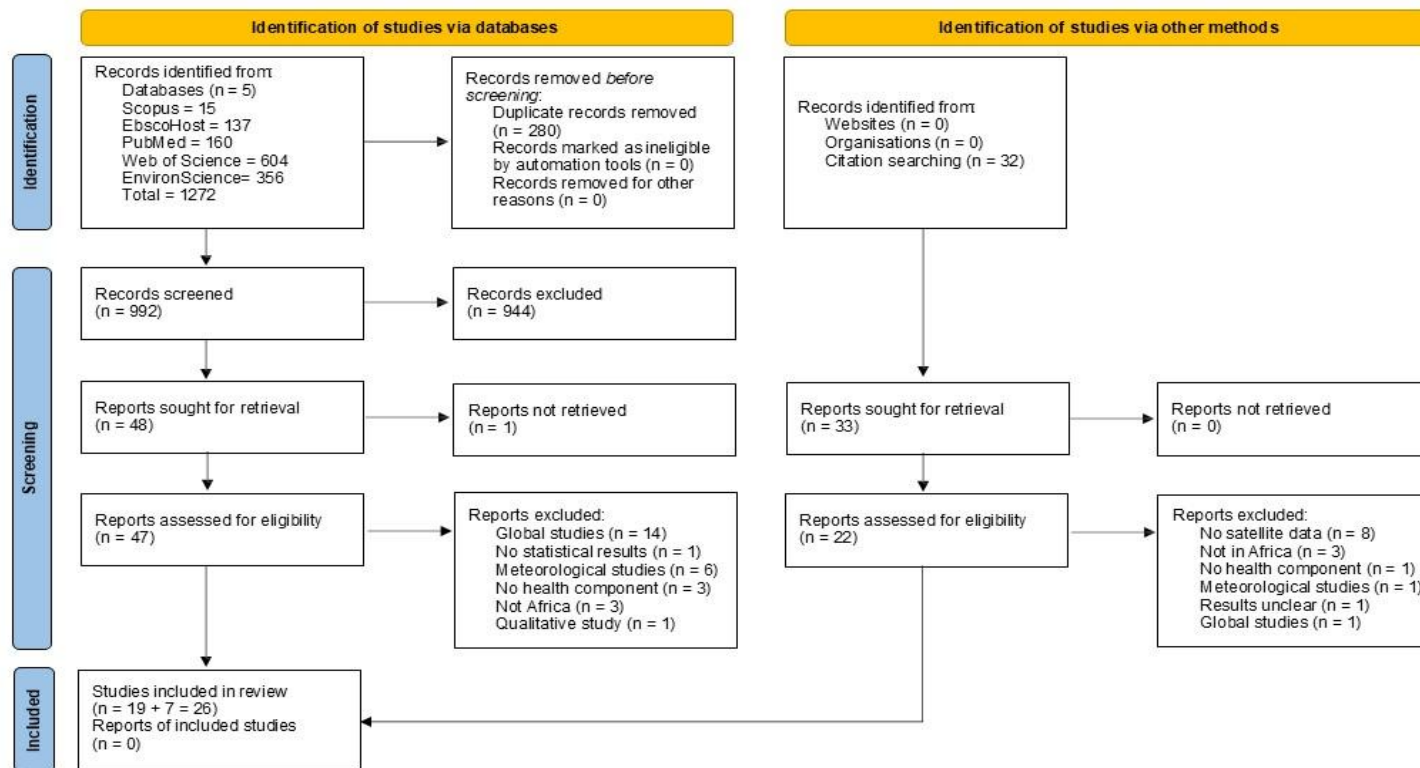


Figure 1. Modified Preferred Reporting Items for Systematic Reviews and Meta-analyses 2020 for Scoping Reviews (PRISMA-ScR). Adapted from

Page et al., (2021) (24)

Study characteristics

The included studies were published between 2006 and 2026, with the greatest proportion published in 2022 (31.11%) (Table 1 and S3 List of included publications in Supplemental Materials). Ecological time-series (n=9; 34.62%) and cross-sectional (n=7; 27.02%) study designs predominated, followed by ecological cross-sectional studies (n=4; 15.38%), while the remaining designs were represented by a single study each. Study durations ranged from two months (10) to 21 years (11), although 21.74% of studies were conducted over less than five years.

Fifteen studies were conducted within a single country and 11 were multi-country studies. West Africa accounted for the largest proportion of studies (35.7%), followed by Southern Africa (25.00%), East Africa (20.60%), Central Africa (14.70%) and North Africa (4.00%). One study did not specify the countries included and was excluded from the regional summary (30). Most studies were conducted at the national scale (65.38%), while fewer examined district (26.92%) or regional populations (3.85%). Fourteen studies included both urban and rural settings (60.91%), reflecting the need to characterise air pollution across diverse environments.

