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People-centric Energy Transition

Methane Emissions from India's Coal Sector: A Review of Domestic and International Evidence

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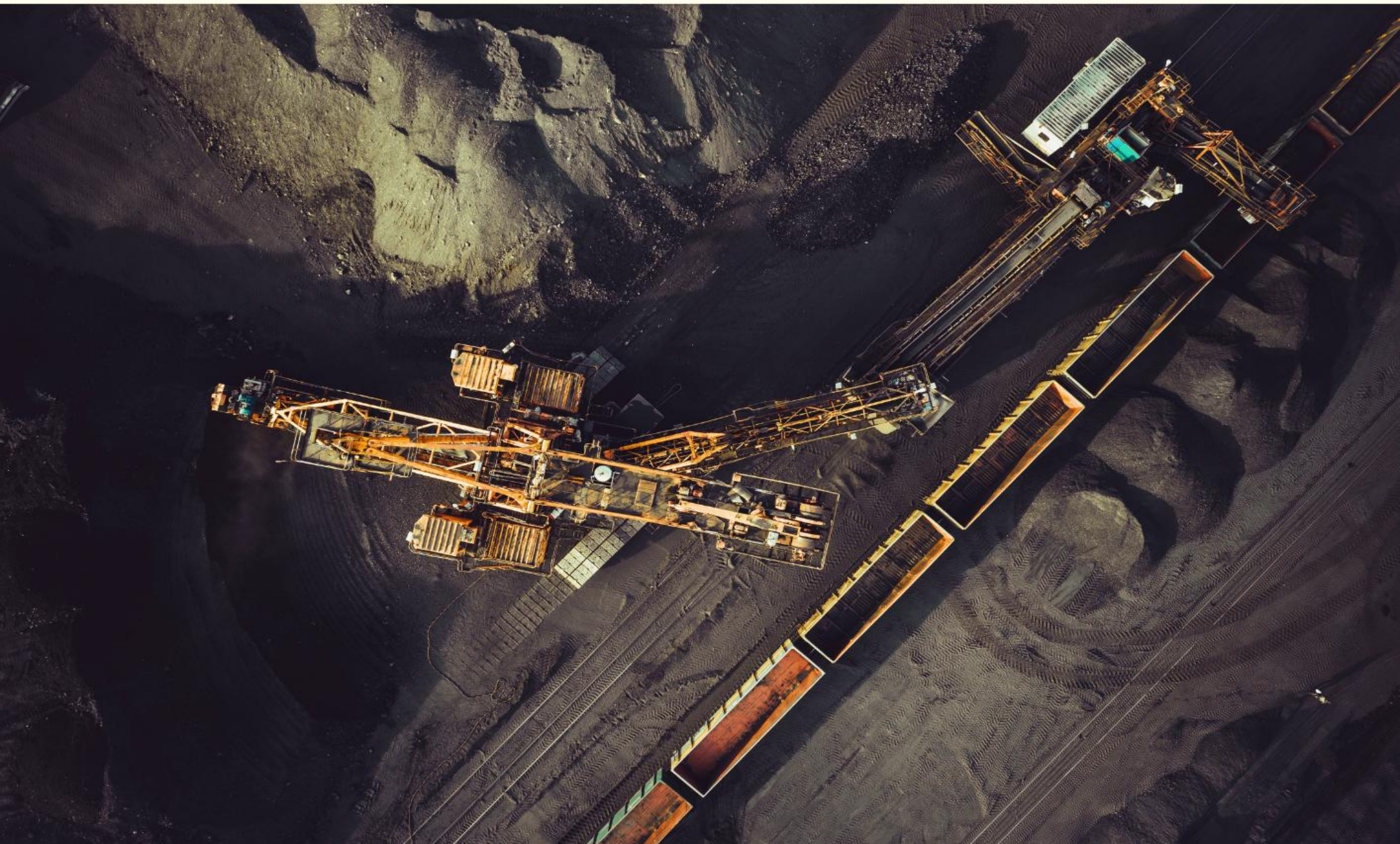

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Executive Summary

Methane emissions from coal mining represent a critical yet uncertain component of India's greenhouse gas profile, with important implications for climate mitigation, energy security, and resource efficiency. This report reviews the existing body of scholarly literature to assess how methane emissions from India's coal sector are estimated, the range and variability of these estimates, and the status of mitigation and utilization pathways, particularly for coal mine methane (CMM) and coal bed methane (CBM).

The review assesses the principal methodologies used to estimate methane emissions from coal mining and identifies two dominant approaches: bottom-up inventories and top-down atmospheric (i.e., satellite-based) methods. Bottom-up approaches, including IPCC-based inventories and national reporting frameworks, rely on activity data such as coal production and mine characteristics, combined with emission factors to generate estimates. It builds estimates from the smallest emission sources and aggregates them to get total emissions. These approaches are widely used in policy and reporting contexts due to their transparency, relative ease of application, and scalability across regions and time periods. However, their estimates are shaped using generalized emission factors, limited availability of disaggregated mine-level data, and system boundaries that may not fully capture all emission sources across the coal value chain.

Top-down approaches draw on atmospheric observations, particularly satellite measurements, to infer methane emissions at broader spatial coverage using atmospheric transport models. These approaches provide additional insights into the geographic distribution of emissions and help identify potential emission hotspots that may not be captured through inventory-based approaches. While top-down approaches are increasingly applied in the Indian context, their integration into official national reporting frameworks remains limited, and they are subject to uncertainties related to source attribution, atmospheric transport modeling, and data resolution. Nevertheless, they offer an important complementary perspective that can help refine and validate bottom-up estimates.

The report highlights the different underlying assumptions, data inputs, and spatial resolution of bottom-up and top-down approaches, which contributes to variation in reported emission estimates. Using both approaches in concert provides a more comprehensive understanding of methane emissions from the coal sector while also underscoring key data and methodological gaps.

