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Review

Satellite-Based Methane Emission Monitoring: A Review Across Industries

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Highlights

What are the main findings?

- This paper presents a comprehensive cross-sector review of satellite-based methane emission monitoring in the oil and gas, coal mining, agriculture, waste management, and biomass combustion sectors.
- The review distinguishes between point-source imagers (e.g., GHGSat, WorldView-3) and area flux mappers (e.g., TROPOMI, GOSAT) and compares their strengths in the context of different industries.

What is the implication of the main finding?

- The study recognizes technical and operational obstacles, encompassing trade-offs among spatial resolution, revisit frequency, and detection thresholds.
- Prospective research avenues and policy implementations are identified, highlighting the significance of satellite data in facilitating transparent greenhouse gas reporting and mitigation efforts.

Abstract

Satellite remote sensing has become an increasingly important approach for detecting and quantifying methane emissions across spatial and temporal scales. While most reviews in the literature have addressed aspects of methane monitoring, they often focus primarily on satellite platforms or provide discussions on retrieval methodologies. This review offers an integrated assessment of recent developments in satellite-based methane detection, combining technical evaluations of satellite instruments with detailed analysis of retrieval techniques and sector-specific applications. The paper distinguishes between area flux mappers and point-source imagers and reviews both established and recent satellite missions, including GHGSat, MethaneSAT, and PRISMA. Retrieval methods are critically compared, covering full-physics models, CO_2 proxy approaches, optimal estimation, and emerging data-driven techniques such as machine learning. The review further examines methane emission characteristics in key sectors, i.e., oil and gas, coal mining, agriculture, and waste management, and discusses how satellite data are applied in emission estimation and mitigation contexts. The paper concludes by identifying technical and operational challenges and outlining research directions to enhance the accuracy, accessibility, and policy relevance of satellite-based methane monitoring.

Keywords: methane; satellite remote sensing; emission monitoring; greenhouse gases; fugitive emission

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1. Introduction

Methane (CH_4) is a significant greenhouse gas, with an atmospheric lifetime of approximately nine years and a global warming potential 28 times that of carbon dioxide (CO_2) over a 100-year time horizon [1]. While atmospheric methane concentrations remained relatively stable throughout much of Earth's history, they have increased significantly since the pre-industrial era, rising from 722 ppb to 1895.7 ppb, a 2.6-fold increase. [2] In response, many countries have initiated mitigation efforts targeting anthropogenic methane emissions, which are considered both technically feasible and cost-effective to reduce [3]. However, effective mitigation requires accurate and spatially resolved emission data. Traditionally, methane emissions have been estimated using generalized emission factors, which often lack the resolution and specificity needed for reliable accounting. Limited measurement coverage and sparse on-site monitoring contributed to high uncertainty and variability in reported emissions, leading to substantial discrepancies in national inventories [4]. Only a few jurisdictions require direct measurement of emission sources; most rely on top-down estimation methods based on reported activity data. While these methods facilitate standardized reporting across sectors and regions (e.g., EPA AP-42, IPCC guidelines), multiple studies have demonstrated that such approaches often lead to systematic underreporting, highlighting the need for improved monitoring frameworks.

Recent studies using top-down assessments have shown that bottom-up methane inventories often underestimate or omit key emission sources. The Institute for Energy Economics and Financial Analysis reports that fugitive methane emissions are underestimated by roughly 80% for coal and 90% for oil and gas operations. This discrepancy highlights a significant gap between reported and actual emissions, as also noted by the International Energy Agency (IEA) [5]. Similarly, Chan et al. found that Canadian government inventories may underestimate emissions by a factor of two [6]. In the United States, Brandt et al. estimate that unreported or underestimated methane sources contribute roughly 14 Tg/year (ranging from 7 to 21 Tg/year), representing up to 50% (25–100%) of total anthropogenic emissions [6]. Identifying the sources of these missing emissions requires methods that can attribute atmospheric methane levels, derived from top-down data, to specific sources [7]. Bottom-up approaches play a key role in closing this gap. Methane emissions can be measured using various technologies, including vehicle-mounted sensors, drones, metal oxide detectors, satellite remote sensing, airborne spectrometry, and ground-based systems. These methods vary in coverage, accuracy, and cost, supporting both localized and large-scale detection. Continuous monitoring networks and direct measuring tools, such as flux chambers and eddy covariance systems, further enhance the precision of emission estimates.

Airborne platforms, both manned and unmanned, offer high-resolution, aerial perspectives for methane detection, but they are limited by their inability to provide continuous, long-term monitoring [8,9]. Mobile systems, such as vehicle-mounted laser spectrometers and drone-based infrared sensors, enable flexible and rapid detection, making them well-suited for pinpointing leaks at industrial sites. However, their limited range requires frequent redeployment to ensure comprehensive coverage.

Ground-based remote sensing methodologies offer a viable alternative, enabling precise, wide-area measurements. Techniques like open-path Fourier Transform Infrared (FTIR) spectroscopy and Differential Absorption Lidar (DIAL) allow for real-time monitoring of methane plumes, though their effectiveness depends on favorable weather and unobstructed sightlines to emission sources. Cavity Ring-Down Spectroscopy (CRDS) delivers highly accurate methane concentration data at ground level, but it is restricted to fixed locations. Direct measurement tools, such as flux chambers and eddy covariance systems, are commonly used in sectors like agriculture, landfills, and wastewater treatment

to estimate emissions. However, these methods are not scalable for larger industrial sites. Many ground-level technologies are further constrained by their inability to offer continuous, long-duration monitoring at low cost. Satellite-based remote sensing addresses these limitations by enabling broad, long-term observation of methane emissions across large geographic regions. This approach delivers consistent, reliable data that supports deeper, large-scale analysis.

Satellite sensors typically offer broad spatial coverage and are commonly used to measure methane concentrations on global, national, or regional scales. The latest satellite point source imagers provide high spatial resolution data, enabling the detection and quantification of individual emission sources [10]. Although satellite remote sensing faces certain limitations, it has proven to be a powerful tool for emission monitoring across various industries. This success stems from its ability to conduct wide-ranging, continuous, and autonomous surveillance. With satellite data, emissions from oil and gas facilities, landfills, wastewater treatment plants, and agricultural operations can be identified and quantified remotely, eliminating the need for on-site inspections. Thanks to their fine geographic resolution and frequent revisit rates, satellites can monitor emission dynamics, pinpoint super-emitters, and support regulatory compliance at a lower cost than ground-based monitoring systems. Given the recent surge in research employing satellite-based methane detection, this review will critically assess the current satellite remote sensing technologies, explore their applications across industries, and highlight promising avenues for future development. This work provides a comprehensive viewpoint by connecting instrument capabilities, retrieval methods, and sector-specific applications, in contrast to previous evaluations that concentrated mainly on retrieval approaches or satellite platforms. It specifically highlights underrepresented industries, such as wastewater treatment and biomass combustion, which are frequently neglected in previous evaluations.

Several recent review articles have examined the utilization of satellite remote sensing for monitoring methane emissions, each highlighting different facets such as retrieval techniques, sensor efficacy, or sector-specific applications. Nonetheless, these reviews differ significantly in their breadth, methodological framework, and scope of review. Table 1 offers a comparative assessment of the most pertinent review studies to elucidate the research landscape and contextualize the current study.

As indicated in Table 1, previous assessments have generally focused on a singular industry (e.g., oil and gas, coal mining, or waste management) or on particular technical components such as retrieval algorithms and sensor design. Although these studies have yielded significant insights into certain facets of methane detection, none have thoroughly integrated cross-sectoral trends, satellite capabilities, and methodological obstacles within a cohesive framework. This review addresses the gap by synthesizing findings from five primary anthropogenic methane sources, providing a comprehensive overview of satellite-based methane monitoring and potential multi-tier observation strategies.