Children under five years and maternal health were the most frequently investigated populations (n=14) (31-44), followed by general populations (n=8), (45-52), adults and adolescents (n=3) (30, 53, 54), and hospital admissions (n=1) (55). Meteorological variables, including precipitation, humidity and temperature, were commonly included as covariates. Study leadership was predominantly from high-income countries (HICs), with first or second authors from these settings in 65.38%. Only 30.77% of studies were led by researchers based in Africa (35, 40, 44, 46, 47, 51, 52, 55), of which three had both first and last authors based on the continent (35, 44, 52). One study was led by authors from a low and middle income

country (LMIC) outside of Africa (32). Table S5 in supplementary information contains the full characteristics of included studies.

Table 1: Characteristics of the included studies

Study Characteristics (n=26)		Number of studies n (%)*
Year of publication	2006	1 (3.85%)
	2013	1 (3.85%)
	2016	1 (3.85%)
	2017	2 (7.70%)
	2018	2 (7.70%)
	2019	1 (3.85%)
	2020	1 (3.85%)
	2021	3 (11.54%)
	2022	8 (31.11%)
	2023	3 (11.54%)
	2024	1 (3.85%)
	2025	1 (3.85%)
	2026	1 (3.85%)
Study design	Ecological time-series	9 (34.62%)
	Cross-sectional	7 (27.02%)
	Ecological cross-sectional	4 (15.38%)
	Ecological case-control	1 (3.85%)
	Ecological	1 (3.85%)
	Longitudinal case-control	1 (3.85%)
	Ecological Difference-In Difference approach (DID)	1 (3.85%)
	Time-stratified case-crossover	1 (3.85%)
	Correlational case study	1 (3.85%)
Geographical context	National	17 (65.38%)
	Regional (and district)	1 (3.85%)
	Regional	1 (3.85%)
	District-level	7 (26.92%)
	Urban	3 (13.04%)
	Rural	1 (4.35%)
	Urban and rural	16 (61.54%)
	Not specified	6 (26.08%)
Study duration	<1 year	4 (15.38%)

	1-4 years	3 (11.54%)
	5-10 years	5 (19.23%)
	11-15 years	6 (23.07%)
	> 15 years	4 (15.38%)
Populations	Children under-five and maternal health	14 (53.85%)
	General populations	8 (34.80%)
	Adult and adolescent	3 (11.54%)
	Hospital admissions	1 (4.35%)
Percentage of the number of countries that had studies conducted in them	North Africa	8 (3.7%)
	Central Africa	37 (14.70%)
	West Africa	90 (35.7%)
	East Africa	52 (20.60%)
	North Africa	10 (4.00%)
	Southern Africa	63 (25.00%)
*Percentages do not add up to 100% as some studies share the same data		

Health outcomes

Figure 2 summarizes the distribution of health outcomes investigated in the included studies.

Respiratory conditions were the most frequently studies, including acute respiratory infections (ARI) and symptoms (n=4) (31, 38, 43, 53), acute lower respiratory infections (ALRI) (n=1) (39), pneumonia (n=1) (55), asthma (n=1) (55), and COVID-19 (n=2) (47, 51), followed by meningitis (n=6) (45, 46, 48-50, 52). Child and maternal health outcomes included infant health, pregnancy loss (including stillbirths and miscarriages) (n=3) (34, 40, 41), maternal mortality (n=1) (36), preterm birth (PTB) and low birth weight (LBW) (n=1) (42) and under-five health outcomes (n=5) (31, 32, 35, 38, 44). Less frequently investigated outcomes included anaemia (n=2) (30, 33), gastrointestinal illness (n=1) (55), mortality burden (n=1) (54) and malaria (n=1) (55)

Most studies assessed exposure-response relationships using regression analyses (n=20), reporting odds ratios (OR) (n=11), prevalence ratios (PR) (n=1), incidence rate ratios (IRR) (n=2), incidence rates (IR) (n=1), relative risks (RR) (n=3), or correlation coefficients (n=3)

(30-45, 48-50, 54). Correlation analyses included Pearson (n=4), Spearman (n=2), Kendall (n=1), and wavelet analyses (n=2) (44, 46, 47, 50, 51, 55). One study described temporal comparisons between dust events and meningitis occurrence without formal statistical testing (52).

