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Advances in Satellite Remote Sensing for Air Quality Assessment: A Comprehensive Review

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Abstract

Satellite remote sensing has become an important tool for air pollution monitoring, especially in regions where ground stations are limited. This review explains how different satellite instruments, such as MODIS, MISR, OMI, VIIRS, and Sentinel-5P/TROPOMI, help measure key pollutants like aerosols (AOD), PM2.5 (indirect), NO_2, SO_2, CO, O_3, and CH_4. We describe how satellite data are processed, how column measurements are converted to ground-level concentrations, and how statistical models, chemical transport models, and machine learning improve the accuracy of these estimates. The review also highlights major applications, including mapping pollution hotspots, studying long-term trends, supporting health research, and monitoring special events like wildfires and dust storms. Although satellite data offer wide coverage, challenges such as cloud interference, limited resolution, and difficulties in linking column data to surface values remain. Future advances such as high-resolution sensors, geostationary satellites, improved retrieval algorithms, and AI-based data fusion are expected to further strengthen satellite-based air quality monitoring. Overall, this review emphasises the growing role of multi-satellite data, when combined with ground measurements and models, in building better air pollution assessments and supporting public-health decisions.

Keywords: Satellite Remote Sensing; Air Pollution; AOD; PM2.5; NO_2; Sentinel-5P; Machine Learning; Exposure Assessment

1. Introduction

Air pollution is a major global environmental and public-health issue affecting millions of people worldwide. The increasing burden of disease linked to polluted air has highlighted the urgent need for advanced and reliable monitoring systems[1], [2]. Although traditional ground-based monitoring networks provide highly accurate measurements, they suffer from limited spatial coverage, particularly in rural regions and in many developing countries where monitoring stations are sparse or absent. This limits our ability to understand pollution variability, long-range transport, and population exposure across wide geographic areas.

To overcome these gaps, satellite-based air pollution monitoring has emerged as a powerful and invaluable tool. Satellite remote sensing offers extensive spatial coverage, improved temporal resolution, and the ability to observe atmospheric composition on regional and global scales. These capabilities allow researchers to assess pollution distribution, identify hotspots, track seasonal and long-term trends, and study transboundary movement of pollutants [3], [4]. Compared with ground monitors, satellites provide uniform measurements over large areas, offering a consistent and continuous view of the atmosphere.

Over the past few decades, satellite technologies have evolved significantly. Early satellite missions provided only basic information on aerosols or trace gases, whereas modern instruments like MODIS, MISR, OMI, VIIRS, and especially

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Sentinel-5 Precursor (carrying the TROPOMI instrument) offer higher spatial and temporal resolution along with improved accuracy. These sensors measure or infer a wide range of pollutants, including Aerosol Optical Depth (AOD), PM2.5 (indirectly), NO_2, SO_2, CO, O_3, CH_4, and formaldehyde. Their combined datasets have transformed our understanding of atmospheric composition and enhanced the scientific basis for air quality research [5].

This review aims to provide a comprehensive understanding of satellite-based air pollution monitoring by discussing:

- The evolution and capabilities of key satellite instruments,
- The pollutants detectable from space and their measurement principles,
- The pollutants detectable from space and their measurement principles,
- The methodologies and algorithms used to process and interpret satellite datasets,
- The integration of satellite products with ground monitors and models,
- Major applications in environmental science, public health, and policy, and
- Current challenges and future opportunities in the field.

By examining these aspects together, the review highlights how satellite remote sensing complements traditional monitoring systems and supports more effective air quality management, epidemiological research, and policy decision-making across both developed and developing regions.

2. Evolution and Capabilities of Satellite Remote Sensing for Air Quality

Satellite remote sensing of atmospheric composition has progressed rapidly over the past several decades. Early satellite missions provided only basic or coarse information on trace gases and aerosols, whereas modern instruments now offer higher spatial and temporal resolution, improved spectral capability, and a wider range of detectable pollutants. These advancements have enabled more detailed assessments of pollution sources, transport pathways, and long-term environmental trends[4], [6], [7].