The review also indicates significant variability in methane emission estimates for India's coal sector. Annual estimates made between 2019 and 2024, range from less than 1 Tg CH_4 per year to approximately 2.9 Tg CH_4 per year. This variation reflects differences in methodological approaches as well as inconsistencies in key inputs, including emission factors, spatial coverage, and the extent to which sources such as post-mining activities and abandoned mines are incorporated. Differences in temporal scope and underlying datasets further shape the range of reported estimates. This variability is not limited to comparisons between bottom-up and top-down approaches; notable discrepancies exist even within bottom-up studies, pointing to the influence of methodological choices and data constraints. At the same time, recent advances, particularly measurement-based studies and basin-specific assessments, suggest a gradual move toward more refined and context-specific estimation techniques. While these developments improve the granularity and relevance of estimates, the analysis indicates that a consistent and harmonized national-scale framework for methane estimation in the coal sector is still evolving.

The report examines mitigation opportunities associated with CMM and CBM through a review of the literature, project-level evidence, and international experience, considering both emissions reduction potential and energy supply contributions. Despite significant theoretical potential, commercial deployment remains virtually non-existent due to technical challenges such as low permeability, heterogeneous coal seams, and low methane concentrations that constrain recovery potential, while economic and institutional barriers, including high upfront costs, infrastructure gaps, regulatory complexity, limited commercial experience, and socio-political challenges affecting local communities further hinder scale-up. Despite these challenges, international best practices demonstrate that targeted interventions, improved data systems, and integrated policy support can enable viable methane capture and utilization pathways.

Overall, the report outlines key knowledge and policy gaps relevant to methane management in India's coal sector. It highlights the need for expanded mine-level measurement efforts, improved development of context-specific emission factors, and greater harmonization of system boundaries across existing studies. It also points to the importance of strengthening integration between bottom-up inventories and top-down atmospheric approaches to enable more comprehensive estimation. Finally, it underscores the role of enhanced data transparency, the establishment of long-term monitoring systems, and closer alignment between observational datasets and inventory frameworks. Addressing these areas is central to improving the consistency, reliability, and policy relevance of methane emission estimates in India's coal sector.

Acronyms

AIRS	Atmospheric Infrared Sounder
AMM	Abandoned Mine Methane
BCCL	Bharat Coking Coal Limited
BUR	Biennial Update Report
CBM	Coal Bed Methane
CEDS	Community Emissions Data System
CIMFR	Central Institute of Mining and Fuel Research
CMM	Coal Mine Methane
CMPDI	Central Mine Planning and Design Institute
COMET3	Coal Mine Methane Economics Tool (Version 3)
DGH	Directorate General of Hydrocarbons
EDGAR	Emissions Database for Global Atmospheric Research
EF	Emission Factor
EMIT	Earth Surface Mineral Dust Source Investigation
EPA	Environmental Protection Agency
GAINS	Greenhouse Gas–Air Pollution Interactions and Synergies
GEF	Global Environment Facility
GEOS	Geostationary Operational Environmental Satellite system
GFEI	Global Fuel Exploitation Inventory
GHG	Greenhouse Gas
GIS	Geographic Information Systems
GOSAT	Greenhouse Gases Observing Satellite
GWP	Global Warming Potential
IEA	International Energy Agency

IEF	International Energy Forum
IIASA	International Institute for Applied Systems Analysis
IPCC	Intergovernmental Panel on Climate Change
IRR	Internal Rate of Return
MMSCMD	Million Metric Standard Cubic Metres per Day
MoEFCC	Ministry of Environment, Forest and Climate Change
MoPNG	Ministry of Petroleum and Natural Gas
NPV	Net Present Value
OECD	Organisation for Economic Co-operation and Development
PRISMA	PRecursore IperSpettrale della Missione Applicativa (Hyperspectral Precursor of the Application Mission)
SWIR	Shortwave-infrared
TROPOMI	TROPOspheric Monitoring Instrument
UNDP	United Nations Development Programme
UNFCCC	United Nations Framework Convention on Climate Change
VAM	Ventilated Air Methane

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Introduction

Methane gas (CH_4) is a potent greenhouse gas (GHG) with a global warming potential (GWP)[1] 80 times higher than carbon dioxide (CO_2) over a 20-year period (UNEP, 2024). Experts suggest that to limit global warming to 1.5°C, methane emissions need to be cut by at least 30% from 2020 levels by 2030 (UNEP, 2024). The energy sector accounts for more than a third of global anthropogenic methane emissions, with interventions in the fossil fuels industry representing some of the lowest-cost options for reducing emissions (IEA, 2024) Between 2010–2019, methane emissions from coal mining comprised 33% of total fossil-fuel-related emissions of methane (Saunois et al., 2025). The International Energy Agency (IEA, 2025a) estimates that globally coal mining contributes over 40 Mt of CH_4 annually, including emissions from both operating and abandoned mines, placing coal alongside oil and gas as a leading source of methane emissions from the fossil-fuel sector.

CH_4 emissions through coal mining occur through the release of gas stored in the coal seams and in the adjacent strata during mining and post-mining processes. The volume and rate of methane emissions vary based on the mining method and the mechanisms involved in gas release. CMM is collected from the drainage system of the coal mine during mining (Su, Beath, Guo, & Mallett, 2005). A significant part of CMM is expelled into the mine ventilation system in the form of ventilation air methane (VAM), which is characterized by low concentrations of methane and large volumes of air (typically in the range of 0.1% to 1.0% by volume) (Karakurt, Aydin, & Aydiner, 2011). Conversely, CBM refers to methane which is deliberately recovered out of unmined coal seams through surface boreholes as an independent source of energy that has no relation to mining (Directorate General of Hydrocarbons, 2025) . Even after mining activity ceases, abandoned mine methane (AMM) persists in escaping out of closed or abandoned mines for several decades (Kholod et al., 2020; Karacan & Warwick, 2019).

Although global coal consumption declined between 2014 and 2020, it has continued to play a pivotal role in India's energy sector, contributing to over 70% of the nation's electricity generation (Ministry of Coal, 2024; PwC India, 2022; Saunois et al., 2025). India is the second-largest producer and consumer of coal globally, with the national production target reaching approximately 1.15 billion tonnes for FY 2025–26, and plans for over 1.5 billion tonnes for FY 2030–31 (Ministry of Coal, 2025). Coal resources in India occur mainly in the Gondwana basins, which hold over 99% of national reserves (including major coking coalfields such as Jharia), and the Tertiary basins containing

[1] Global warming potential is a measure of how much heat a greenhouse gas traps in the atmosphere over a specific time period, typically 100 years, compared to carbon dioxide (CO_2), which has a GWP of 1.

generally low- to moderate-rank deposits and occurring in northern, western, southern, and northeastern India (Singh et al., 2018; Singh, 2022).