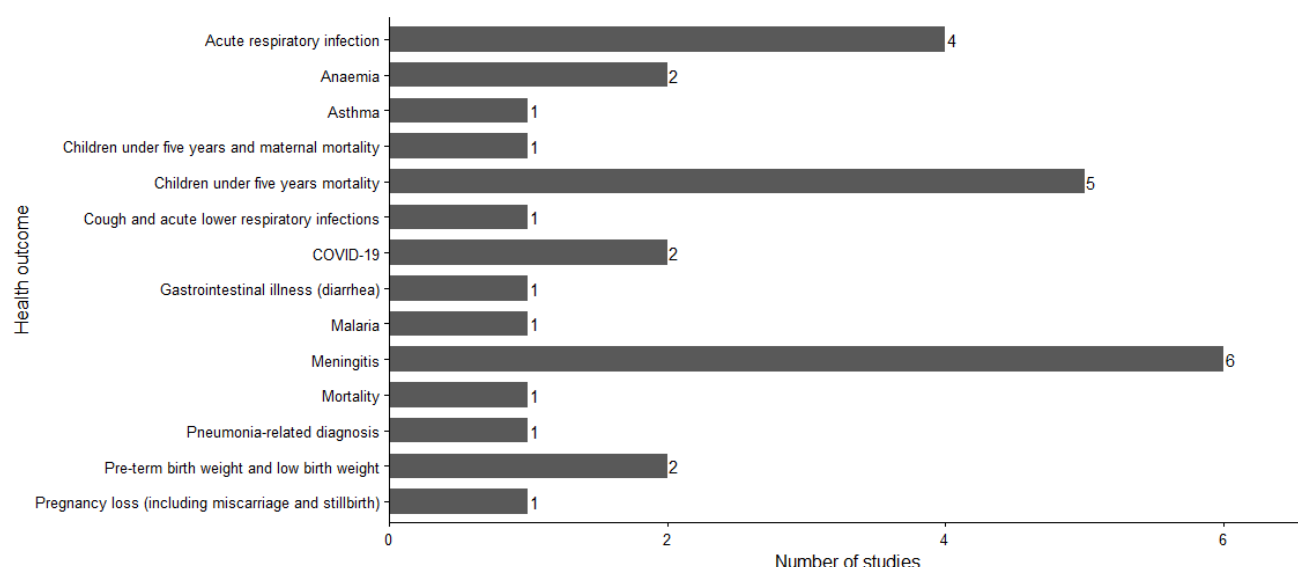


Figure 2: Distribution of health outcomes investigated using satellite remote sensing (Number of studies (n) does not total 26, as some studies investigated several health outcomes)

Satellite data products and methodologies

The included studies investigated a limited range of pollutants, primarily PM_{2.5} (n=14), dust (n=7), NO₂ and sulphur dioxide (SO₂) (n=2), and combinations of pollutants (n=3) (Table 2). PM_{2.5} studies examined a range of health outcomes, including under-five and maternal mortality, infant mortality, pregnancy loss, anaemia, ARI, PTB, LBW and COVID-19 (30, 32-38, 40-43, 51, 54). Dust studies primarily investigated meningitis incidence, childhood respiratory symptoms and COVID-19 (31, 45, 46, 48-52), trace gas studies examined respiratory outcomes (38, 44, 53). Three studies investigated combinations of PM_{2.5}, NO₂, SO₂,

carbon monoxide (CO) and fire activity in relation to COVID-19, gastrointestinal illness, pneumonia, malaria, asthma, and upper respiratory tract infections (44, 47, 55).

Most PM_{2.5} studies used surface estimates, meaning they used modelled surface concentration products derived from aerosol optical depth (AOD), while one study used AOD directly as proxy for surface PM_{2.5}. Most of the PM_{2.5} data products catalogued were surface estimates. The Atmospheric Composition Analysis Group (ACAG) was the most frequently reported data source (n=10), with some studies also using Modern-Era Retrospective Analysis for Research Application Version-2 (MERRA-2) (n=2), or the Socioeconomic Data and Applications Centre (SEDAC) database (n=1). The Moderate Resolution Imaging Spectroradiometer (MODIS) was the most used instrument (n=6), followed by Multi-Angle Imaging SpectroRadiometer (MISR) (n=4), Sea-viewing Wide Field-of-View Sensor (SeaWiFS) (n=3) and Cloud–Aerosol Lidar with Orthogonal Polarization (CALIOP) (n=1). Seventeen studies did not report explicitly state the satellite platform used (30, 32-35, 39-43, 45, 48-51, 53, 55).

Dust studies employed a range of AOD-based products, aerosol index (AI), dust optical depth and dust surface concentration products. The Moderate Resolution Imaging Spectroradiometer (MODIS) was the most frequently used instrument (31, 45, 46, 52), followed by Total Ozone Mapping Spectrometer (TOMS) (49, 50) and Ozone Monitoring Instrument (OMI) (50). NO₂ was measured using Tropospheric Monitoring Instrument (TROPOMI) onboard Sentinel-5P to investigate ARI (38) while SO₂ was measured using OMI to examine acute respiratory symptoms associated with volcanic emissions (53). Three additional studies combined multiple satellite products and instruments to investigate associations between PM_{2.5}, NO₂, SO₂, CO, and fire activity and a range of health outcomes (47, 53, 55).

Table 2: Summary of the satellite remote sensing techniques and health outcomes studied