2.1. Evolution of Satellite Instruments

Initially, satellite sensors were designed to observe broad Earth system processes, including land surface, clouds, and climate parameters. Although these missions provided important foundational data, their ability to detect specific air pollutants was limited. Over time, however, technological advancements in sensor design, radiometric calibration, and spectral resolution led to the development of specialised atmospheric instruments capable of monitoring key trace gases and aerosols at much finer scales[8], [9].

Today, two types of satellite platforms play a major role in air quality research.

- Polar-orbiting satellites, which provide global coverage with revisit times of 1–2 days.
- Geostationary satellites, which continuously observe the same region, enable hourly or sub-hourly monitoring of pollution episodes and diurnal variations.
- Together, these platforms complement each other and provide a comprehensive picture of atmospheric pollution at multiple scales.

2.2. Key Satellite Instruments and Their Capabilities

Modern satellite missions vary in spatial resolution, spectral capability, revisit time, and pollutant sensitivity. Each instrument has unique strengths and limitations, making them useful for different research and monitoring objectives. Understanding these characteristics is essential for selecting the appropriate satellite dataset for any specific air quality study.

Each satellite instrument is designed with specific monitoring goals and technical specifications[3], [10], [11]. For air quality applications, it is often necessary to combine data from multiple sensors to obtain a complete understanding of pollution patterns. The table below summarises key features of widely used satellite instruments

Table 1 Comparison of Satellites for Air Pollution Monitoring

Feature	**Sentinel-5P**	**MODIS**	**OMI**	**Sentinel-1**	**Sentinel-2**
Focus	Air quality and pollution	General Earth observation	Historical NO_2 trends	Radar imaging	Land cover and vegetation
Spatial Resolution	7 × 3.5 km	~10 km	13 × 24 km	5–40 m	10 m
Temporal Coverage	1 day	1–2 days	1 day	12 days	5 days
Key Pollutants	NO_2, CO, CH_4, SO_2, aerosols	AOD	NO_2, O_3	—	—
Advantages	High precision and urban-scale mapping	Long AOD record	Long-term NO_2 data since 2004	High-resolution radar	High-resolution land imaging
Limitations	Limited to post-2017	Low NO_2 precision	Lower spatial resolution	No air quality data	No air quality data

2.3. Detailed Description of Major Instruments

The Moderate Resolution Imaging Spectroradiometer (MODIS), onboard NASA's Terra and Aqua satellites since 1999, is one of the most widely used instruments for aerosol monitoring. Its primary pollutant product is Aerosol Optical Depth (AOD), which serves as the basis for estimating ground-level $PM_{2.5}$ and PM_{10} using statistical and physical models [12]. MODIS offers several strengths, including a long-term dataset spanning more than two decades, frequent global coverage every 1–2 days, and high spectral resolution across 36 bands. However, its limitations include relatively coarse spatial resolution compared to newer sensors, high sensitivity to cloud contamination, and the indirect nature of PM estimation from AOD, which requires calibration with ground measurements[12], [13].

The Multi-Angle Imaging SpectroRadiometer (MISR), aboard NASA's Terra satellite, provides a unique multi-angle observation capability. By capturing data from nine different viewing angles, MISR enables detailed aerosol characterisation, including particle size, shape, and vertical distribution [12]. This multidirectional advantage improves the accuracy of aerosol retrievals compared to single-view instruments. Nevertheless, MISR has a narrower swath width, which reduces its global coverage frequency and limits its applicability for daily monitoring at regional scales[12], [13]

The Sentinel-5 Precursor (Sentinel-5P), launched in 2017 under the European Copernicus Programme, represents a major advancement in air quality monitoring. Equipped with the TROPOspheric Monitoring Instrument (TROPOMI), Sentinel-5P measures a wide range of pollutants, including NO_2, SO_2, CH_4, CO, O_3, HCHO, the Aerosol Index, and AOD. Its superior spatial resolution (7 × 3.5 km) makes it highly suitable for urban-level studies, and its daily global coverage allows researchers to track short-term pollution episodes with high precision[5]. The instrument directly measures several gaseous pollutants and provides open-access, near–real-time data, making it extremely valuable for air quality research. However, Sentinel-5P has limitations such as a relatively short historical record (post-2017 only), the need for column-to-surface conversions, and susceptibility to cloud-related data gaps[9], [14].