This research mostly utilized Scopus and Google Scholar to search for literature. It integrated general terms such as “methane emission” and “satellite remote sensing” with sector-specific keywords, including “oil and gas,” “coal mining,” “agriculture,” “waste management,” and “biomass burning.” Boolean operators were applied to refine the results, and the query was limited to publications from 2000 to 2025 to capture the evolution of satellite-based methane monitoring technologies. Following the initial search, all retrieved records were compiled, and duplicate entries were removed. Titles and abstracts were then reviewed to exclude studies unrelated to methane or those that did not employ satellite-based remote sensing methods. Subsequently, the full texts of the remaining papers were examined, and publications were excluded if they focused on other greenhouse gases, relied solely on laboratory or ground-based measurements, or were not peer-reviewed (such

as conference abstracts, editorials, or commentaries lacking methodological detail). The final selection included over 220 peer-reviewed journal articles and authoritative technical reports from organizations such as the U.S. Environmental Protection Agency (EPA) and the International Energy Agency (IEA). In addition, the reference lists of key review papers were manually examined to ensure that all relevant and high-quality studies were captured within the scope of this research.

Table 1. Comparative summary of major review studies on satellite-based methane studies.

Review Paper (Year)	Primary Focus/Scope	Review Approach	Organization/Structure	Key Distinction
Mehrdad & Du (This study)	Cross-sector review of CH_4 monitoring across five industries	Cross-sector Integrated Assessment	By industry (O&G, Coal, Agriculture, Waste, Biomass)	Integrated assessment across five major industries Introduces tiered monitoring framework concept
Mohammadimanesh et al. (2025) [11]	Satellite-based methane point source monitoring	Systematic (PRISMA)	By monitoring stages (retrieval → masking/detection → quantification)	Specializes in facility-scale CH_4 detection and quantification
Jiang et al. (2024) [12]	Methane retrieval algorithms (area & point sources)	Technical/Algorithm-centric	By retrieval model (physical, DOAS, optimal estimation, ML)	Deep dive into mathematical and algorithmic formulations
Chauhan & Raval (2024) [13]	Coal Mine Methane (CMM) emissions	Focused/Sector & uncertainty-based	By platform type and region	CMM-exclusive with uncertainty quantification
Karimi et al. (2023) [14]	Satellite imagery for Solid Waste Disposal (WDS) applications (2012–2021)	Systematic/Bibliometric	By study type, satellite platform, and analytical method	Exclusive focus on WDS applications including landfill siting and anomaly detection
Zhang et al. (2023) [15]	Atmospheric RS for anthropogenic CH_4 emissions	Comprehensive/Sector-centric	By emission sector (Energy, Waste, Agriculture, Urban)	Multi-platform integration (ground, airborne, satellite)
Papale et al. (2023) [16]	Landfill monitoring using optical (VIS–NIR–SWIR, TIR) and SAR data	Narrative/Parameter-based	By parameter type (single vs. multi-parameter analysis)	Integrates case studies (Mongolia, Pakistan)
Erland et al. (2022) [17]	Transparent CH_4 monitoring across scales	Critical/Taxonomy-based	By spatial scale (bottom-up to top-down)	Integrates validation and uncertainty frameworks

2. Satellite Remote Sensing Technologies and Methane Quantification Methods

2.1. The Development and State-of-the-Art in Satellite Methane Sensing Systems

The detection of methane using satellites has advanced significantly in the last twenty years, transitioning from broad worldwide assessments to precise monitoring at the facility level. The inaugural generation of instruments, commencing with SCIAMACHY on Envisat (2002), established the viability of detecting near-surface methane from space. Subsequent missions like GOSAT (2009) enhanced these capabilities using shortwave-infrared (SWIR) solar backscatter methods, delivering column-averaged methane concentrations with sub-percent accuracy. Collectively, these initial systems laid the methodological groundwork for regional flow estimation and long-term atmospheric trend research [18,19].

The second generation of sensors attained enhanced spatial and temporal coverage. TROPOMI, initiated in 2017 on the Sentinel-5 Precursor platform, offered near-daily global mapping with kilometer-scale resolution across ultraviolet, visible, and shortwave infrared bands. The enhanced signal-to-noise ratio and swift return time facilitated worldwide methane monitoring, allowing for systematic identification of regional hotspots and emission trends. These advancements signified the shift from experimental retrievals to ongoing global monitoring of methane [20–22].

Recent missions have concentrated on addressing specific emission sources. Since 2016, GHGSat has pioneered facility-scale detection with high-resolution imaging spectrometers that can identify particular industrial plumes [23]. MethaneSAT, inaugurated in 2024 by the Environmental Defense Fund and the New Zealand Space Agency, enhances this methodology with an expanded coverage and 100 m resolution to estimate emissions from whole production basins while preserving source-level sensitivity [24].

TROPOMI (TROPOspheric Monitoring Instrument), launched in 2017 aboard the Sentinel-5 Precursor satellite, expanded global methane mapping capabilities. Operating in a Sun-synchronous orbit at ~824 km altitude, TROPOMI covers a 2600 km swath daily with a resolution of $3.5/7 \times 7$ km^2 and provides near-global coverage every 24 h. Its two spectrometers span UV, visible, near-infrared (NIR), and SWIR bands centered at 2.3 μm, enhancing the detection of methane plumes [25,26].

Commercial satellites like WorldView-3 enhance spatial resolution to several meters, facilitating the validation and precise monitoring of leaks from pipelines, wellheads, and waste sites. These point-source imagers collectively signify a transformative approach to actionable monitoring for mitigation and regulatory adherence. WorldView-3 data combined with atmospheric corrections and targeted acquisition protocols, it serves as a powerful validation tool for coarse-resolution systems like TROPOMI or Sentinel-2 [27].

In addition to these specialized platforms, several hyperspectral and multispectral land imaging satellites contribute to methane monitoring using SWIR bands. These include PRISMA, Sentinel-2, Landsat-8/9, and WorldView-3. Though not initially intended for greenhouse gas observation, they have proven effective in identifying major methane sources.

Landsat-8 (2013) and Landsat-9 (2021), operated by NASA and the USGS, provide 30 m SWIR data through the Operational Land Imager (OLI). Though primarily designed for land surface imaging, Landsat data have been successfully used to detect major methane emissions when combined with statistical or machine learning methods [28,29].

Sentinel-2A and -2B with more precise spatial resolution bands were launched by the European Space Agency in 2015 and 2017. Although not optimized for methane detection, SWIR bands 11 (∼1560–1660 nm) and 12 (∼2090–2290 nm) have been leveraged to identify large methane sources under favorable conditions. Sentinel-2′s frequent revisit time (2–5 days) and wide swath enhance its utility for temporal monitoring [30].

PRISMA (PRecursore IperSpettrale della Missione Applicativa), launched in 2019 by the Italian Space Agency, is a hyperspectral mission offering 30 m spatial and 12 nm spectral resolution across a broad range from visible to SWIR. Although not originally designed for greenhouse gas monitoring, PRISMA's spectral accuracy supports the detection of key methane absorption features when paired with radiative transfer models and advanced processing methods. Its efficacy has been demonstrated in industrial and landfill methane studies [31].

Satellite methane sensing systems are categorized into two complimentary types: area-flux mappers, which collect extensive concentration fields at kilometer resolution, and point-source imagers, which provide facility-level quantification. The integration of these datasets across various scales while employing coarse-resolution instruments like TROPOMI to identify anomalies and fine-resolution sensors such as GHGSat or Sentinel-2 to characterize sources has revolutionized methane monitoring into a multi-tiered, operational framework that increasingly enhances and exceeds conventional ground-based methods. Table 2 offers a list of the most used satellites in different industrial applications.

Table 2. Comparative summary of major satellites used for methane quantification across industrial sectors.