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Pollutant	No. of studies	Main satellite products	Main satellite instruments	Main health outcomes investigated
Dust	8 (31-37, 52)	AOD ¹ , Dust surface concentration (D2), Dust Surface Mass Concentration (DSMC) (D4), Aerosol Index (AI) (proxy for dust)	MODIS, OMI, TOMS	Meningitis, childhood respiratory infections, COVID-19
PM _{2.5}	14 (38-51)	AOD, satellite-derived PM _{2.5} , surface PM _{2.5}	MODIS, MISR, CALIOP, SeaWiFS	Maternal and child health, respiratory infections, pregnancy outcomes, anaemia, COVID-19
PM _{2.5} , NO ₂ and fire activity	2 (47, 55)	Surface PM _{2.5} and NO ₂ , AOD, fire products	MODIS, OMI, VIIRS	Gastrointestinal disease, pneumonia, malaria, asthma, COVID-19
NO ₂ , SO ₂ , CO and AOD	1 (30)	Tropospheric NO ₂ , SO ₂ , CO, monthly AOD	TROPOMI, MODIS	Upper respiratory infection
NO ₂	1 (54)	Tropospheric NO ₂	TROPOMI	Acute respiratory infection
SO ₂	1 (53)	Volcanic SO ₂ columns	OMI	Acute respiratory symptoms
<u>AI (aerosol index) is a product that is particularly sensitive to absorbing aerosols, such as dust and smoke</u> <u>MODIS: Moderate Resolution Imaging Spectroradiometer</u> <u>TOMS: Total Ozone Mapping Spectrometer</u>				

1

A range of different AOD dust products were used:

1. Deep Blue Aerosol Optical Thickness (AOT) product. (collection 6); proxy for surface PM $\leq 10^{\mu}$
2. Multi-angle Implementation of Atmosphere Correction (MAIAC) Land AOD data product (MCD19A2.006)
3. Satellite-based AOD
4. Dust optical depth data (D1)

<u>OMI: Ozone Monitoring Instrument</u> <u>MISR: Multi-angle Imaging Spectroradiometer</u> <u>SeaWiFS: Sea-viewing Wide Field-of-View Sensor</u> <u>CALIOP: Cloud–Aerosol Lidar with Orthogonal Polarization</u> <u>VIIRS: Visible Infrared Imaging Radiometer Suite</u> <u>TROPOMI: TROPospheric Monitoring</u>

Relationships identified between air quality parameters and health outcomes

PM_{2.5}

Most studies reported positive associations between PM_{2.5} exposure and adverse health outcomes, including infant mortality, pregnancy loss, (including miscarriage and stillbirth), under-five mortality, PTB, LBW, ARI, anaemia and COVID-19 (30, 32-37, 39-43, 51, 54). Significant associations were reported in ten studies (30, 32-36, 41, 42, 47, 51), while three reported positive but non-significant associations with ALRIs, stillbirth and mortality burden (39, 44, 53). Studies examining PM_{2.5} speciation consistently reported significant associations with infant mortality, anaemia, under-five mortality, and maternal mortality (33, 36, 41, 46).

Dust

Most studies reported positive associations between dust exposure and health outcomes, particularly meningitis and respiratory outcomes (31, 45, 46, 48-52). Significant correlations were observed between dust exposure and meningitis during the onset and peak of the meningitis season in Senegal (46), while dust exposure was associated with increased cough symptoms in Benin (OR = 1.32) following two-and four-week exposure periods (31). Dust was also positively correlated with COVID-19 cases in Nigeria (51). Wavelet analyses demonstrated stronger associations between dust and meningitis than meteorological variables alone (48, 50), although one study found no association between dust and localised meningitis epidemics (45). Temporal relationships between elevated dust concentrations and meningitis incidence were also reported (52).

Gaseous pollutants

Only two studies investigated the association between gaseous pollutants and health outcomes. NO₂ was significantly associated with ARI symptoms, with cough used as a proxy outcome (OR = 1.27) among individuals exposed to concentrations above the WHO AQG (38). In contrast, no association was observed between volcanic SO₂ exposure and acute respiratory symptoms in the Democratic Republic of Congo (DRC) (53).

Multiple pollutants

Three studies investigated combinations of pollutants. Positive correlations were reported between AOD, NO₂, fire activity and COVID-19 during the second wave of the pandemic in Nigeria, although associations varied during the first wave (47). Kapwata et al. (2021) reported increased pneumonia hospital admissions during periods of elevated PM_{2.5} and NO₂ (55). The third study found statistically significant associations between trace gases and upper respiratory tract infections, although associations with AOD were weak (44).

Air quality measurement techniques and patterns identified

Most studies (n=18) used hybrid air quality measurement approaches that combined satellite observations with atmospheric models, ground monitoring data, low-costs sensors, or multiple data sources, whereas fewer studies (n=8) relied exclusively on satellite-derived products. Several studies reported pollutant concentrations exceeding the WHO AQG (33, 35, 36, 40), although varying levels of poor air quality were observed across all study settings.

Spatial and temporal variation in air pollution was evident across the included studies. Higher PM_{2.5} concentrations were reported in West Africa than elsewhere on the continent, largely reflecting contributions from Saharan dust and anthropogenic sources (37). Poorer air quality associated with seasonal dust transport and biomass burning was also reported in West and Southern Africa, with elevated NO₂ concentrations observed in parts of Nigeria (47).

Discussion

This scoping review provides the first comprehensive synthesis of studies using satellite remote sensing to investigate the relationship between air pollution and human health in Africa. The review identified 26 eligible studies published between 2006 and 2026, with most published after 2015 following the launch of newer satellite instruments with improved spatial and temporal resolution (16). This trend is consistent with the broader global expansion of satellite-based air quality research and demonstrates the increasing accessibility of Earth Observation data for environmental health applications (5, 12).