Several other satellite instruments also contribute essential information for atmospheric pollution monitoring. The Ozone Monitoring Instrument (OMI) provides a long-term dataset for NO_2, O_3, and SO_2 since 2004 [9]. The Geostationary Environment Monitoring Spectrometer (GEMS) offers hourly atmospheric observations over Asia, enabling the study of diurnal pollution cycles. The CALIPSO mission contributes vertical aerosol profiling through laser-based lidar measurements, helping differentiate aerosol layers. MOPITT specialises in carbon monoxide (CO) detection, while GOSAT focuses on greenhouse gases such as CH_4 and CO_2. Additionally, VIIRS provides nighttime lights and AOD data, which are increasingly used for PM estimation and urban emission analysis. Together, these instruments complement one another by offering diverse pollutant measurements with varying spatial, temporal, and spectral capabilities[15].

2.4. Pollutants Extractable from Satellites

Satellites detect pollutants based on their spectral absorption and scattering characteristics:

- Particulate Matter ($PM_{2.5}$, PM_{10}): Inferred from AOD using MODIS, MISR, VIIRS.
- Nitrogen Dioxide (NO_2): Directly measured by TROPOMI, OMI, GOME-2.
- Sulphur Dioxide (SO_2): Detected by OMI, TROPOMI.
- Carbon Monoxide (CO): MOPITT and TROPOMI provide high-quality CO retrievals.
- Ozone (O_3), Methane (CH_4), Formaldehyde (HCHO): Derived from UV, visible, and IR bands.
- Ammonia (NH_3) and Carbon Dioxide (CO_2): Emerging measurements supporting agricultural and climate research.

3. Methodologies in Satellite-Based Air Pollution Monitoring

Transforming raw satellite observations into meaningful air quality information involves several stages of data retrieval, modelling, and validation. Satellites measure reflected or emitted radiation at various wavelengths, and these radiance values are translated into pollutant concentrations using sophisticated retrieval algorithms. These algorithms correct for atmospheric scattering, absorption, surface reflectance, and cloud effects, and employ radiative transfer models to convert top-of-atmosphere signals into geophysical quantities such as Aerosol Optical Depth (AOD) or tropospheric NO_2 columns [3]. Improved retrieval algorithms, especially for high-resolution instruments like Sentinel-5P/TROPOMI, have significantly enhanced the precision and reliability of atmospheric pollutant estimates [5].

A central methodological challenge is that satellites generally provide column-integrated measurements rather than direct surface-level concentrations. To estimate ground-level pollution—which is critical for exposure and health assessments—researchers use statistical models, chemical transport models, machine learning systems, and hybrid approaches[16], [17]. Statistical models remain widely used because of their simplicity and regional adaptability. These models establish empirical relationships between satellite-based AOD or trace gas columns and ground monitoring data. They often incorporate meteorological variables, boundary-layer height, land-use characteristics, and seasonal factors to improve prediction accuracy[3], [8]. Common statistical approaches include: Multiple linear regression, Linear mixed-effect models, geographically weighted regression (GWR), and Land-use regression (LUR).

These techniques help adjust satellite measurements to reflect local conditions and have been effectively used for $PM_{2.5}$ and PM_{10} estimation in regions worldwide [10], [11].

Chemical Transport Models (CTMs) provide a physically grounded method for estimating atmospheric pollution. CTMs simulate emissions, transport, chemical transformations, dispersion, and deposition of pollutants, capturing key atmospheric processes that statistical models may overlook. When satellite observations such as AOD, NO_2, SO_2, or CO are assimilated into CTMs, they help correct systematic model biases, improve vertical distribution estimates, and enhance the accuracy of surface-level pollutant fields [18]. This integration of observational and modelling data is essential for understanding the complete atmospheric column and improving long-term air quality assessments.

Machine learning and artificial intelligence (AI) have emerged as powerful tools for integrating diverse datasets and capturing nonlinear relationships. ML/AI models can combine satellite retrievals, meteorological fields, ground observations, emission inventories, and land-use variables to generate high-resolution pollution estimates [4]. Common machine learning approaches used in satellite-based air quality estimation include: Random Forests, Gradient Boosting Machines, Support Vector Machines, Artificial Neural Networks, and Deep learning models such as LSTM and CNNs.