Name	Type	Pixel Size (km × km)	Spectral Resolution (nm)	Coverage	Revisit Time	Spectral Bands for CH_4	Launch Year
SCIAMACHY	SWIR spectrometer	30 × 60	1.4	Global	6 days	1.65 μm, 2.3 μm	2002
GOSAT	SWIR spectrometer	10 × 10	0.06	Global	3 days	1.6 μm, 2.0 μm	2009
TROPOMI	SWIR spectrometer	7 × 7	0.25	Global	daily	2.3 μm	2017
MethaneSat	SWIR spectrometer	0.13 × 0.4	0.3	Target 200 × 200 km^2	weekly	1.65 μm, 2.3 μm	2024
GHGSat	SWIR spectrometer	0.05 × 0.05	0.1	Target 12 × 12 km^2	every 2–3 days	2.3 μm	2016
GF-5	hyperspectral imaging camera	0.03 × 0.03	10	Target 60 × 60 km^2	3–5 days	2.1–2.3 μm	2018
ZY-1	hyperspectral imaging camera	0.03 × 0.03	20	Target 60 × 60 km^2	unknown	2.1–2.3 μm	2021
PRISMA	hyperspectral imaging camera	0.03 × 0.03	10	Target 30 × 30 km^2	7 days	2.1–2.3 μm	2019
EnMap	hyperspectral imaging camera	0.03 × 0.03	10	Target 30 × 30 km^2	4 days	2.1–2.3 μm	2022
EMIT	hyperspectral imaging camera	0.06 × 0.06	7.5	Mineral dust emitting region	on demand	2.3 μm	2022
Landsat-8	multispectral imaging camera	0.03 × 0.03	200	Global	16 days	2.1–2.3 μm	2013
WorldView-3	multispectral imaging camera	0.004 × 0.004	50	Target 66.5 × 112 km^2	daily	2.1–2.3 μm	2014
Sentinel-2	multispectral imaging camera	0.02 × 0.02	200	Global	5 days	Band 11 & 12	2015
Sentinel-3	multispectral imaging camera	0.5 × 0.5	50	Global	2 days	Band 11 & 12	2016

2.2. The Progress of Methane Retrieval and Quantification Algorithms

The progression of satellite-based methane monitoring systems, from coarse-resolution global mappers to fine-resolution point-source imagers, has been accompanied by significant advancements in retrieval methodologies. These methods are crucial for converting raw spectral data into quantitative estimates of methane concentrations or fluxes. The selection of an appropriate retrieval technique depends on multiple factors, including the spatial and spectral characteristics of the satellite sensor, atmospheric conditions, surface reflectance, and the temporal and spatial scales of the emission source. This section provides an overview of the primary retrieval approaches utilized for area flux mapping and point source imaging, followed by a discussion of methods for estimating emission rates from the retrieved enhancements.

2.2.1. Retrieval Techniques for Area Flux Mappers

Satellites functioning at low spatial resolutions are intended to observe methane emissions on regional and global levels, enhancing detection across extensive geographic regions [32]. While these instruments have lower spatial granularity, they provide high-precision measurements of atmospheric methane columns. Despite their restricted geographical resolution, these sensors deliver exceptionally accurate observations of atmospheric methane concentrations. In the last twenty years, retrieval techniques have transitioned from computationally demanding physical inversions to more efficient or statistically optimized methodologies. The primary strategies encompass full-physics retrieval, the CO_2 proxy method, and the optimal estimation method (OEM), each reflecting a distinct equilibrium among physical precision, computational efficiency, and resilience to measurement uncertainty.

- Full-Physics Retrieval Method

The full-physics retrieval method is the most thorough and scientifically robust technique for calculating methane from satellite data. It inverts solar backscattered radiation through comprehensive radiative-transfer modeling to ascertain vertical column concentrations of CH_4, while concurrently extracting ancillary data like aerosol optical depth, surface albedo, and scattering properties [32–35]. By carefully modeling the interaction of sunlight with the atmosphere and surface across many spectral bands, it delineates methane's absorption characteristics and reduces interference from clouds and aerosols.

A primary advantage of the full-physics approach is its comprehensive treatment of atmospheric physics, which enables high-accuracy retrievals under favorable observational conditions. It performs particularly well in clear-sky scenarios over bright surfaces, such as deserts or open ocean, where surface reflectance and atmospheric conditions are well characterized.

This method provides precise retrievals in clear-sky situations and over bright, uniform surfaces like deserts or oceans. Nonetheless, it is computationally intensive and susceptible to inaccuracies in surface reflectance, atmospheric variability, and cloud interference. These obstacles frequently diminish retrieval success rates on land and restrict spatial coverage [33,36]. Notwithstanding these limitations, the full-physics approach continues to serve as the standard for satellite-based methane monitoring and supports Level-2 CH_4 outputs from missions including SCIAMACHY [18,37], GOSAT [38,39], TROPOMI [25,33], and GOSAT-2 [39,40]. Under optimal conditions, it yields reliable, physically coherent estimates that have enhanced comprehension of global methane fluxes and facilitated the validation of emission inventories.

- CO_2 Proxy Method

The CO_2 proxy method provides a computationally efficient substitute for the full-physics approach. It utilizes the analogous optical properties of CO_2 and CH_4 in the shortwave-infrared (1.6–2.3 μm) spectrum. Rather than directly measuring methane, it deduces CH_4 concentrations by examining differential absorption in CH_4/CO_2 spectral windows and adjusting the ratio using a reference CO_2 field obtained from transport models or climatological datasets [41,42]. Due to the generally uniform distribution of atmospheric CO_2 over brief periods, it functions as a reliable tracer for normalizing methane absorption.

The simplicity of this method facilitates swift, extensive processing while diminishing sensitivity to errors in aerosol scattering, surface pressure, and albedo. Proxy-based retrievals have been effectively executed in GOSAT and demonstrated significant concordance with ground-based TCCON measurements [41–44]. Nonetheless, their precision may diminish in areas with significant local CO_2 sources or sinks, where discrepancies from presumed CO_2 distributions result in bias. Reliance on external CO_2 reference fields may potentially transmit uncertainties, particularly in regions exhibiting significant temporal or geographical fluctuation in atmospheric composition. Notwithstanding these constraints, the CO_2 proxy method continues to be an invaluable instrument for effective global mapping and longitudinal trend analysis.

- Optimal Estimation Method

The OEM is a Bayesian inversion framework extensively utilized in satellite remote sensing for the retrieval of atmospheric trace gases, including CH_4. OEM integrates spectrally measured radiances with pre-existing data on atmospheric and surface conditions to deliver a statistically optimal solution that addresses measurement noise and model uncertainties. Full-physics retrievals are generally executed inside this framework, utilizing a forward model that distinctly characterizes radiative transmission, surface reflectance, and scattering phenomena. This makes it particularly effective for stabilizing the inversion

of ill-posed problems, even when observational data alone are insufficient to uniquely determine the target variables [45].

In practice, OEM involves iterative refinement of a state vector, representing atmospheric quantities such as gas concentrations, to minimize a cost function that balances the fit to observed data with deviations from the prior estimate [46]. A forward model, typically a radiative transfer model, simulates the expected measurements based on the current state estimate. The strength of OEM lies in its formal incorporation of uncertainties from both the observations and prior information, resulting in more robust and reliable retrievals. OEM has been successfully applied in multiple satellite missions, including GOSAT [41] and MetOp/IASI [47,48], enabling the generation of global methane distribution products with well-characterized and quantifiable uncertainties.

2.2.2. Retrieval Techniques for Point Source Imagers

Point-source imagers are satellite instruments with high spatial resolution (usually <100 m) intended to identify and measure methane emissions from specific facilities, including oil and gas installations, landfills, and waste treatment plants. Their high resolution enables the detection of minor, fleeting emission events that evade recognition by low-resolution sensors. These systems utilize retrieval methods to improve plume visibility by maximizing the contrast between methane-affected and background pixels, hence optimizing the signal-to-noise ratio and adjusting for atmospheric and surface fluctuation. The primary retrieval methods encompass matched-filter techniques, multi-pass and multi-band strategies, transmittance-based algorithms, and data-driven models, each demonstrating a unique equilibrium between physical accuracy and computing efficiency.

- Matched Filter Technique

The matched-filter (MF) method is one of the most commonly utilized techniques for detecting methane in hyperspectral imaging. It juxtaposes each observed spectrum with a background reference that signifies surface and air conditions devoid of methane. The system identifies pixels with anomalous absorption by convolving the background with established CH_4 absorption characteristics about 2.3 μm, suggesting the presence of probable plumes. MF retrievals exhibit computational efficiency, necessitate minimum atmospheric adjustment, and are ideally suited for the swift processing of extensive datasets. Initially designed for airborne sensors, they have been effectively utilized in satellites like PRISMA [49,50], EnMAP [51], and Carbon Mapper for routine detection of strong methane emitters.