Several important patterns emerged from the review. Research was concentrated in relatively few African countries despite the continent experiencing one of the highest global burdens of disease attributable to air pollution (1). Respiratory diseases, child and maternal health outcomes, and meningitis dominated the health outcomes, while PM_{2.5} and NO₂ were the most frequently investigated pollutants. Most studies adopted ecological or cross-sectional designs and commonly combined satellite observations with ground monitoring networks, atmospheric models, or other complementary datasets. Together, these findings demonstrate the growing role of satellite remote sensing in exposure assessment in Africa. As satellite products continue to improve and become increasingly integrated with atmospheric models, artificial intelligence and machine learning (AI-ML) techniques, and

emerging Earth Observation missions, their contribution to epidemiological research and environmental health surveillance is likely to increase substantially (15). However, realizing this potential will require addressing the geographical, methodological, and research capacity gaps identified in this review, which are discussed in the following sections.

Health outcomes remain narrowly represented

Respiratory health outcomes dominated the literature identified in this review, with most studies focusing on respiratory infections, asthma, pneumonia, and acute respiratory morbidity among children under five years of age. Maternal health outcomes, including adverse birth outcomes, were also investigated. This emphasis is consistent with the well-established vulnerability of children and pregnant women to ambient air pollution, as developing respiratory and immune systems, together with fetal development during pregnancy, are particularly susceptible to air pollution exposure (56). Given that children and pregnant women experience a disproportionate share of the health burden attributable to air pollution, their prominence in the African literature aligns with regional public health priorities (57).

Compared with recent global reviews, however, the African evidence base remains relatively narrow. Reviews such as Folkmann et al. (2024), reported chronic respiratory diseases, cardiovascular disease, diabetes, and cancer (19) whereas relatively few African studies focused on these outcomes. This disparity likely reflects differences in disease surveillance, the availability of routinely collected health data, and the shorter history of environmental epidemiological research in many African countries (49, 53). As the burden of NCDs continues to rise in Sub-Saharan Africa, expanding research beyond acute respiratory outcomes represents an important priority for understanding the long-term health impacts of air pollution (1).

An important finding unique to the African evidence base was the substantial number of studies that investigated the association between desert dust exposure and meningitis outbreaks in West Africa (45, 46, 48-50, 52). These studies illustrate how satellite remote sensing can address environmental health challenges that are particularly relevant to African settings, where seasonal Harmattan dust events (cool, dusty, and dry trade winds that blow from the Sahara Desert into West Africa) influence disease transmission and population exposure over large geographic areas. This finding highlights the importance of ensuring that African research priorities are shaped by the continent's environmental, climatic and epidemiological contexts rather than simply reflecting research agendas established in high-income countries.

Satellite remote sensing is strengthening air pollution exposure assessment, but methodological challenges remain

PM_{2.5} and NO₂ were the most frequently investigated pollutants, reflecting advances in satellite retrieval algorithms and the availability of validated satellite data products for these pollutants. Similar patterns have been reported in recent global reviews of air quality and public health research (9, 16). Instruments such as MODIS onboard the Terra and Aqua satellites have substantially improved aerosol optical depth (AOD) retrievals, while datasets produced by organisations such as the Atmospheric Composition Analysis Group (ACAG) have enabled estimation of surface-level PM_{2.5} concentrations by integrating satellite observations with atmospheric models and ground-based measurements. These developments have facilitated exposure assessment and epidemiological research in Africa, specifically in regions where regulatory monitoring networks remain sparse (9, 19, 41, 42).

Despite these advances, important methodological limitations remain. Most satellite instruments measure atmospheric column concentrations rather than pollutant concentrations at breathing height, requiring statistical, chemical transport or ML models to estimate near-

surface exposure (45). The accuracy of these estimates depends on the availability of ground-based observations for calibration and validation, which remain limited across much of Africa. Furthermore, cloud cover, surface reflectance, vegetation, complex terrain and temporal resolution of satellite overpasses can introduce uncertainty into exposure estimates (58).

More than half of the included studies employed hybrid exposure assessment approaches that combined satellite observations with ground monitoring networks, atmospheric models or other ancillary datasets. This supports growing international consensus that satellite observations are most effective when complementing rather than replacing conventional monitoring systems (9, 59).

The review also identified inconsistent reporting of satellite methodologies across studies. Key methodological information including satellite instruments, retrieval algorithms, spatial resolution, temporal aggregation, validation procedures and uncertainty estimates, was frequently omitted. This limits reproducibility and makes comparisons across studies difficult. As satellite remote sensing becomes increasingly integrated into public health research, greater methodological transparency and standardized reporting will be essential. Emerging satellite missions, including the National Aeronautics and Space Administration (NASA's) Multi-Angle Imager for Aerosols (MAIA) (60), together with advances in AI-ML (61), are expected to further improve exposure assessment by providing more accurate estimates of near-surface pollutant concentrations and information on particulate composition, which require attention to validation studies and methodological reporting standardization.