Methane generation and emission patterns are influenced by several factors including the type of mining, basin geology, and coal rank. The amount of methane in coal increases directly with depth and deeper deposits emit one to two orders of magnitude more methane when mined (IPCC, 2006). In India, lower emitting surface mining dominates, with the share of underground activities having decreased steadily over the past decade (Ministry of Coal, 2021). Coal seams in India are generally of inferior quality, with high ash content, and release less methane compared to higher-quality coal, which has low ash content. Emissions also vary with mining methods, with longwall mining generally producing higher emissions than the board-and-pillar method due to greater disturbance of coal seams and surrounding strata. About 98% of coal production in India uses the board-and-pillar method, while only a small share comes from longwall operations (Nayak & Dalai, 2010).

In India, mine-wise coal production data are compiled annually by the Directorate General of Mines Safety (DGMS). Mines are classified according to degree of gassiness only for underground mines (DGMS, 1957). Degree I mines emit less than 1 m^3 of methane per tonne of coal, Degree II mines emit between 1–10 m^3 per tonne, and Degree III mines emit more than 10 m^3 per tonne. Although developed for operational regulation, this framework underpins many national estimates of fugitive methane emissions from coal mining (Singh and Kumar,2016; Singh et al., 2022; DGMS, 2015).

There are significant discrepancies in estimates of methane emissions associated with India's coal mining and post-mining activities, which has implications for the country's policy action, mitigation pathways, and net zero commitments. India's fourth national communication to the UNFCCC in 2024 reported 0.81 $Tg\ CH_4\ yr^{-1}$ of methane emitted, although this did not account for abandoned and other non-producing mines (MoEFCC, 2021). The reason for this, according to the Government of India, is that abandoned mines are limited in number, with low production during historic operations, and thus account for only a negligible amount of emissions (Bajpai et al., 2024). Meanwhile, international evaluations, like those by the IEA, calculated India's emissions at 2.8 million tonnes in 2023, more than three times the government-reported amounts (IEA, 2024; Bhatt & Singh, 2025).

It is worth noting the differing methodologies used by both sources; India's UNFCCC figure relies on field measurements taken across a sample of mine sites, which researchers note can underestimate emissions due to limited spatial coverage and reliance on emission factors (Scarpelli et al., 2020) . The IEA's figure, on the other hand, relies on remote sensing approaches which have inherent limitations of spatial resolution and ambiguity in the signatures from various sources (Bhatt & Singh, 2025;

IEF & Kayrros, 2021) . Additionally, IEA's assigned emission factor for India in 2023 (8.4 m^3 of emissions per tonne of coal mined for surface coal mining activities) differed significantly from India's own estimates to the UNFCCC (1.18 m^3), leading to vastly higher overall emission estimates (Bhatt & Singh, 2025) .[2]

Discrepancies aside, annual CMM emissions are expected to grow as low-cost extraction opportunities from shallow deposits plateau, with some estimates suggesting underground activities may double from 812 kt in 2019 to over 1670 kt by 2029, primarily as higher-emitting underground mining activities are projected to increase after years of declining production (Garg et al., 2021; Wright et al., 2024) .[3] Specifically, as per Coal India Limited's recent announcements, the goal is to increase underground mining by 100 million tonnes of coal by 2027–28 (Ministry of Coal, 2024). In addition to increased production, the estimated global warming potential of methane has been revised by the IPCC from 21 over a 100-year time period (in the Second Assessment Report of 1995) to 25 (in 2007), to 28 (in 2013), indicating a parallel increase in the share of fugitive methane emissions from coal mining to 0.98% and 1.07%, and highlight an urgent need for emissions reduction((Singh & Singh, 2018). Furthermore, using a 20-year evaluation period—which Howarth (2014) suggests is more suitable for addressing immediate GHG mitigation—could raise the contribution of coal-based fugitive methane emissions to 2.09% (Howarth, 2014).

CBM/CMM capture and utilization offers an opportunity to supplement India's limited natural gas reserves through the use of a previously discarded energy resource, support the national goal of reducing India's dependence on imports of natural gas to facilitate energy security, and minimize the emission of greenhouse gases (Corbeau et al., 2018). However, CBM has had limited historical success in India; despite awarding numerous blocks and contracts, only a handful are currently in production. However, with the goal of increasing the share of natural gas to 15% in its energy mix by 2030, India's CBM sector is gaining "fresh traction" through the investment of USD 2.7 billion in exploration, development, and production activities in eight operational CBM blocks, as well as a new CBM Bid Round 2025 offering three blocks across two basins (Directorate General of Hydrocarbons, 2025) . Meanwhile, gassy coal mines and unmined coal blocks in Raniganj, Jharia and East Bokaro coalfields have total CMM resources on the order of 30 billion cubic metres which could meet roughly 2–3 % of India's natural gas demands, assuming a 25-year project lifetime (Singh & Kumar, 2016; Singh et al., 2025) . Nevertheless, there are currently no active commercial CMM projects in the country, even though some research suggests using excess CMM alone

[2] IEA revised this estimate down to 6.4 m^3 per tonne of coal equivalent in 2024.

[3] Studies like Singh (2022) caution, however, that despite technological advances in improving underground production, it is likely that India will have to depend mostly on surface mines for meeting its increasing coal demand over the next decade or two.

could displace USD 980 million worth of gas imports by 2030(Bajpai et al., 2024; Wright et al., 2024) .

There remain, however, two major challenges to measuring, monitoring, and mitigating India's methane emissions from coal mining. The first pertains to the very wide range of estimated emissions from the coal sector in India as well as globally. For instance, previous studies have offered global estimates of CH_4 emissions from coal mining ranging between 29–61 Tg CH_4 yr−1 for 2008–2017, though this has since been revised down to 37–44 Tg CH_4 yr−1 for 2010–2019 (Saunois et al., 2020, 2025). These discrepancies are pronounced in the case of India as evident in global methane tracker suggested emissions IEA (2025a) and India's Third National Communication estimates (among others), and further research may be necessary to increase the robustness of the country's emissions inventory (MoEFCC, 2021). The second relates to the relatively limited efforts to commercialize CBM/CMM in India, despite international evaluations suggesting that mitigating emissions from coal mining is among the most technically and financially viable options requiring relatively minimal additional investment (IEF & Kayrros, 2021; United States Environmental Protection Agency [EPA], 2019; IEA, 2025a).