- Single-Band Multi-Pass Retrieval (SBMP)

The SBMP method detects methane by comparing reflectance in a single absorption-sensitive spectral band across a multispectral satellite overpass. One overpass captures a methane plume, while another provides a baseline under similar conditions. By evaluating the reflectance difference between the two, the method isolates methane-related absorption, ideal for identifying intermittent emissions such as equipment leaks. Sentinel-2 is commonly used due to its 20 m spatial resolution in SWIR bands and frequent revisit time [52,53]. Though simpler than full-physics approaches, SBMP offers a reliable and computationally efficient solution for monitoring point source emissions.

- Multi-Band Single-Pass (MBSP) Retrieval

This technique identifies methane plumes by comparing reflectance in two adjacent SWIR bands during a single overpass: one sensitive to methane absorption (e.g., Sentinel-2 Band 12, covering approximately 2115–2290 nm) and one less affected (e.g., Band 11, covering approximately 1560–1660 nm). The differential absorption reveals plume presence. MBSP assumes uniform surface and atmospheric conditions across bands and benefits

from using widely available multispectral data. It has been effectively applied to oil and gas fields in Algeria and Turkmenistan using Sentinel-2 imagery [53,54]. The method is simple, fast, and scalable for frequent monitoring but may be influenced by surface and atmospheric variability.

- Multi-Band Multi-Pass (MBMP) Retrieval

Combining SBMP and MBSP, the MBMP approach improves detection accuracy by subtracting the MBSP result of a reference pass from a plume-containing pass. This strategy compensates for surface and atmospheric variation, enhancing plume detection reliability. Widely used with Sentinel-2 data, MBMP supports advanced applications like CH4Net, a deep learning network trained on MBMP-processed imagery for identifying methane super-emitters [55].

- Transmittance-based Multispectral Algorithms

These methods detect methane by comparing transmittance in absorption-affected versus unaffected spectral bands using basic radiative transfer calculations. The reflectance differences are attributed to methane presence. Landsat-8 and Sentinel-2 are suitable for such analyses, with Band 12 used for methane sensitivity and Band 11 as a reference [52,53].

- Data-Driven Approaches

Machine learning and statistical techniques offer powerful tools for analyzing hyperspectral data without relying on explicit background models. Algorithms like convolutional neural networks (CNNs), transformers, and support vector machines (SVMs) detect subtle methane signals within complex scenes [56–58]. These models, trained on datasets from sensors such as AVIRIS-NG, PRISMA, and EnMAP, have demonstrated strong performance. For instance, HyperSTARCOP employs semantic segmentation to detect plumes [59], MethaneMapper uses transformers to identify spectral absorption patterns [60]. These approaches enable scalable, accurate methane monitoring with operational potential for spaceborne platforms [61].

Table 3 concisely summarizes the primary methane retrieval methodologies employed in satellite remote sensing, as delineated in the prior methodological discourse. The table outlines the fundamental attributes, benefits, constraints, and common application scenarios of both large-scale area flux mappers and high-resolution point-source imagers. These retrieval algorithms collectively enhance accuracy, computational efficiency, and geographical detail across various observation platforms. Jiang et al. (2023) offer the most thorough technical study of satellite-based methane retrieval algorithms among the referenced studies, serving as an essential resource for readers desiring a detailed comprehension of retrieval formulation and implementation [12].

Algorithms for satellite-based methane retrieval varies in complexity, accuracy, and relevance to various emission sources. Area flux mappers are mostly utilized for regional or worldwide surveillance, necessitating broad spatial coverage and the identification of long-term patterns. The OEM method provides statistically robust retrievals with measurable uncertainty and is extensively utilized in satellites like the GOSAT satellite. Nevertheless, it is heavily reliant on prior atmospheric data, which may introduce bias in areas with insufficient characterization. The Full-Physics Retrieval approach attains exceptional physical precision, rendering it optimal for scientific study and the confirmation of national inventories. Nonetheless, it is computationally demanding and operates optimally over luminous, cloudless surfaces which are not frequently found in agricultural, waste management areas, or urban settings. The CO_2 Proxy Method, extensively utilized by GOSAT, offers a computationally efficient option for extensive analyses and prolonged datasets. Nonetheless, it is inappropriate for areas with significant CO_2 fluctuations or when satellite sensors do not possess the requisite spectral bands (e.g., TROPOMI).

Table 3. Comparative overview of methane retrieval algorithms.

Category	Algorithm/Method	Key Features	Advantages	Limitations	Typical Applications/Satellites
Area Flux Mappers	Optimal Estimation Method (OEM)	Bayesian inversion using prior info	Robust retrieval with quantified uncertainty	Requires prior constraints on atmospheric states	GOSAT, MetOp/IASI
	Full-Physics Retrieval	Radiative transfer modeling of sunlight-atmosphere interaction	High accuracy; physically comprehensive	Computationally heavy; sensitive to clouds and surface heterogeneity	SCIAMACHY, GOSAT, TROPOMI, GOSAT-2
	CO_2 Proxy Method	CH_4 inferred via CH_4/CO_2 ratio	Simple and fast; reduced sensitivity to aerosols	Biased where CO_2 varies; limited spectral range	GOSAT
Point Source Imagers	Matched Filter	Compares observed vs. background spectra	Efficient, robust; minimal atmospheric correction	Less effective for weak or diffuse plumes	PRISMA, EnMAP
	SBMP/MBSP/MBMP	Multi/single-band reflectance differencing	Fast; scalable; MBMP most accurate	Sensitive to surface/atmospheric variability	Sentinel-2, GHGSat
	Data driven Models	CNNs, transformers for spectral analysis	Automates detection; can outperform physics models on trained data	Needs large training datasets; interpretability limited	TROPOMI, PRISMA

Point source imagers are superior for facility-level detection, especially in industrial contexts. These approaches are swift, resilient, and effective for detecting methane plumes from specific sources; however, they may be influenced by variations in surface reflectance and atmospheric conditions. The sophisticated MBMP method combines temporal and spectral differencing to improve detection precision in intricate industrial settings. Emerging data-driven and machine learning algorithms provide near-real-time detection and automatic plume segmentation across several sectors, contingent upon the availability of adequate training data. Nonetheless, these models remain deficient in interpretability and consistency for regulatory purposes.

No algorithm is universally optimal in practice. The choice of a retrieval method is contingent upon the emission scale and attributes of the source. Area flux detection methods are more appropriate for diffuse or fugitive emissions, while point source imaging approaches focus on concentrated plumes. A hybrid or tiered structure that amalgamates both methodologies offers the most dependable and thorough coverage for methane monitoring across various industrial sectors.

2.3. Methods for Methane Flux Quantification

The quantification of methane flux, or emission rate, after obtaining atmospheric methane concentrations (usually expressed as the column-averaged dry-air mixing ratio, XCH_4), is essential for converting satellite or airborne observations into practical emission estimates. The choice of an appropriate quantification method is mostly contingent upon the spatial scale of the emission source and the availability of supplementary data, especially regarding wind and transport dynamics. The methodologies utilized in the literature can be broadly classified into two categories: area flux quantification and point-source measurement.

2.3.1. Quantification of Area Sources (Regional and Global Scales)

In extensive investigations, including continental, basin-wide, or worldwide evaluations, methane flux estimation predominantly depends on air transport models that connect surface emissions to observed concentration patterns.

Atmospheric Inverse Modeling (Bayesian Inference) is the primary top-down methodology utilized in regional and worldwide methane research employing equipment like TROPOMI or GOSAT [62–64]. This method optimizes spatially resolved emission fluxes

by minimizing the discrepancy between observed methane columns and prior emission estimates, utilizing a transport model represented by the Jacobian matrix, which quantifies the sensitivities between surface fluxes and atmospheric concentrations. The answer is derived by minimizing a Bayesian cost function that integrates both observational and prior uncertainties via covariance matrices. The standard formulation presumes Gaussian error distributions; however, lognormal and other heavy-tailed models have been developed to more accurately represent the unpredictability of natural gas emissions and ensure non-negativity [32,65].