Study designs reflect the realities of African research infrastructure

The predominance of ecological and cross-sectional study designs appears to reflect the practical realities of conducting environmental health research in Africa. Similar patterns have

been observed in other resource-constrained setting with limited access to longitudinal health records, sparse environmental modelling networks and constrained research resources (49, 53). Although these designs provide valuable evidence for identifying spatial and temporal relationships between air pollution and health, they provide more limited evidence for causal inference than longitudinal epidemiological studies (62).

Many studies relied on short observation period due to the relatively recent availability of high-resolution satellite-derived air quality products. Short study durations limit opportunities to investigate cumulative exposure and chronic health effects, which requires extended periods of follow up (63). As satellite archives continue to expand and electronic health records become increasingly available across Africa, future studies will be better positioned to undertake longitudinal cohort studies, case-crossover analyses and other epidemiological designs capable of providing stronger evidence for causal interference.

Research equity and capacity building challenges

An important finding of this review was the predominance of first and senior authors affiliated with institutions in high-income countries, despite all studies being conducted in African settings. While previous reviews of satellite-derived air pollution and health research have largely focused on advances in satellite technologies, exposure assessment methods and health applications (9, 12, 19, 20), none have examined patterns of research leadership within the African evidence base. By mapping authorship characteristics, this review extends the existing literature by highlighting research equity as an important consideration for the future development of satellite-based environmental health research in Africa. The predominance of authors from high-income countries reflects broader inequities in global environmental health and air quality research, where studies undertaken in low- and middle-income countries are frequently led by researchers and institutions based elsewhere (64-66). Similar patterns

have been reported across global health research, where African researchers remain underrepresented in leadership positions despite the continent contributing substantially to the global burden of environmentally related disease (67). Although international collaborations have been instrumental in advancing satellite-based environmental health research in Africa, the unequal distribution of research leadership raises concerns regarding research equity, local ownership of data, and the long-term sustainability of scientific capacity on the continent.

The increasing availability of freely accessible satellite datasets has substantially lowered barriers to accessing Earth observation data and has been identified as a major opportunity for expanding environmental health research globally (9, 19). However, the findings of this review suggest that open-access data alone has not translated into equitable participation in satellite-based environmental health research across Africa. While previous reviews have highlighted improvements in satellite retrieval algorithms, exposure assessment methods and emerging Earth observation missions (9, 12, 19, 61), comparatively little attention has been given to the institutional and technical capacity required to apply these increasingly sophisticated datasets. The selection, processing, interpretation and validation of satellite products require specialised expertise that remains limited in many African institutions (68, 69). These challenges are compounded by shortages of trained personnel, computational infrastructure and sustained research funding, which continue to restrict the wider adoption of satellite remote sensing in environmental health research (69). Consequently, the benefits of open satellite data have not yet translated into proportional growth in African-led research.

The findings also reinforce the importance of interdisciplinary collaboration for translating satellite observations into meaningful public health evidence. Similar to the conclusions of Potts et al. (2024), the effective application of satellite-derived air quality products depends on stronger engagement between remote sensing scientists, atmospheric scientists, epidemiologists, environmental health researchers and policymakers (68). Previous studies have identified differences in perceptions regarding the operational use of satellite-derived air quality products, with satellite scientists generally expressing greater confidence in their application than environmental health practitioners (9). Bridging this gap through interdisciplinary collaboration will be essential to ensure that satellite products are appropriately selected, interpreted and applied to address environmental health priorities across diverse African contexts.

This review further highlights that strengthening African leadership in satellite-based environmental health research requires investment in both technical expertise and institutional capacity. Existing training initiatives provided by organisations such as NASA and the European Space Agency (ESA) have improved access to satellite datasets, analytical tools and educational resources (19). However, there remains a need for regionally relevant training programmes that address African environmental conditions, priority health outcomes and the practical challenges encountered by researchers and policymakers working in resource-constrained settings (69). Universities, national space agencies such as the South African National Space Agency (SANSA), public health institutions and international partners all have important roles in developing interdisciplinary training programmes, communities of practice and research networks that strengthen satellite data literacy and facilitate knowledge exchange. Ultimately, equitable international partnerships that prioritise African leadership, shared decision making and long-term institutional investment will be essential to ensure that satellite remote sensing contributes not only to scientific advancement but also to sustainable

environmental health research capacity and evidence-informed air quality policy across the continent.

Recommendations for the selection and use of satellite data and policy application

1. Strengthen satellite-based exposure assessment

It is recommended that methodologies and data accuracy be strengthened through the application of hybrid monitoring that integrates satellite observations with other monitoring systems (59). For example, more than half of the studies in this review used hybrid systems, which help address common satellite retrieval limitations, including cloud cover, high surface reflectivity (70), and biomass burning, which result in missing data. Moreover, where possible, satellite-derived exposure estimates should be validated against available ground monitors, adjunct datasets and models to enhance accuracy and interpretability for health research and policy. It is further recommended that surface-level pollutant measurements, for example, the new MAIA instrument on PLATiNO-2 satellite, be used in place of proxies to ensure more accurate data for health research (60). The MAIA mission has both Primary and Secondary Target Areas (STAs) of coverage. Primary Target Areas (PTAs) are areas with dense populations, such as large cities, where MAIA epidemiologists will conduct health research on various particulate matter particles. For example, there are centres in Johannesburg and Pretoria, South Africa and in Addis Ababa and Adama, Ethiopia. STAs are other areas outside of PTAs where aerosol or cloud research may be relevant. Such centres are located in, for example, Dakar, Senegal and Lagos, Nigeria (71). Future research should also expand beyond PM_{2.5} and NO₂ to investigate understudied pollutants, including ozone (O₃), methane (CH₄), carbon monoxide (CO), sulphur dioxide (SO₂) and particulate matter composition. Similarly, greater attention should be given to chronic health outcomes, including cardiovascular disease,