This report responds to these challenges by reviewing the scholarly literature on methane emissions from India's coal sector, including the types and ranges of current estimation methods, reported levels of emissions, capture and utilization efforts, and related research gaps. It is motivated by three overarching research questions:

R1: What are the predominant methodologies used to estimate methane emissions from coal mining in India and internationally, and what are their respective strengths and limitations?

R2: What is the range of methane emission estimates for India's coal mining activities, and how wide are the discrepancies among different sources?

R3: What is the state of knowledge on mitigation strategies, capture technologies, and utilization practices for methane emissions from coal mining in India, and what best practices exist?

The report begins with an overview of the various methods and data sources used for estimating methane emissions from coal mining activities. It then reviews the scholarly literature applying these methods to the Indian and international contexts. Finally, it discusses pathways for CBM and CMM mitigation and utilisation in India and concludes with a synthesis of the information reviewed and recommendations for future work.

Methods and Data Used for Estimating Methane Emissions From Coal Mining Activities

A wide range of approaches exist for estimating methane emissions from coal mining activities. These can be broadly divided into two categories: top-down and bottom-up. Bottom-up approaches estimate methane emissions using activity data and emission factors. Examples include methods like the tiered IPCC inventory approaches, ventilation airflow-based methane quantification, static flux chamber measurements for surface mines, degasification and gas drainage accounting. Approaches that use gridded inventories are also considered bottom-up because they use activity data (i.e., coal production, mine locations, sectoral statistics and emission factors for emission estimates) in addition to spatially allocating emissions across grids. Estimation of AMM using the empirical decay function is also classified as bottom-up as it uses source-specific parameters and empirical emission relationships rather than atmospheric measurements. In contrast, top-down approaches analyze atmospheric concentration data by using remote sensing technologies to estimate overall emissions. These include approaches like satellite-based plume detection, spectral methane retrieval, wind-based dispersion modeling, and artificial intelligence (AI)-based inverse modeling. There are also hybrid approaches that combine bottom-up inventories with atmospheric correction. The following sections provide a brief overview of the methods, data sources, and satellites used in bottom-up and top-down approaches to methane emission estimation in India and internationally (see Table 2 for summary).

Bottom-Up Approaches

Bottom-up approaches generally involve estimating emissions by multiplying activity data (e.g., coal production) by emission factors or by using direct mine-level measurements. These approaches are adopted by individual countries (including India) to estimate and report emissions by source to the United Nations in accordance with the UNFCCC, and rely on emission factors (e.g., default IPCC factors, country-specific factors) which vary across countries and may result in large uncertainties (Allen et al., 2015; Brantley et al., 2014; Mitchell et al., 2015; Omara et al., 2016; Robertson et al., 2017). However, this includes, as Scarpelli et al. (2020) note, a possible under-accounting of abnormally high emitters.

IPCC Tiered Method[4]

The IPCC tiered method, which applies emission factors (EFs) to coal production or activity data, is the most popular paradigm for estimating methane emissions from coal mining (IPCC, 2006; IPCC, 2019). In tier 1, country emissions are estimated by multiplying coal production numbers by default global emission coefficients and are typically employed only in the absence of more detailed, country-specific data. Tier 2 utilises the mass balance approach and increases accuracy by employing emission factors specific to a country or basin that are obtained from restricted field observations. While tier 3 employs measurement from individual mines. It depends on mine-specific measures like ventilation airflow and methane concentration data making it most accurate. The general formulation is expressed as:

$$CH_4 = A \times EF$$

where *A* represents coal production or mining activity and *EF* is the methane emission factor. The average amount of a greenhouse gas released per unit of activity or source, such as the amount of methane released per animal annually or per unit of production, is known as the emission factor. It is used as a coefficient to estimate total emissions by multiplying it with pertinent activity data, such as livestock population or production levels (Swamy & Bhattacharya, 2006). Instead of depending on the IPCC's global default values, MoEFCC (2021) has created India-specific emission factors utilizing data, measurements, and conditions unique to India. These variables include national features including fuel qualities, types of technology, management styles, weather patterns, and sector-specific operational variations. As a result, when paired with pertinent activity data in the national greenhouse gas inventory, they offer more precise and representative estimates of greenhouse gas emissions in the Indian context (MoEFCC, 2021). Table 1 presents the emission factor values reported in the Third Biennial Update Report submitted to the United Nations Framework Convention on Climate Change, prepared by the Ministry of Environment, Forest and Climate Change (2024).

[4] Coal is characterized by distinct gas retention and transport mechanisms governed by adsorption and desorption processes, along with relatively low permeability; consequently, the likelihood of methane emissions from coal exploration boreholes is minimal, as the occurrence of methane in a free state within such boreholes is uncommon. As a result, methodologies for estimating emissions associated with coal exploration have historically not been developed and are generally not reported by countries. The 2019 IPCC Refinements, for the first time, provide guidance on coal exploration–related emissions; however, this guidance is included in the appendix rather than the main text, ostensibly due to the limited availability of peer-reviewed literature on the subject.

Table 1: India-specific methane emission factors (MoEFCC, 2021)

	Methane emission factor (m3/tonne)			
Operation	**Surface Mining**	**Underground Mining – Degree I**	**Underground Mining – Degree II**	**Underground Mining – Degree III**
Mining	1.18	2.91	13.08	23.64
Post-mining (Handling)	0.15	0.98	2.15	3.12

Ventilation Airflow

Gas concentration sampling and ventilation airflow measurement can be used to quantify methane emissions at the mine level. After calculating ventilation airflow (Q) by measuring air velocity and airway cross-sectional area, gas chromatography or portable gas analyzers are used to sample the methane concentration. Airflow and methane concentration are multiplied to determine the daily methane make, which is then normalized by coal production to determine the emission factor (Singh & Kumar, 2016; Singh & Sahu, 2018). Although this method is the most accurate for underground mines and serves as the foundation for tier 3 IPCC methodologies, its implementation necessitates precise mine-specific measurements, which are not always available (IPCC, 2019).