Alternative methods implement Tikhonov regularization or LASSO-type sparsity constraints to impose smoothness or localization in flux adjustments. The Degrees of Freedom for Signal (DOFS) metric is commonly employed to measure the enhancement in information content obtained through inversion compared to the preceding [66].

In addition to inversion methods, mass balancing and scaling techniques provide more direct methods for converting observed concentration increases into emission estimates. The Mass Balance Method correlates the observed methane increase with a modeled increase derived from a reference simulation influenced by a known input flux. This methodology has demonstrated efficacy for substantial, transient emission occurrences, such as gas well blowouts or regional emissions detected by TROPOMI [67].

The Gaussian Integral (Regional Mass Balance) Method estimates daily emissions by integrating methane flux over cross-sections perpendicular to the average boundary-layer wind direction. The total column enhancement and mean wind speed are critical parameters for estimating advective flux divergence over the domain [68,69].

The Tracer-to-Tracer Correlation Method, an indirect technique, is frequently utilized in urban or industrial areas where methane emissions correlate with other trace gases like CO_2 or CO. This method utilizes the correlation between CH_4 and a co-emitted tracer with a precisely defined inventory to deduce methane fluxes, especially when independent CH_4 inventories are either ambiguous or lacking [70].

2.3.2. Quantification of Point Sources (Individual Plumes)

At more precise spatial scales, the estimation of methane flux concentrates on isolated plumes (typically <1 km) detected by high-resolution imaging spectrometers such as AVIRIS-NG, GHGSat, or Sentinel-2. These retrievals identify specific emission sources, necessitating approaches that explicitly integrate air transport inside the plume.

The Integrated Mass Enhancement (IME) Method is the most often utilized approach, calculating the total excess methane mass identified within a plume by integrating the concentration enhancement over all pixels in the plume region. The instantaneous emission rate is determined using the effective wind speed and the characteristic plume length scale. Due to the linear relationship between emission rates and wind speed, $U_e$ff presents the most significant source of uncertainty. It is generally derived using 10 m wind speed acquired through meteorological models or in situ data, then modified using Large-Eddy Simulations (LESs) to accurately depict sub-grid turbulence and plume dispersion in accordance with the sensor's resolution [71–73].

The Cross-Sectional Flux (CSF) Method, a commonly employed technique, incorporates methane column increases along a transect perpendicular to the dominant wind direction, multiplying by $U_e$ff to calculate the total emission flux. This methodology frequently produces outcomes that align with IME when utilized on identical datasets and is beneficial for plumes exhibiting clearly delineated cross-sectional structures [74].

In addition to these conventional methods, other innovative and data-driven strategies have arisen. The Plume Angular Width Method assesses source intensity by analyzing the geometric dispersion of the observed plume: narrower plumes indicate stronger winds

and greater emission rates, facilitating approximate flux estimation despite insufficient meteorological data [72]. In recent years, machine learning approaches, especially Convolutional Neural Networks (CNNs) like MethaNet, have been created to deduce emission rates directly from two-dimensional plume images [75]. These models, trained on extensive collections of synthetic plume simulations, acquire spatial dispersion patterns and significantly diminish dependence on explicit wind field data, indicating a possible avenue for near-real-time, data-driven emission measurement.

3. Sectoral Analysis of Methane Emissions

Identifying the sector-specific origins of methane emissions is essential for formulating targeted mitigation strategies. This section offers a thorough analysis of methane emissions across five key sectors: oil and gas, coal mining, agricultural and livestock, waste management, and biomass combustion. Every sector contributes distinctly to global methane levels through its own operational processes.

The U.S. Environmental Protection Agency's 2020 Global Non-CO_2 Greenhouse Gas Emissions Projections and Mitigation Report identifies agriculture as the predominant source of anthropogenic methane, contributing around 51% of the global emissions. Within this sector, livestock production accounts for about 28%, while rice cultivation and other agricultural activities contribute another 21%. The data emphasizes that waste management, including landfills and wastewater, accounts for approximately 15% of global methane emissions, underscoring the persistent challenges of anaerobic organic waste decomposition. In the energy sector, coal mining contributes 6.8%, whilst natural gas and oil systems add approximately 10%. Collectively, these fossil fuel-related activities constitute a significant portion of emissions and are especially well suited for detection and monitoring by advanced satellite-based technology [76].

The distribution of emissions across sectors illustrates both the magnitude of the challenge and the opportunities for intervention. Effective mitigation requires sector-specific strategies, with priority given to agriculture due to its predominant share, while also addressing emissions from waste, energy, and industry. By focusing on these key categories, global initiatives can achieve meaningful methane reductions and directly support international climate objectives. The following subsections examine each sector in greater depth, emphasizing both the challenges and opportunities for monitoring and mitigation.

3.1. Oil and Gas Industry

Methane emissions in the oil and gas business predominantly stem from venting, flaring, equipment failures, and fugitive leaks during the extraction, processing, storage, and transportation of hydrocarbons [77]. Although frequently inadvertent, these emissions are consequential owing to the large and antiquated infrastructure of the global energy sector. The International Energy Agency's Methane Tracker (2023) reports that the global energy sector emitted almost 135 million tonnes of methane in 2022, with oil and gas activities contributing over 40 million tonnes, which is nearly 59% of sectoral emissions [78]. This underscores the critical role the industry plays in global methane mitigation efforts. Major emission hotspots include the United States, Russia, and the Middle East, regions with extensive upstream and midstream activities managing infrastructure, and regulatory gaps that exacerbate emissions [64,79–81]. As a result, these areas have become focal points for satellite-based monitoring and targeted mitigation strategies.

Methane emissions from the oil and gas sector are particularly critical because of their substantial global warming effect and the sector's considerable contribution to anthropogenic emissions [82]. In this setting, satellite remote sensing is essential as it offers continuous, global, and impartial data coverage that is challenging or economically unfea-

sible to obtain through terrestrial or aerial surveys. This top-down observational method facilitates the validation of self-reported emissions and reinforces developing transparency frameworks like the Global Methane Pledge, allowing regulators and companies to evaluate advancements toward reduction objectives [83]. Moreover, satellites are exceptionally proficient at identifying and measuring "super-emitters," which are significant point sources accountable for an excessive share of overall oil and gas methane emissions and are key targets for mitigation initiatives [84]. Diverse satellite systems participate in this monitoring initiative, each possessing unique characteristics. Recent studies have shown the efficacy of satellite remote sensing in identifying and measuring methane emissions within the oil and gas industry. Varon et al. (2019) utilized Sentinel-2 to identify methane plumes from oil and gas facilities with emissions as minimal as 1800 kg/h under optimal conditions [85]. Lauvaux et al. (2022) utilized Sentinel-5P TROPOMI data to identify almost 1800 significant methane-release events ($\geq$25 t/h) globally from 2019 to 2020, with around two-thirds associated with oil and gas operations [86]. These findings highlight the capacity of satellites to detect "super-emitter" occurrences frequently overlooked by bottom-up assessments. High-resolution commercial satellites like GHGSat have enhanced facility-level monitoring by detecting emissions from specific wells, pipelines, and compressor stations [23]. Nonetheless, limitations persist: low-resolution equipment such as TROPOMI are incapable of detecting minor leaks, cloud cover frequently diminishes observation frequency, and existing passive sensors are unable to operate at night. Next-generation missions like MERLIN, an active lidar initiative, seek to address these problems by facilitating methane detection in all weather conditions at any time of the day [87].

3.2. Coal Mining

Methane emissions from coal mining originate mainly from gas trapped within coal seams that is released during excavation and ventilation [88,89]. Coal mining accounts for approximately 41 Tg of methane emissions annually, making it a significant source of anthropogenic methane globally [90]. China remains the world's largest coal producer, increasing its output to 4237 Mt in 2022, followed by India, Indonesia, the United States, Russia, and Australia [91]. These countries collectively dominate global coal production, reflecting strong domestic demand and significant contributions to global methane emissions from coal mining. Long-term satellite and ground-based datasets have shown strong regional growth. Between 2009 and 2022, XCH_4 in South Asia rose from ~1700 to 1950 ppb, with accelerated increases after 2015 and hotspots at coal sites such as Paschim Bardhaman (10.15 ± 0.55 ppb yr^{-1}) [92]. In Shanxi, China, portable FTIR instruments (COCCON) confirmed coal mining as a major source, with average XCH_4 above 2000 ppb in mining areas and enhancements up to 3118 ppb near vents. Comparisons with TROPOMI and CAMS data showed generally good agreement but indicated that models underestimate methane in coal regions [93].