These methods often outperform traditional statistical models, particularly in regions with sparse ground monitoring networks, by capturing complex interactions among multiple environmental variables.

Hybrid and data-fusion approaches integrate satellite data, CTM outputs, ground monitoring observations, and meteorological information into a unified framework. Rather than relying on a single technique, hybrid models exploit the strengths of multiple systems. For example, CTM outputs may serve as additional predictors in machine learning algorithms, or machine learning may be used to correct CTM biases. Some hybrid frameworks merge multiple satellite sensors—such as MODIS, MISR, VIIRS, and Sentinel-5P—to reduce data gaps caused by clouds or sensor limitations. These multi-source approaches often produce the most reliable and accurate estimates of $PM_{2.5}$, NO_2, and other pollutants [3].

Geographic Information Systems (GIS) play an essential role in integrating and visualising satellite-derived air quality data. GIS tools help identify pollution hotspots, analyse spatial patterns, overlay emissions sources, and link satellite pollution maps with demographic or health datasets. Ground-based monitoring networks remain indispensable for calibration and validation. Despite satellites' extensive coverage, validation with surface measurements ensures that satellite-derived products are consistent with real-world observations [5], [18].

Validation is the final, critical step in satellite-based air quality methodology. Satellite-derived estimates are compared with co-located ground measurements using statistical metrics such as correlation coefficients, root mean square error (RMSE), mean absolute error (MAE), and model bias. Validation studies also examine regional and seasonal variability and quantify uncertainties arising from retrieval errors, cloud cover, instrument limitations, and spatial representativeness differences [6]. Continuous validation is essential because atmospheric conditions vary substantially across different climates and geographic regions, influencing the performance of satellite-based models [9].

3.1. Applications of Satellite-Based Air Pollution Monitoring

Satellite-derived air quality data have a wide range of applications in environmental science, public health, policy analysis, and climate research. Because satellites provide extensive spatial coverage and consistent observations over time, they enable researchers and decision-makers to examine pollution patterns even in regions where ground monitoring networks are sparse or completely absent. Their ability to detect aerosols and trace gases at regional, continental, and global scales makes satellite observations highly valuable for understanding exposure, identifying pollution sources, and supporting long-term environmental planning [3], [4].

One of the most significant applications of satellite-based monitoring is in exposure assessment for health studies. Many epidemiological studies rely on accurate estimates of $PM_{2.5}$, NO_2, O_3, and other harmful pollutants to assess their health impacts. However, ground-based networks—particularly in developing countries—often have limited spatial coverage. Satellite datasets help overcome this challenge by providing high-resolution pollution fields that can be integrated with population data to estimate exposure levels more accurately. This has enabled researchers to quantify the relationship between pollution exposure and respiratory illnesses, cardiovascular diseases, and mortality in regions lacking adequate monitoring [4], [19]. Satellite data have also supported new models linking satellite-derived pollutant concentrations to disease burden, especially for understudied populations.

Satellites are equally important for analysing long-term air quality trends and identifying major pollution sources. Long-term datasets from instruments such as OMI, MODIS, and MISR have revealed important patterns, including changes in NO_2 levels due to industrial expansion, transport emissions, and policy interventions [9]. These observations help identify regions with persistent pollution problems as well as areas that have improved due to mitigation measures or technological advancements. Satellite images also reveal source signatures of major pollution contributors, including power plants, industrial clusters, vehicular emissions, agricultural burning, and dust storms [1], [12].

Another key application of satellite monitoring is in air quality management and policy evaluation. Because satellite observations provide consistent and large-scale pollution information, they help governments and regulatory bodies evaluate whether air quality policies are meeting their intended goals. For example, satellite NO_2 data from Sentinel-5P can track reductions in emissions following the implementation of clean-air regulations, shutdown of industrial sources, or introduction of cleaner technologies [5]. Policymakers also use satellite datasets to identify areas that require stricter controls or new monitoring stations, strengthening environmental planning and governance.

Satellites also play a crucial role in monitoring exceptional pollution events, which are often missed or undersampled by ground-based sensors. Events such as wildfires, volcanic eruptions, dust outbreaks, and large-scale biomass burning can cause rapid and widespread deterioration in air quality. Satellites like MODIS and VIIRS can detect fire radiative power, smoke plumes, and aerosol loading in near–real time, helping authorities respond more quickly to emerging environmental hazards [6]. These datasets are vital for disaster management, health advisories, and air quality forecasting during extreme episodes.