Static Flux Chambers

Static flux chambers are widely used for in-situ measurement of methane emissions from coal mining areas, particularly for diffuse surface sources such as exposed coal benches and spoil heaps in surface mines. In this method, a sealed chamber is placed over the ground surface or emission point to capture gases released from the underlying coal seam or mine-related activities, allowing methane to accumulate within the chamber headspace. Methane concentration is then measured over time, and the rate of increase is used to calculate methane flux per unit area. Interestingly, a commonly used field-based configuration involves a sealed chamber with rigid walls (e.g., Plexiglass or stainless steel), fitted with a gas sampling port and secured using a rubber gasket or water seal to prevent leakage. Methane concentrations are measured at regular time intervals (e.g., 0, 5, 10, 15, and 20 minutes), alongside temperature and atmospheric pressure using appropriate sensors, and the resulting concentration-time profile is used to estimate emission flux, typically employing a minimum of 3–5 chambers to ensure representativeness (Pokryszka & Tauziède, 1999). This approach has been applied in field-based assessments of fugitive methane emissions from coal mining and handling activities to derive site-specific emission factors and improve bottom-up estimates (Singh & Kumar, 2016). However, despite its potential to enhance the accuracy of emission factors, the application of measurement-based methods remains limited due to the scarcity of mine-level data, contributing to uncertainties in emission estimates (Singh & Kumar, 2016; Dangeti et al., 2024; Deepshikha et al., 2025).

Degasification Accounting

Degasification systems are used to collect and drain methane from mine seams before or during mining. In greenhouse gas inventories, methane recovered through degasification must be accounted for separately from ventilation emissions because it represents gas that would otherwise have been released to the atmosphere during mining operations. As a result, inventory methodologies estimate total methane generation and then subtract the quantity of methane captured or utilised. This approach is more accurate than IPCC tier 3 methodology because it relies on mine specific measurements and accounting rather than using generalised emission factors, allowing inventories to better reflect variations in geological conditions and mining practices (Irving & Tailakov, 2000; Thakur, 2008).

Empirical Decay Function

Empirical decay function methodology is used to estimate methane emissions from abandoned mines. When mining stops, methane trapped in the surrounding coal seams and fractured rock continues to escape for several years, but the emission rate gradually declines as the gas reservoir becomes depleted. Empirical decay function assumes methane concentrations reduce progressively with time after mine abandonment. In this method initial concentration of methane at the time of mine closure is estimated and applies a time dependent decay curve to simulate the methane estimation in subsequent years. By incorporating factors such as mine age after closure, ventilation characteristics, and gas content, the approach allows emissions from abandoned mines to be estimated dynamically rather than assuming a constant emission rate. This method is used by Kholod et al. (2020) and Karacan and Warwick, (2019) for estimation of AMM.

Gridded Inventories

Gridded methane inventories are developed by spatially distributing sectoral emission estimates, derived from bottom-up inventory methods, into high-resolution grid cells using appropriate spatial proxies. In this approach, total emissions—typically calculated from activity data and emission factors following IPCC guidelines—are allocated across a grid (e.g., 0.1° × 0.1°) based on the geographic distribution of emission sources such as coal mines, agricultural regions, wetlands, and infrastructure, ensuring consistency with national totals. Recent datasets further integrate multiple anthropogenic and natural sources and use geospatial tools (e.g., GIS-based allocation) to refine spatial patterns and improve representation of emission hotspots. This process may also include temporal disaggregation and uncertainty assessment, enabling more accurate spatial characterization of emissions and facilitating comparison with satellite observations and atmospheric modelling frameworks (Sadavarte et al., 2021; Mishra et al., 2025).

Methane Emission Inventories and Data Sources

EDGAR

The EDGAR database provides detailed methane emission estimates through a dedicated CH_4 dataset covering the period 1970–2024, with sectoral and spatial disaggregation at high resolution. Methane emissions are classified according to IPCC categories, including specific sub-sectors such as coal, oil, and gas exploitation, enabling detailed analysis of fossil fuel emissions. The dataset also offers monthly emissions and gridded outputs (0.1° resolution), making it particularly suitable for atmospheric modelling and satellite-based validation studies. Methane estimates are derived using harmonised activity data from sources such as the IEA and FAO, ensuring global consistency. However, as a bottom-up inventory, EDGAR is subject to uncertainties in emission factors and activity data, particularly for fugitive emissions from coal mining (European Commission, 2025).

BUR India

India's Fourth Biennial Update Report (BUR-4), submitted to the UNFCCC, serves as the country's official greenhouse gas inventory and provides detailed sector-wise emissions for the year 2020. The inventory follows IPCC guidelines and uses nationally compiled activity data across sectors such as energy, agriculture, industrial processes, and waste. Within the energy sector, fugitive emissions (IPCC category 1B) include methane released during fossil fuel extraction and handling, with coal mining identified as a major source. BUR-4 highlights that methane is the dominant greenhouse gas from coal mining activities, with emissions estimated using coal production data from surface and underground mines along with emission factors representing methane released per tonne of coal produced. The report underscores the significance of coal mining and post-mining operations in India's methane emissions profile. Importantly, India employs country-specific emission factors for coal mining and handling, which are based on field measurements and reflect national mining conditions. These emission factors were developed and documented in earlier inventories, particularly BUR-3, and continue to be applied and refined in BUR-4, ensuring improved accuracy over default IPCC values (MoEFCC, 2024; MoEFCC, 2021).

CEDS

CEDS is a global anthropogenic emissions inventory developed to provide consistent, long-term datasets for use in climate and atmospheric modeling. It is a data-driven, open-source framework that generates emission estimates by country, sector, and fuel type, with annual time series extending from 1750 to recent years (Pacific Northwest National Laboratory, n.d.). CEDS includes methane (CH_4) among other pollutants and provides both national-level emissions and spatially gridded datasets with monthly resolution, enabling detailed temporal and spatial analysis. Methodologically, CEDS integrates energy consumption data, sectoral activity data, and existing regional and national inventories to produce harmonized emission trends across time while maintaining internal consistency across sectors and species (Hoesly et al., 2018). Emission estimates for recent years are calibrated to align with country-reported inventories where available, while historical emissions are reconstructed using consistent assumptions and proxy data (Hoesly & Smith, 2018). The dataset has been widely used in climate modeling exercises such as CMIP6 due to its ability to provide standardized inputs across models (Feng et al., 2020). However, as a globally harmonized inventory, CEDS may differ from national inventories due to the use of generalized assumptions, scaling approaches, and variability in the availability of country-specific data.