At larger scales, TROPOMI inversions estimated Shanxi's coal methane emissions at 8.5–8.6 Tg yr^{-1} in 2019–2020, close to the upper bound of bottom-up inventories. Importantly, hotspots missing in prior datasets were revealed, including southwestern Shanxi, contributing ~10% of emissions. Methane emission factors increased significantly with mining depth (r = 0.88), suggesting deeper extraction may intensify future emissions [94]. Facility-scale analysis with GHGSat-D demonstrated the ability to quantify point sources: mean source rates were 2320 ± 1050 kg h^{-1} at the San Juan mine (U.S.), 5850 ± 2360 kg h^{-1} at the Appin mine (Australia), and 2410 ± 1000 kg h^{-1} at the Bulianta mine (China) [95]. These findings underscore the necessity of satellite-based monitoring for the comprehensiveness and openness of coal methane inventories. Multi-scale satellite data can corroborate national accounts and pinpoint underreported areas.

3.3. Agriculture and Livestock

Agriculture constitutes the predominant source of anthropogenic methane emissions, chiefly resulting from biogenic processes in cattle and rice production. Methane is mostly generated through enteric fermentation, a digestive process in ruminant animals like cattle, sheep, and goats, as well as through the anaerobic decomposition of manure during storage in lagoons or pits [96,97]. Enteric fermentation alone accounts for nearly 90% of all livestock-related methane, with cattle representing the dominant contributors [97]

According to the Royal Meat Institute (RMI), the United Nations Environment Programme (UNEP), and the Financial Times, agriculture is the largest source of anthropogenic methane emissions, as estimated by. Emissions from livestock, encompassing enteric fermentation and manure, constitute approximately 32 percent of total anthropogenic methane emissions [98]. Countries such as India, Brazil, and the United States are major contributors due to their large livestock populations and intensive agricultural systems. In 2019, for example, India's cattle sector alone emitted approximately 11.63 Tg of methane [99]. Mitigating these emissions remains particularly challenging due to their diffuse and decentralized nature, often requiring innovative solutions, such as regional-scale satellite monitoring, to effectively track and reduce emissions.

Rice cultivation is one of the largest agricultural methane sources, and recent satellite studies have improved both mapping and quantification. Chen et al. (2025) [100] used 30 m Landsat data to produce a monthly global rice distribution, estimating 39.3 ± 4.7 Tg CH_4 yr^{-1} in 2022—higher than earlier inventories. Five countries (China, India, Bangladesh, Vietnam, and Thailand) contributed 78% of emissions, with China the largest emitter (8.2 Tg yr^{-1}). Regionally, Moon et al. (2024) showed that Sentinel-5P detected high methane (>1870 ppb) over Korean rice paddy areas, with spatial correlations up to r = 0.75, and also found strong livestock contributions (up to r = 0.89), pointing to agriculture as a dominant sectoral source [101].

At finer scales, rice mapping in Tamil Nadu, India, was advanced by Pazhanivelan et al. (2024), who used Sentinel-1A SAR to delineate paddy fields with >88% accuracy and estimated emissions between 19–26 Gg yr^{-1} (2017–2022) using both IPCC and LST-based methods, validated against field data at >80% [102]. Livestock sources are also increasingly studied: Bi and Neethirajan (2024) [103] combined Sentinel-5P methane retrievals with machine learning across 11 Canadian dairy farms, finding that herd genetics and feeding practices strongly shaped emissions. Notably, methane correlated negatively with cows' breeding value for milk protein, and their Random Forest model achieved excellent predictive performance (R^2 = 0.97). Collectively, these studies underscore the capacity of satellites to quantify agricultural methane at scales ranging from global rice inventories to local dairy operations.

3.4. Waste Management

Methane emissions in the waste management sector mostly result from the anaerobic decomposition of organic matter in landfills and during wastewater treatment processes. In anaerobic environments, bacteria break down organic waste, producing methane as a metabolic byproduct. Temperature fluctuations significantly influence methane production in landfills by affecting microbial activity and the rate of anaerobic decomposition [104]. Landfill and wastewater treatment plants' gas typically contains 40–60% methane, produced gradually as organic waste breaks down over time [105].

In rapidly urbanizing regions, especially in developing countries, inadequate waste management infrastructure contributes to rising methane emissions from both landfills and wastewater facilities [106]. Monitoring these emissions is particularly challenging due to variations in landfill practices, climatic conditions, and waste composition. To improve

emission tracking and support mitigation efforts, satellite observations are increasingly used to detect and quantify methane released from waste sources.

Zhang et al. (2025) [107] found that, at large Indian landfills, primarily uncontrolled dumps, contributed the highest percentage of observed methane signals (80%), whereas sanitary landfills with gas capture in China and the U.S. exhibited fewer detections. Hyperspectral photography validated landfill plumes and revealed weak alignment with IPCC projections; however, the Midong dump exhibited episodic emissions up to 20 t/h during system malfunctions. In the United States, Balasus et al. (2024) discovered that TROPOMI-derived estimates from four Southeastern landfills were sixfold greater than EPA reports, with discrepancies tied to errors in reporting models [108]. Similarly, Silva et al. (2025) identified Brazil's Caieiras landfill as a persistent hotspot despite recovery technologies, with in situ concentrations reaching 44 ppm and estimated emission rates between 11,000 and 23,000 kg/h, indicating ongoing fugitive emissions [109].

Methane emissions from wastewater treatment plants (WWTPs) are also gaining attention. Mehrdad et al. (2024) [110] conducted the first long-term Sentinel-2 analysis of a Canadian WWTP (2019–2023), revealing strong daily-to-seasonal variability and persistent hotspots in sludge processing and clarifier units. Emissions peaked in autumn, lagging behind wastewater temperature trends, whereas hotspots exhibited seasonal variation across different process units. Collectively, these studies illustrate that satellites, often combined with hyperspectral data, inversion models, and in situ validation, are essential for revealing underestimated inventories and tracking fugitive methane emissions from landfills and WWTPs.

3.5. Biomass Combustion

Biomass combustion, encompassing wildfires, agricultural residue incineration, and deforestation-related fires, constitutes a major source of atmospheric methane due to the incomplete combustion of organic matter. During these occurrences, methane is emitted in conjunction with carbon monoxide and other trace gases, augmenting regional and global greenhouse gas concentrations. Emission intensity depends on fuel type, combustion efficiency, and fire severity. Tropical and boreal forest fires are recognized as significant episodic producers of methane, especially during droughts and El Niño years that amplify fire activity [111]. Satellite platforms, including TROPOMI and MODIS, have been widely utilized to monitor fire activity and evaluate the corresponding methane emissions from large-scale biomass burning [25,112–114]. Recent studies have shown the efficacy of combining fire radiative power (FRP) data with satellite-derived methane retrievals to generate near real-time emission estimates, enhancing emission inventories and aiding climate mitigation initiatives [115].

Shi et al. (2020) estimated average annual CH_4 emissions of 10.85 Tg from tropical continents (2001–2017), with Africa as the predominant contributor, driven by savanna and shrubland fires [116]. In China, Qiu et al. (2016) attributed 666 Gg of CH_4 emissions in 2013 to open burning, with approximately 80% linked to farmland residue [117]. Wu et al. (2018) extended the record to 2003–2015, estimating cumulative emissions of 3050 Gg CH_4 in central and eastern China, about one-third came from rice straw burning, with peaks during harvest seasons [118].