cancer, diabetes and chronic respiratory diseases, which remain underrepresented in the African literature.

2. Expand the spatial and temporal coverage of research

Future research should improve the geographic representation of satellite-based air pollution and health studies across Africa. Although studies were concentrated in a small number of countries, particularly in West Africa, many regions, including Central, East and Southern Africa, remain underrepresented despite experiencing substantial air pollution burdens. Expanding research across these regions would improve understanding of population exposure under diverse environmental, climatic and epidemiological conditions.

Longer study periods should also be prioritised to better characterise cumulative exposure and chronic health effects. Geostationary satellite observations have the potential to improve temporal coverage by providing more frequent measurements over the same location, thereby reducing retrieval gaps and improving the detection of short-lived pollution episodes (72). However, current and planned geostationary air quality missions provide limited coverage of the tropics and Southern Hemisphere, leaving much of sub-Saharan Africa underserved (73). Addressing this gap through the development of a global constellation of geostationary sensors would substantially strengthen long-term air quality monitoring and environmental health research across the continent. Where higher spatial resolution is required, satellite observations should be complemented by ground-based monitoring, low-cost sensors and other remote sensing technologies to improve estimates of surface-level pollutant concentrations (74).

3. Strengthen African methodological capacity and research leadership

Building sustainable capacity in satellite-based environmental health research should be a strategic priority across Africa. Although freely accessible satellite datasets have reduced

barriers to data access, their effective selection, processing, interpretation and validation require specialised expertise that remains limited in many institutions. Investment in interdisciplinary training programmes, technical workshops and communities of practice would improve satellite data literacy among environmental health researchers, epidemiologists and policymakers while strengthening collaboration across disciplines (19). Greater investment in African research institutions and equitable international collaborations is also needed to strengthen local research leadership and ensure the long-term sustainability of satellite-based environmental health research. Advances in machine learning and artificial intelligence offer additional opportunities to improve exposure estimation, process increasingly large Earth observation datasets and support more timely environmental health surveillance, particularly in resource-constrained settings.

4. Improve the translation of satellite evidence into environmental health decision making

The findings of this review highlight opportunities to strengthen the use of satellite-derived air pollution data within environmental health surveillance and air quality management, particularly in regions where conventional monitoring networks are sparse. Satellite observations can complement existing monitoring systems by improving spatial coverage, identifying pollution hotspots and supporting exposure assessment for vulnerable populations. As the quality and availability of satellite-derived products continue to improve, greater collaboration between remote sensing specialists, environmental health researchers and government agencies will be important to ensure that these data are appropriately interpreted and translated into evidence that informs air quality management and public health planning. Beyond supporting environmental health surveillance, satellite-derived evidence has considerable but underexplored potential to strengthen community engagement and advance environmental justice (9, 58). By identifying spatial inequalities in pollutant exposure and populations at greatest risk, satellite data can improve transparency, support

risk communication and enable communities to participate more meaningfully in environmental decision making. Sayyed et al. (2024) found that most studies focused on informing targeted interventions and policy planning, with comparatively little attention given to community-centred applications (58). Expanding the use of satellite-derived information in environmental justice research and community engagement could therefore strengthen the translation of scientific evidence into more equitable public health action.

Future research should evaluate how satellite-derived evidence is currently used in environmental decision making across Africa, including barriers to implementation and opportunities for integrating satellite observations into routine environmental health surveillance. Greater integration of satellite-derived exposure estimates with health impact models would also strengthen understanding of the relationships between air pollution and health outcomes and improve the operational use of Earth observation technologies for environmental health decision making (15).

Limitations

This review had several limitations. Firstly, the review deviated from the protocol regarding the screening process. Rather than dual screening all records, the second author independently screened 10% of the retrieved articles. This approach aligns with standard calibration procedures in systematic and scoping reviews, in which 5–10% of papers are double-screened to ensure consistency in inclusion decisions. If agreement among reviewers is high (commonly $\geq 90\%$), the remaining articles can be screened by a single reviewer with confidence in the reliability of the inclusion criteria (28). Consequently, this deviation is unlikely to have substantially influenced the review findings, given the high level of reviewer agreement achieved during calibration and the relatively small number of eligible studies identified.