IIASA GAINS Model

The GAINS model is an integrated assessment framework developed by IIASA to quantify emissions of air pollutants and greenhouse gases and to evaluate cost-effective mitigation strategies. It employs a bottom-up methodology, combining detailed activity data with emission factors and a comprehensive database of sector-specific abatement technologies, including their efficiencies and costs. The model simulates emissions across key sectors such as energy, industry, agriculture, and waste, and links them to environmental impacts, allowing for the assessment of both air quality and climate outcomes. A key strength of GAINS is its ability to explore policy scenarios and least-cost optimization pathways, highlighting trade-offs and synergies between pollution control and climate mitigation measures (Höglund-Isaksson et al., 2020).

Top-Down Approaches

A number of studies indicate that uncertainty in methane emission estimates are linked to the use of bottom-up method alone (IPCC, 2019; Ganesan et al., 2019; Wang et al., 2019; Sun et al., 2021) These uncertainties result from poor representation of some source categories, limits in activity data, and unpredictability in emission parameters. Saunois et al. (2020) demonstrate that there are discrepancies between inventory-based and observation-based methods, with bottom-up estimates differing from emissions deduced from atmospheric measurements at the global scale. In a similar vein, the IPCC (2019) noted that comparing inventory results with atmospheric observations should enhance the uniformity and openness of national and international methane budgets. In recent years, satellite-based plume detection has emerged as an important top-down complement to bottom-up inventories, which are often affected by large uncertainties in emission factors and activity data for coal mining (Chauhan & Raval, 2025). Xu et al., (2025) for instance, identified significant systematic variances between satellite inversion inventories and ground measurements by over 20%. A variety of satellite-based methodologies exist for estimating methane emissions from coal mining activities, each with their own strengths and limitations. Measuring diffuse surface-mine emissions from space comes with several potential error sources including wind variability, topographical influences, surface reflectance artifacts, and temporal sampling bias (see Sherwin et al., 2023; 2024; Chauhan & Raval 2025; Mehradad et al. 2025; Mohammadimanesh et al., 2025). The following section provides a brief overview of these satellite-based methods and their application in top-down methane estimation.

Spectral Methane Retrieval

The process of estimating atmospheric methane concentrations by examining the absorption characteristics of CH_4 in reflected or emitted radiation as determined by satellite spectrometers is known as spectral methane retrieval. In order to distinguish methane absorption from the interfering effects of surface reflectance, aerosols, clouds, and other gases, it is based on fitting measured spectra in methane-sensitive wavelength bands (mostly near-infrared and shortwave-infrared [SWIR]) with radiative transfer models. By utilizing the distinct spectral signature of CH_4 and using inversion or least-squares optimization method to translate radiance observations into gas concentrations, these approaches recover column-averaged methane (XCH_4) (Jiang et al., 2024).

AI-Based Inverse Modeling

This approach entails the use of machine learning or deep learning algorithms to infer surface methane emission fluxes from satellite-observed atmospheric methane concentrations, by identifying the nonlinear relationships between observed CH_4 fields and underlying source strengths. AI-based methods approximate the inverse problem, mapping atmospheric enhancements back to emission sources while lowering computational cost and partially compensating for uncertainties in transport, clouds, and surface reflectance, by integrating satellite data, meteorological variables, and ancillary geospatial information rather than depending only on conventional physical transport models. Large satellite datasets and intricate, heterogeneous emission patterns are especially well-suited for these methods (Yuan et al., 2025).

Wind-Based Dispersion Modeling

Wind-based dispersion modeling refers to a class of flux quantification methods that infer emission rates from source locations by combining observed methane plume enhancements with wind speed and direction. These methods estimate emissions by connecting the excess column methane (ΔXCH_4) downwind of a source to the advective flux across a control plane, assuming that near-surface wind fields dominate the horizontal transport of methane. Mass-balance and cross-sectional flux approaches, which compute emission rates by combining plume width, enhancement magnitude, and wind velocity, are common implementations. While computationally efficient and suitable for single overpasses, their accuracy is strongly dependent on the quality of wind data and assumptions about plume shape and atmospheric stability (Chauhan & Raval, 2025).

Plume Detection Algorithms

Plume detection algorithms are presented as an essential part of point-source methane monitoring in a thorough review of satellite methane retrieval algorithms by Jiang et al. (2024). These methods concentrate on identifying and isolating methane enhancements in high-resolution satellite data by detecting spectral and spatial perturbations associated with plumes (e.g., from fossil fuel infrastructure) relative to background levels. They frequently use models like transmittance-based enhancement estimators that compare methane-sensitive and methane-free spectral bands to derive concentration enhancements, which are converted into plume masks (e.g., ΔXCH_4) that highlight plume extent and intensity for additional analysis (Jiang et al., 2024). The review notes the growing role of data-driven methods, such as machine learning and segmentation models, for automated plume detection and quantification by extracting features characteristic of plumes from multispectral and hyperspectral imagery. It also highlights matched filter and optimization algorithms used with hyperspectral imagers to enhance plume signals by maximizing signal-to-noise ratios against background variability, enabling clearer identification of methane plumes in complex scenes (Jiang et al., 2024). These methods work together to form the foundation of contemporary satellite-based methane plume detection, enabling satellites to assist emission quantification using integrated masking and subsequent flux modeling in addition to detecting big point sources (Jiang et al., 2024).

Inverse Atmospheric Modeling

Using an atmospheric transport model and statistical optimization approaches, inverse atmospheric modeling is an approach that calculates surface methane emissions by working backward from measured atmospheric methane concentrations (Saunois et al., 2025). In this framework, observations from surface networks or satellites are integrated with previous (bottom-up) emission inventories, and the model modifies sectoral or regional emission strengths to best match simulated methane fields with measurements (Peng et al., 2023).