Other regions have comparably substantial contributions. Potter et al. (2002) estimated that in the Brazilian Amazon, deforestation and biomass burning released 4.2 Tg CH_4 per year in the early 1990s, with emissions peaking in September [119]. Zhao et al. (2023) [120] evaluated five inventories (2010–2020) in boreal fire zones, revealing CH_4 emissions of 2.02–5.84 Tg in Canada and 3.97–14.23 Tg in Russia, peaking in July. They observed delayed correlations between fire activity and atmospheric CH_4, concluding that the QFED2.5 inven-

tory most accurately aligned with satellite measurements. Collectively, these investigations underscore biomass burning as a significant and fluctuating source of methane in tropical, temperate, and boreal ecosystems.

4. Discussion

Satellite remote sensing has evolved into a highly effective method for monitoring methane emissions across diverse sectors. Its capacity to deliver autonomous, large-scale, and consistent observations renders it indispensable for detecting super-emitters, verifying inventories, and tracking progress toward mitigation commitments. No single platform or algorithm is universally optimal; instead, each sector requires a customized amalgamation of tools and techniques, depending on emission characteristics and monitoring goals.

In the oil and gas sector, coarse-resolution platforms like Sentinel-5P TROPOMI are effective in identifying ultra-emitter events and regional methane anomalies, whereas high-resolution sensors such as GHGSat, Sentinel-2, PRISMA, and EnMAP are proficient in detecting emissions from individual facilities. A tiered technique is thus most efficacious—utilizing TROPOMI to flag hotspot, followed by high-resolution platforms for precise verification and quantification. In coal mining regions, TROPOMI inversions have uncovered underestimated emissions and spatial hotspots, whilst GHGSat enables precise quantification of methane from individual mine vents. These findings underscore the necessity of broad-scale surveillance with site-level verification, especially given that deeper mining activities correlate with elevated emission factors.

Agriculture and livestock present distinct monitoring requirements. Sentinel-1 SAR and Sentinel-2 optical imagery are particularly effective for mapping rice paddies, even under persistent cloud cover, and for quantifying emissions through the integration of agronomic data. Sentinel-5P has captured methane increases over rice and livestock areas, while machine learning approaches that combine satellite data with farm-level information have successfully predicted dairy farm emissions, illustrating the influence of genetics, feeding, and management on methane production. In waste management, satellites have detected emissions at both urban and facility scales. TROPOMI and inversion techniques provide reliable regional estimates, whereas hyperspectral devices like EMIT and commercial platforms such as GHGSat detect emissions from particular landfill surfaces or wastewater treatment processes. Sentinel-2 facilitates the long-term mapping of intra-plant variability, revealing seasonal cycles and persistent hotspots.

Biomass combustion benefits most from multi-sensor methodologies. MODIS Fire Radiative Power products support global, long-term fire inventories by providing data that enable the indirect quantification of methane emissions from biomass burning, whereas TROPOMI and inversion systems document seasonal fluctuations and annual budgets. In the boreal and Amazon regions, comparisons of inventories like GFED4.1s and QFED2.5 with satellite observations have uncovered significant errors while also indicating which datasets align best with atmospheric methane signals. FRP-based methodologies are more effective in detecting tiny, ephemeral agricultural fires, but burned-area techniques are superior for extensive forest fires.

Several practical lessons emerge from sectoral applications of remote sensing. First, a tiered monitoring framework—initial screening with low-resolution sensors followed by confirmation with high-resolution or hyperspectral instruments—optimizes detection and quantification precision. Second, sector-specific selections are critical: Sentinel-1/2 and machine learning for agriculture, GHGSat and Sentinel-2 for oil, gas, and coal sources, TROPOMI with inversion models for landfills, and FRP-based techniques for biomass burning. Third, ground validation remains crucial: despite their coverage advantages, satellites face challenges such as atmospheric scattering, cloud interference, revisit inter-

vals, and detection thresholds, all of which require calibration with in situ data. Finally, advanced analytics, including machine learning and inversion modeling, can significantly enhance source attribution and prediction, ensuring that satellite observations translate into actionable insights. Table 4 summarizes key industrial sectors emitting methane and the conventional satellite platforms used to monitor them.

Table 4. Cross-sector comparison of methane emission characteristics and satellite monitoring applications.

Sector	Primary Emission Sources	Dominant Satellite Platforms	Monitoring Strengths/Advantages	Key Limitations and Challenges
Oil & Gas	Fugitive leaks, venting, flaring, compressor stations, storage tanks	GHGSat, Sentinel-2, PRISMA, EnMAP, TROPOMI	High spatial precision from hyperspectral sensors; enables detection of point-source plumes and super-emitters	Limited detection under cloud cover; complex facility layouts introduce spectral interference
Coal Mining	Ventilation shafts, degassing boreholes, post-mining emissions	TROPOMI (inversion), GHGSat, Sentinel-5P	Broad-scale mapping of regional hotspots; GHGSat supports mine-level quantification	Subsurface variability affects retrieval; limited revisit frequency for smaller mines
Agriculture & Livestock	Enteric fermentation, rice paddies, manure storage	Sentinel-1, Sentinel-2, TROPOMI, GOSAT	Multi-sensor fusion (SAR + optical) effective for crop mapping and seasonal trends	Diffuse, low-intensity emissions; influenced by vegetation and humidity
Waste Management	Landfills, wastewater treatment plants, anaerobic digesters	GHGSat, Sentinel-2, EMIT, TROPOMI	Detects localized plumes; effective for hotspot mapping and seasonal emission trends	Urban complexity, background reflectance, and thermal interference affect precision
Biomass Combustion	Forest fires, crop residue burning, peatland degradation	MODIS, VIIRS, TROPOMI, Sentinel-3	Long-term global FRP datasets; useful for emission inventories and fire event tracking	Temporal variability; difficulty isolating CH_4 from co-emitted gases (CO, aerosols)

Satellite-based methane monitoring demonstrates specific operational benefits and drawbacks across several sectors. High-resolution sensors, like GHGSat, PRISMA, and Sentinel-2, provide the precise identification of concentrated industrial emissions, whilst wide-swath instruments such as TROPOMI and GOSAT provide essential insights into regional and global flux patterns. The agricultural and waste management sectors provide distinct problems because of dispersed sources and surface variability, necessitating multi-sensor and model-integrated methodologies. Conversely, oil, gas, and coal companies gain from regular, high-contrast detections that are appropriate for regulatory compliance and mitigation monitoring. Monitoring biomass combustion utilizes extensive fire datasets to measure intermittent methane emissions. These findings collectively underscore the importance of a tiered observation strategy that integrates coarse-resolution area mapping with fine-resolution point-source measurement to ensure comprehensive methane monitoring across all principal industrial sectors.

In summary, satellite remote sensing serves as a transformational supplement to ground monitoring, offering transparency, scalability, and autonomy. When implemented strategically, with sector-specific platform selection and algorithm development, it enables regulators, industry, and researchers to detect super-emitters, refine inventories, and expedite advancements towards global methane reduction objectives.

5. Challenges and Future Directions

Satellite remote sensing, similarly to other monitoring techniques, faces notable challenges. Platforms such as Sentinel-5P TROPOMI offer daily global coverage but lack the fine resolution to detect smaller or short-lived emission events. Conversely, high-resolution sensors like GHGSat or Sentinel-2 can pinpoint site-level emissions but are constrained by revisit frequency. Additional barriers encompass sensitivity limits that hinder detection of diffuse or low-level emissions, persistent cloud cover, air dispersion, and dependence on sunlight for passive retrievals. These constraints highlight the need for advanced sensing technology and refined retrieval algorithms.

Recent investigations have primarily focused on addressing established constraints, including spatial resolution, cloud masking, and revisit intervals. Nonetheless, insufficient focus has been directed to the standardization of inter-satellite calibration techniques, which is essential for maintaining data consistency across missions such as TROPOMI, GHGSat, and Sentinel-2. A pertinent gap exists in the amalgamation of active and passive sensing methodologies, which would markedly enhance methane detection efficacy under fluctuating atmospheric circumstances. Moreover, the inconsistency in uncertainty quantification within retrieval and inversion models across platforms hinders the comparability and repeatability of global methane budgets.