Satellite observations additionally contribute to climate change research, as many air pollutants—such as methane, carbon monoxide, and aerosols play a dual role in both air quality and climate processes. Instruments like GOSAT and Sentinel-5P provide valuable insight into greenhouse gas emissions, enabling researchers to study emission hotspots, track atmospheric transport, and evaluate the effectiveness of climate mitigation strategies [4], [11]. Satellites help quantify aerosol–cloud interactions and radiative forcing, both of which are key to understanding global climate systems [7].

In summary, satellite-based air quality data support a broad range of applications, including:

- Health exposure assessment and epidemiological research
- Trend analysis and source identification
- Policy evaluation and regulatory planning
- Monitoring of special events (wildfires, dust storms, volcanic eruptions)
- Climate change and greenhouse gas analysis

These diverse applications underscore the growing importance of satellite technology in building robust air quality monitoring systems and formulating evidence-based management strategies [3], [20], [21].

4. Challenges and Limitations

Despite the significant advancements, satellite-based air pollution monitoring faces several challenges:

- Spatial and Temporal Resolution: While improving, satellites often provide broad coverage but may struggle with capturing highly detailed, localised data, especially for urban street-level pollution [7]. Polar-orbiting satellites typically offer one or two snapshots a day, which can limit the capture of rapid changes. Geostationary satellites address temporal limitations but have regional coverage [4]. Temporal and spatial resolution are other limitations, as satellites like Sentinel-5P provide daily data, which may not capture short-term pollution events. Even high-resolution sensors like TROPOMI may average pollution across several kilometres, smoothing fine-scale gradients near traffic corridors and industrial zones [5].
- Column-to-Surface Conversion: The relationship between column-integrated observations and ground-level concentrations can be complex and is influenced by various factors like atmospheric mixing height, humidity, and aerosol vertical profiles [3], [8]. This remains a key area of research and modelling. Large uncertainties arise during temperature inversions, dust storms, and convection events, when the vertical distribution of pollutants deviates from the satellite's assumptions [12].
- Cloud Cover: Cloud cover can obstruct satellite observations, leading to data gaps, particularly in persistently cloudy regions [3]. Thin clouds or haze layers not detected by cloud masks can introduce subtle errors in AOD and gas retrievals, which later affect $PM_{2.5}$ estimation [10]
- Retrieval Accuracy and Validation: The accuracy of satellite-derived products is dependent on the retrieval algorithms and requires continuous validation against ground-based measurements [9]. Discrepancies can arise due to differences in measurement techniques and spatial representation [3]. Validation is especially difficult in under-monitored regions such as India, where sparse ground-level networks limit calibration. Complex terrains such as coasts, mountains, and dense urban environments further complicate retrieval accuracy due to surface reflectance variability [18].
- Data Integration and Interoperability: Integrating diverse data types from various satellite instruments, ground sensors, and chemical transport models can be computationally intensive and requires advanced analytical tools [4]. Cross-platform comparative analyses between MODIS, OMI, and Sentinel-5P are limited, leaving gaps in understanding their relative performance. Inconsistencies in spatial resolution, overpass times, retrieval algorithms, and calibration techniques make multi-sensor fusion challenging and can introduce artificial biases in long-term trend analyses [5].
- Limited Historical Records for New Sensors: New-generation satellites such as Sentinel-5P provide exceptional detail but only from 2017 onward, limiting long-term trend analysis. Combining older instruments like OMI with Sentinel-5P introduces compatibility issues due to differences in resolution and retrieval physics [9].
- Computational and Storage Demands: High-resolution satellite datasets require significant computational resources for downloading, processing, and storing large amounts of data [13], [22]. Many developing countries lack access to high-performance computing or cloud platforms, creating barriers for researchers handling multi-sensor satellite datasets.
- Uncertainty Over Bright Surfaces: Bright surfaces such as deserts, snow, and reflective urban landscapes can interfere with aerosol and trace gas retrievals. Retrieval errors are also higher during dust storms, wildfires, and intense biomass burning events, as complex aerosol types reduce algorithm sensitivity [23].