Remote Sensing Data Sources

Gaofen-5

China's Gaofen-5 satellite series, which was created as part of the country's high-resolution Earth observation program, has sophisticated instrumentation for detecting greenhouse gases and is devoted to monitoring the atmosphere and environment. Based on spatial heterodyne spectroscopy, the Greenhouse Gases Monitoring Instrument onboard Gaofen-5 Satellite-II (GMI-II) measures high-resolution spectra of reflected solar radiation to retrieve column-averaged concentrations of gases like carbon dioxide and methane (Luo et al., 2023). Its optical configuration, which includes an offset interferometer design and an optimized imaging system, improves spectral resolution and signal-to-noise ratio, allowing sensitive detection of greenhouse gas absorption features under nadir and sun-glint viewing conditions (Luo et al., 2023). By applying machine learning methods to Gaofen-5 hyperspectral imagery, the CH_4Vision approach builds on these hyperspectral capabilities to estimate methane emission fluxes from point sources by learning the relationship between known release rates and observed spectral plume signatures. This shows that data-driven methods can supplement physical retrievals for fine-scale methane quantification (Li et al., 2026). These investigations together show that the Gaofen-5 platform is capable of both advanced emission flux estimation and spectroscopic greenhouse gas retrieval, underscoring its potential for localized and regional methane monitoring from space (Luo et al., 2023; Li et al., 2026).

GHGSat

GHGSat is a commercial satellite mission created especially to identify and measure emissions of greenhouse gases, especially carbon dioxide (CO_2) and methane (CH_4), from individual point sources like coal-related infrastructure, power plants, landfills, and oil and gas facilities. In contrast to coarse-resolution atmospheric satellites, GHGSat measures gas absorption features and retrieves column enhancements over targeted sites using a high-resolution imaging spectrometer that operates in the SWIR. Starting with the demonstration satellite GHGSat-D ("Claire"), the system is developing into a constellation to allow for site-level monitoring on a regular basis. The ability to resolve facility-scale emission plumes (<100 m spatial resolution), which enables direct attribution of emissions to specific sources and supports measurement-based verification of reported inventories, is its primary innovation (Ligori et al., 2019; McLinden et al., 2024).

GOSAT

Launched by the Japan Aerospace Exploration Agency in 2009, the GOSAT, "Ibuki" was the first mission dedicated to global monitoring of atmospheric CO_2 and CH_4. It retrieves column-averaged methane (XCH_4) using its TANSO-FTS spectrometer in the near-infrared and thermal infrared. In the study by Turner et al. (2015), GOSAT methane observations for 2009–2011 were assimilated with the GEOS-Chem transport model in an inverse framework to infer surface emissions at high spatial resolution.

MethaneSAT

MethaneSAT is a specialized Earth-observation satellite that combines extensive regional coverage with high spatial resolution to close a significant gap in global methane monitoring. It was created to systematically monitor methane emissions from major oil and gas producing regions, which account for a significant portion of global methane releases, under the direction of the Environmental Defense Fund in collaboration with scientific and engineering institutions (MethaneSAT.org; Rohrschneider et al., 2021). In contrast to broad-coverage sensors that map atmospheric methane at coarse scales, MethaneSAT uses high-precision spectrometers optimized for carbon dioxide and methane retrievals, offering greater spatial resolution (~100 m × 400 m at nadir) and higher sensitivity (as low as a few parts per billion) over large swaths (~200 km) to detect both concentrated point sources (such as oil/gas infrastructure) and diffuse regional emissions (Rohrschneider et al., 2021). In order to enhance science, policy, and mitigation efforts, the mission aims to quantify overall methane emissions, identify emission hotspots, and provide publically accessible data. The mission has encountered difficulties, such as a communication breakdown in mid-2025, even though first activities started after launch in March

2024. Current efforts are focused on optimizing the value of the data already gathered for climate action (MethaneSAT.org; Rohrschneider et al., 2021).

PRISMA

The Italian Space Agency's PRISMA hyperspectral satellite is capable of obtaining high-spectral-resolution imagery in the visible to SWIR domain at a spatial resolution of roughly 30 m, which makes it appropriate for identifying trace-gas absorption features at local scales. In the study by Settembre et al. (2025), atmospheric methane column concentrations were retrieved using PRISMA data by taking advantage of methane absorption bands in the SWIR area using specialized retrieval algorithms that take surface reflectance effects into account.When compared to other Earth observation products, such as spaceborne methane datasets with lower resolution, the resulting PRISMA-derived methane columns demonstrated generally acceptable consistency, suggesting that PRISMA may produce accurate, fine-scale methane information. The study reveals PRISMA's use as a supplementary sensor to global-coverage missions for in-depth monitoring of methane emissions and emphasizes its added value for locating and analyzing localized methane boosts.

Sentinel-5P (TROPOMI)

A European Space Agency Earth-observation satellite called Sentinel-5P (Sentinel-5 Precursor) was created as part of the Copernicus program to track atmospheric composition and fill in observational gaps prior to the full Sentinel-5 mission. The TROPOMI, a nadir-viewing[5] hyperspectral imaging spectrometer that operates across ultraviolet, visible, near-infrared, and SWIR wavelengths, is the only instrument carried by Sentinel-5P. By measuring Earth-emitted radiance and top-of-atmosphere reflected solar radiation, TROPOMI makes it possible to retrieve column concentrations of important atmospheric trace gases like NO_2, SO_2, CO, O_3, and CH_4. It is appropriate for regional-to-global air quality and greenhouse gas monitoring due to its [6]push-broom scanning design, which offers a broad swath (~2600 km), near-daily global coverage, and moderate spatial resolution (≈3.5 × 5.5 km at nadir) (Reshi et al., 2024; Bodah et al., 2022).

AIRS

AIRS is a satellite-based instrument widely used for monitoring atmospheric trace gases, including methane, at regional to global scales. By measuring infrared radiation

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[5] Nadir: The point on the Earth's surface directly beneath a satellite as it orbits.

[6] A push-broom scanning design is a remote sensing imaging method in which a linear array of detectors captures an entire ground swath at once while the satellite's forward motion builds the image line by line.

released from the Earth's atmosphere, AIRS, which is onboard the Aqua satellite, determines methane concentrations. The AIRS Level-3 dataset, which offers worldwide retrievals of trace gases, including methane, from the Aqua satellite platform, provides observations of atmospheric methane (AIRS Science Team & Texeira, 2013). The dataset provides gridded atmospheric retrievals from infrared measurements that are converted into daily or monthly global products for climate and atmospheric research. The methane products produced by AIRS are thought to be helpful for describing regional patterns and temporal variability in methane concentrations since they have been verified through independent atmospheric observations (Xiong et al., 2008).