Secondly, because a scoping review provides a broad overview rather than in-depth information on a topic of interest, some literature may be missed (75). This means the review cannot claim exhaustive coverage of all available evidence, and findings should be interpreted as a mapping of the current landscape rather than a definitive account of all satellite-based air quality and health research in Africa. Nevertheless, the comprehensive search strategy, which included five electronic databases together with backward and forward citation searching and grey literature searching, maximized the likelihood of identifying relevant studies.

Thirdly, as only studies written in English were included, studies in other languages were excluded. This may potentially exclude important studies across Africa, given the broad native languages spoken across the continent. Furthermore, given that Francophone countries (Senegal, Burkina Faso, Mali, DRC) dominated the included studies, studies published in French that are directly relevant were excluded, which may have introduced a systematic bias toward English-language and HIC research and contributed to the underrepresentation of locally led African scholarship. That said, English remains the dominant language of publication in the fields of environmental health and remote sensing, and the inclusion of grey literature partially mitigated the risk of missing non-English evidence.

Fourthly, relevant studies may have been missed because of differences in terminology used across the disciplines of remote sensing, atmospheric sciences, and environmental health (58). Nevertheless, the review employed a broad, interdisciplinary search strategy across five databases, supplemented by backward and forward citation searching and grey literature searches, thereby enhancing the comprehensiveness of the evidence identification process and reducing the likelihood that major studies were overlooked.

Lastly, only articles and grey literature accessible through the University of Cape Town or open-access journals were included, which may have further excluded literature. However, the University of Cape Town provides access to a wide range of international databases, and open-access publishing is increasingly standard in global health research, limiting the likely impact of this restriction on the overall findings.

Conclusion

This scoping review provides the first comprehensive synthesis of using satellite remote sensing to investigate the relationship between air pollution and human health in Africa. Although the evidence base has expanded considerably over the past decade, research remains geographically concentrated and focused on respiratory diseases, child and maternal health, and meningitis. PM_{2.5} was the most frequently investigated pollutants, followed by desert dust and NO₂, while relatively few studies examined other pollutants and lack of chronic non-communicable disease studies.

Satellite remote sensing has become an important tool for air pollution exposure assessment in Africa, particularly where conventional monitoring networks are sparse. Most studies adopted hybrid approaches that integrated satellite observations with atmospheric models or ground-based measurements. However, methodological reporting was often inconsistent, and ecological and cross-sectional designs dominated, limiting opportunities for stronger causal inference.

The review also identified important geographical and research equity gaps. Much of the evidence originated from a small number of African countries, and study leadership was

798 predominantly based in HICs. Addressing these disparities will require investment in African
799 research capacity, interdisciplinary collaboration, and equitable international partnerships.

800

801 Future research should expand to underrepresented regions, improve methodological
802 transparency and validation of satellite-derived exposure estimates, investigate a broader range
803 of pollutants and chronic health outcomes, and leverage emerging Earth Observation missions
804 and advances in ML-AI to strengthen environmental health research. Collectively, these efforts
805 will enhance the contribution of satellite remote sensing to air quality surveillance,
806 epidemiological research, and evidence-informed environmental health policy in Africa.

807 Acronyms and Abbreviations

808

809 ACAG: Atmospheric Composition Analysis Group

810 AI: Aerosol Index

811 AI-ML: Artificial Intelligence and Machine Learning

812 ALRI: Acute lower respiratory infection

813 AOD: Aerosol Optical Depth

814 AQG: Air Quality Guidelines

815 ARI: Acute respiratory symptoms

816 CALIOP: Cloud–Aerosol Lidar with Orthogonal Polarization

817 CO: Carbon monoxide

818 DRC: Democratic Republic of Congo

819 DSMC: Dust Surface Mass Concentration

820 ESA: European Space Agency

821 IR: Incidence Rates

822 IRR: Incidence Rate Ratio

823 JBI: Joanna Briggs Institute

824	LBW: Low Birth Weight
825	LMICs- Low and Middle Income Countries
826	MAIA: Multi-Angle Imager for Aerosols
827	MERRA-2: Modern-Era Retrospective Analysis for Research and Applications Version 2
828	MISR: Multi-angle Imaging SpectroRadiometer
829	ML: Machine Learning
830	MODIS: Moderate-resolution Imaging Spectroradiometer
831	NASA: National Aeronautics and Space Administration
832	NO ₂ : Nitrogen Dioxide
833	OMI: Ozone Monitoring Instrument
834	OR: Odds Ratios
835	PM: Particulate Matter
836	PM _{2.5} : Particulate Matter with diameters of 2.5 micrometres or smaller
837	PR: Prevalence Ratio
838	PRISMA-ScR: Preferred Reporting Items for Systematic Reviews and Meta-Analyses
839	extension for Scoping Reviews
840	PTB: Pre-term birth
841	RR: Relative Risk
842	SANSA: South African National Space Agency
843	SeaWiFS: Sea-viewing Wide Field-of-View Sensor
844	SEDAC: Socioeconomic Data and Applications Centre
845	Sentinel-5P: Sentinel-5 Precursor
846	SO ₂ : Sulphur Dioxide
847	TOMS: Total Ozone Mapping Spectrometer
848	TROPOMI: TROPOspheric Monitoring
849	WHO: World Health Organization

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