To rectify these deficiencies, hybrid frameworks that integrate physics-based radiative transfer models with data-driven machine learning methodologies can significantly improve retrieval precision under diverse aerosol concentrations and lighting circumstances. Integrating these retrieval algorithms with atmospheric inversion models and facility-level operational data would provide near-real-time emission quantification and source identification. Implementing cross-sector benchmarking systems—via standardized emission inventories and cooperative validation databases—would create a cohesive framework for assessing performance across industries like oil and gas, agriculture, waste management, coal mining, and biomass combustion.

The upcoming significant advancement is the creation of global open-access methane intelligence systems that integrate satellite data with Internet of Things (IoT) sensor networks and meteorological data. These platforms, in conjunction with machine learning-driven retrieval systems, could facilitate the development of predictive and self-optimizing monitoring systems that provide continuous oversight and rapid identification of emission issues. These enhancements would transform satellite-based methane detection from a research domain into an operational system that aids in policy formulation and immediately informs compliance actions and mitigation strategies.

Beyond technical challenges, satellite data possess significant policy and regulatory implications. They provide independent and transparent verification of reported emissions, revealing underestimation in national inventories, identifying super-emitters, and tracking progress toward mitigation pledges such as the Global Methane Pledge. Policymakers are progressively utilizing satellite data to formulate methane reduction objectives, devise sector-specific strategies, and enhance regulatory structures. For these statistics to be successful, they must be incorporated into decision-making processes, necessitating both capacity-building and consistency in reporting standards.

International cooperation is essential for this integration. Initiatives like the United Nations Environment Programme's International Methane Emissions Observatory (IMEO) illustrate the harmonization of multi-source satellite observations to deliver reliable worldwide estimates. These initiatives promote transparency, enhance data accessibility, and assist nations with inadequate terrestrial monitoring infrastructure. Collaborative frameworks promote data exchange among governments, industry, and research organizations, thereby closing the divide between scientific advancements and practical application.

Future prospects in methane monitoring are exceedingly exciting. Upcoming satellite missions are anticipated to provide enhanced geographical resolution, reduced revisit intervals, and multi-gas detection capabilities. The amalgamation of IoT networks with real-time terrestrial sensors and machine learning algorithms will enable dynamic, near-continuous pollution monitoring. Integrating these data streams with atmospheric inversion modeling and facility-level operational statistics will improve the precision of source attribution and the predictive comprehension of emission behavior. These developments will enhance scientific understanding and furnish practical intelligence for industry and regulators, thereby expediting global initiatives to reduce methane emissions and fostering a more sustainable, transparent, and data-driven climate policy framework.

6. Conclusions

Satellite-based remote sensing has become a revolutionary method for monitoring methane, providing benefits over traditional ground and air techniques for spatial coverage and temporal consistency. Satellite observations have greatly enhanced our comprehension of industrial methane emissions by facilitating detection at many scales, ranging from global flux mapping to the identification of facility-level super-emitters. The examined evidence indicates that oil and gas operations, coal mining, agriculture, waste management, and biomass combustion each pose unique monitoring issues, necessitating tailored combinations of observation platforms, retrieval algorithms, and validation procedures.

In the oil and gas sector, emissions are often highly intermittent and spatially heterogeneous, originating from diverse sources such as leaks, venting, and flaring. This variability complicates temporal consistency in satellite detection and requires high-resolution and frequent observations. In coal mining, methane is released both continuously from ventilation shafts and episodically from degassing boreholes or post-mining seepage. Subsurface origin and atmospheric mixing make satellite-based quantification challenging, particularly under varying topographic and wind conditions. Agricultural emissions are diffuse, low in concentration, and seasonally variable, making them difficult to distinguish from background methane and other surface signals. Retrieval accuracy is further affected by vegetation cover, humidity, and surface reflectance. In waste management facilities, emissions are spatially clustered within urban environments where background reflectance, thermal interference, and mixed land-use signals complicate plume isolation. Additionally, dynamic operational conditions like waste turnover, digestion and aeration cause fluctuating emission rates. Biomass combustion produces short-lived, high-temperature emission events where methane co-occurs with CO, NO_2, and aerosols. This chemical and spectral overlap makes retrieval difficult, and rapid fire evolution limits the temporal alignment between satellite overpasses and emission peaks.

No singular platform or retrieval method can satisfy all monitoring requirements. A tiered and sector-specific framework is essential: coarse-resolution instruments like TROPOMI are optimal for regional hotspot identification, whilst high-resolution sensors such as GHGSat, Sentinel-2, PRISMA, and EnMAP enable facility-level measurement. The amalgamation of machine learning and inverse modeling with satellite data significantly improves retrieval precision, particularly for intricate emission patterns. When integrated with terrestrial validation and atmospheric transport modeling, these methodologies create a solid basis for transparent and verifiable emissions reporting.

Notwithstanding these developments, existing monitoring systems encounter ongoing difficulties concerning spatial–temporal trade-offs, cloud interference, and diminished sensitivity to diffuse or intermittent sources. Addressing these constraints necessitates advanced satellite missions featuring enhanced radiometric sensitivity, multi-angle and all-weather functionalities, and the ability to retrieve several gases concurrently.

Future research must emphasize the sector-specific integration of satellite data and machine learning to enhance quantification precision and interpretability. In the oil and gas industry, machine-learning-driven plume segmentation, along with thermal and SWIR images, facilitates the automatic differentiation between combustion flares and non-flaring leaks, enhancing the precision of source attribution and flux estimation. In coal mining, regression-based learning used on long-term satellite time series can effectively model emission variability from ventilation shafts amid fluctuating atmospheric and operational conditions, resulting in more dependable temporal patterns. Integrating vegetation indices (NDVI, LAI) and soil moisture maps with neural network models might enhance the characterization of methane dynamics in rice paddies and manure storage regions by considering phenological and climatic variability. In the waste management industry, the integration of Sentinel-2 optical imaging and TROPOMI concentration fields, analyzed by deep learning-based dispersion models, may distinguish overlapping urban sources and more accurately estimate methane fluxes in intricate landfill settings. Ultimately, in biomass combustion, the integration of FRP data from MODIS or VIIRS with convolutional neural networks facilitates the differentiation of co-emitted gases like CH_4, CO, and NO_2 hence enhancing the estimation of combustion-related methane emissions and post-burn flow estimates.

These examples illustrate that algorithmic integration improves quantification by addressing sector-specific uncertainties, such as spectral confusion in oil and gas, subsurface variability in coal mining, and spatio-temporal heterogeneity in agriculture and waste sectors. Machine learning algorithms enhance satellite observations from mere detection to dynamic source classification, facilitating predictive monitoring and mitigation planning.

In conclusion, satellite remote sensing ought to be seen not as a replacement but as a potent enhancement of current monitoring systems. Its ability to provide transparent, scalable, and actionable data when integrated with intelligent algorithmic systems renders it essential for expediting global methane reduction. As data integration, algorithm improvement, and international collaboration progress, satellite-based methane monitoring will become a crucial element of comprehensive climate change mitigation efforts.

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Abbreviations

The following abbreviations are used in this manuscript:

CH4	Methane
CNN	Convolutional Neural Network
CO2	Carbon Dioxide
CRDS	Cavity Ring-Down Spectroscopy
DIAL	Differential Absorption Lidar
FTIR	Fourier Transform Infrared spectroscopy
GOSAT	Greenhouse gases Observing SATellite
IEA	International Energy Agency

MBMP	Multi-Band Multi-Pass
MBSP	Multi-Band Single-Pass
NIR	Near-Infrared
OEM	Optimal Estimation Method
OLI	Operational Land Imager
PRISMA	Peecursore Iperspettrale della Missione Applicativa
SBMP	Single-Band Multi-Pass
SCIAMACHY	SCanning Imaging Absorption spectroMeter for Atmospheric CartograpHY
SNR	Signal-to-Noise Ratio
SVM	Support Vector Machine
SWIR	Shortwave Infrared
TCCON	Total Carbon Column Observing Network
TROPOMI	TROPOspheric Monitoring Instrument
UNEP	United Nations Environment Programme
WWTP	Wastewater treatment plants
XCO_2	Column-averaged CO_2

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