Future Perspectives

The field of satellite-based air pollution monitoring is continuously evolving, with promising future developments that will further enhance the accuracy, resolution, and applicability of satellite-derived air quality information.

- Enhanced Satellite Missions: Upcoming geostationary and low-Earth orbit missions with advanced sensors will further improve spatial and temporal resolutions, enabling more comprehensive and near–real-time monitoring. New missions such as GEMS, TEMPO, and Sentinel-4 are expected to provide hourly measurements, allowing for detailed analysis of diurnal pollution patterns. Constellations of small satellites (CubeSats) are also being developed to provide ultra-high temporal frequency and localised monitoring at a fraction of current mission costs.
- Advanced Retrieval Algorithms: Continued research and development in retrieval algorithms will lead to more accurate and robust pollutant measurements. Innovations in radiative transfer modelling, aerosol classification, and trace gas retrievals will help reduce uncertainties caused by clouds, aerosols, or high surface reflectance. Machine-learning–assisted retrieval algorithms are now being explored to improve accuracy in challenging environments such as bright surfaces, complex terrains, and highly polluted regions.
- Synergistic Use of Multi-Source Data: Increased integration of satellite data with ground-based measurements, low-cost sensor networks, and meteorological models through advanced data fusion techniques—especially artificial intelligence (AI) and machine learning—will provide a more complete picture of air quality. Multi-sensor fusion across MODIS, MISR, VIIRS, OMI, and Sentinel-5P will help overcome limitations of individual sensors and generate more continuous, gap-free datasets suitable for high-resolution modelling.
- Improved Health Impact Assessments: With more accurate and higher-resolution exposure data from satellites, epidemiological studies will be able to more precisely quantify the health burden of air pollution. This will support the development of targeted public-health interventions in high-risk communities. Satellite-derived pollution estimates will increasingly be integrated with electronic health records, geocoded patient data, and cohort studies to assess long-term exposure outcomes.
- Support for Global Air Quality and Climate Initiatives: Satellite data will play an increasingly vital role in supporting international collaborations and agreements aimed at monitoring and mitigating global air pollution. Observations of greenhouse gases such as methane and carbon dioxide from missions like GOSAT-2 and Sentinel-5 will be essential for climate change tracking and compliance with global emission targets. Near–real-time satellite monitoring will support rapid-response systems for wildfire smoke, dust transport, volcanic ash dispersion, and industrial accidents, helping agencies act quickly during extreme events.
- Higher Spatial Resolution and Urban-Scale Mapping: Future instruments will likely provide spatial resolution approaching sub-kilometre scales, enabling the detection of street-level pollution variation within dense urban areas—something current sensors still struggle with. Advances in hyperspectral imaging will allow satellites to distinguish between different aerosol types (e.g., dust, smoke, industrial emissions), improving source attribution for air quality models.
- Integration with Low-Cost Sensors: Low-cost ground sensors are becoming more reliable, and their integration with satellite data will dramatically enhance spatial coverage. These hybrid systems will enable real-time monitoring at neighbourhood-level scales, especially in developing countries where monitoring infrastructure is limited.

Overall, future developments in satellite technology, retrieval algorithms, data fusion, and health integration will strengthen the role of satellite remote sensing in air quality monitoring. These advancements will provide more accurate, timely, and actionable data to support environmental management, public health, and climate policy globally.

5. Conclusion

This review highlights how advancements in satellite remote sensing have significantly improved the monitoring of key air pollutants, enabling broader coverage, better detection of aerosols and trace gases, and stronger integration with statistical, chemical transport, and machine-learning models to enhance accuracy. Despite challenges such as cloud interference, column-to-surface conversion uncertainties, and differences in sensor resolution, the growing synergy between multi-satellite data, ground observations, and advanced analytical techniques is steadily strengthening the reliability of satellite-derived air quality assessments. With emerging geostationary missions, improved retrieval algorithms, and AI-driven data fusion, satellite monitoring is poised to deliver even more precise, real-time pollution insights. Ultimately, this study supports society by promoting stronger evidence-based air quality management and providing a pathway for future technologies to improve environmental health and public well-being.

Compliance with ethical standards

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Disclosure of conflict of interest

The authors declare that there is no conflict of interest.

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