Tanager -1

Tanager-1 is a satellite part of the Carbon Mapper program designed to detect and quantify methane and carbon dioxide at facility scale using high resolution imaging spectroscopy (Duren et al., 2025). Methane is identified by analysing its characteristic absorption features in the SWIR band (around 2100–2430 nm). The instrument has a spatial resolution of about 30 m, a swath width of around 19 km, and can image approximately 250,000 km^2 per day which enables it to detect methane from individual sources like coal mines (Duren et al., 2025; Duren et al., 2020). However, its observation depends on sunlight and it is highly sensitive to atmospheric conditions like cloud cover, aerosols and surface reflectance.

Table 2: Summary of CMM estimation methods with characteristics and reference studies.

Method	Approach	Platform / Tool	Analytical methods	Input Data	Spatial Scale	Temporal Scale	Output	Strengths	Limitations	References
IPCC tier 1/2/3	Bottom-up	National inventory system	Emission factor-based calculation (tier 1 default EF, tier 2 country-specific EF, tier 3 site/process models)	Coal production, mine type, emission factors	National / regional	Annual	Total CH_4 emissions	Standardized, easy to apply, policy-relevant	High uncertainty, depends on EF quality, weak spatial detail, lacks mechanisms to rapidly incorporate emerging scientific knowledge (tier 1).	IPCC (2006, 2019); Yona et al. (2020)
Ventilation airflow measurement	Bottom-up	Underground mine sensors, anemometers, gas analyzers	Direct measurement of airflow × CH_4 concentration	Airflow rate, methane concentration	Mine / shaft	Hourly–daily	CH_4 emission rate (m^3/day or kg/s)	High accuracy for operating mines	Only for ventilated underground mines, labor intensive, mine specific	IPCC, (2019); Singh & Kumar, (2016); Singh & Sahu, (2018)

Static Flux chamber	Bottom-up	Field chamber + gas analyzer	Enclosure method measuring CH_4 accumulation rate	CH_4 concentration change, chamber area	Point scale (m^2)	Minutes–hours	Surface flux (mg m^{-2} h^{-1})	Direct surface measurement	Limited spatial representativeness	Kholod et al. (2020); Singh & Kumar, (2016)
Degasification accounting	Bottom-up	Mine degasification systems	Accounting of extracted methane volume	Gas drainage flow and CH_4 fraction	Mine scale	Daily–monthly	CH_4 removed (m^3 or kg)	Uses operational data, accurate for gassy mines	Not representative of total fugitive emissions	IPCC (2006); Irving & Tailakov, 2000; Thakur, 2008
Empirical decay function (Abandoned mine)	Bottom-up	GIS + emission models	Empirical decay or pressure-driven models	Mine depth, age, geology	Site–regional	Annual	AMM emissions	Captures legacy emissions	High uncertainty, scarce data, mine flooding affects estimation,	IPCC (2019); Kholod et al. (2020); Karacan and Warwick, (2019)
Inverse Atmospheric modeling	Top-down	Satellite observations, primarily TROPOMI combined with an atmospheric inversion framework	Bayesian inverse modelling, where atmospheric methane observations are assimilated into a chemical transport model to optimize prior	Column-averaged methane concentrations (XCH_4) from TROPOMI, prior emission inventories ,meteorological fields, and atmospheric transport	Local–regional (km)	Monthly-annual	Posterior methane emission estimates that are constrained by atmospheric observations and can identify emission hotspots	Provides observation-constrained emission estimates; can reveal discrepancies between reported inventories and atmospheric measurements; useful for identifying regional	Dependent on model, complex, uncertainty due to cloud cover.	Peng et al (2023)

			emission estimates	model outputs				emission hotspots		
Spectral methane retrieval	Top-down	Satellite data and hyperspectral sensors like AVIRIS-NG	Radiative transfer modelling and the Beer-Lambert law,	Satellite radiance, meteorology	Regional to global depending on sensor resolution	Daily to multi-day revisit depending on satellite orbit	Column-averaged methane concentration (XCH_4) and spatial distribution of atmospheric methane	Enables large-scale monitoring of methane	Accuracy affected by clouds, aerosols, and surface reflectance; coarse resolution may limit detection of small point sources	Jiang et al., 2024

Plume detection algorithms	Top-down	Satellite (e.g., hyperspectral or SWIR sensors)	Spectral anomaly / matched filter / plume segmentation	Satellite radiance, meteorology	Local–regional (km)	Days–weeks	Plume location, ΔXCH_4, flux	Independent, direct observation, detects super-emitters, validates bottom-up approaches, repeated observations for temporal monitoring	Cloud sensitive, detection threshold, Dependence on retrieval algorithms	Chauhan & Raval, (2025); Lama et al. (preprint); Mostafa and Du (2025); ; Romana et al (2022)
AI-based inverse modeling	Top-down	Satellite datasets such as TROPOMI, GOSAT, combined with machine-learning frameworks (e.g., neural networks)	Machine learning or deep learning algorithms that learn nonlinear relationships between atmospheric methane concentrations and underlying surface emissions to approximate the inverse problem	Satellite-derived methane concentrations (e.g., XCH_4), meteorological variables prior emission inventories, and geospatial ancillary data	Regional to global scale, depending on satellite coverage and model design	Typically monthly to annual emission estimates derived from large satellite datasets	Optimized methane emission flux estimates and spatial emission maps derived from atmospheric observations	Handles nonlinear relationships between atmospheric methane and emissions; computationally efficient models; emission sources	Requires large training datasets; results depend on training data quality and model assumptions; may have limited physical interpretability compared with traditional transport-based inversion models	Yuan et al., (2025)

Wind-based dispersion modeling	Top-down	Satellite instruments (e.g., TROPOMI, GHGSat) or airborne imaging spectrometers	Mass-balance or cross-sectional flux calculation linking methane plume enhancement with wind speed and direction	Column methane enhancement (ΔXCH_4), wind speed and direction, plume geometry, atmospheric stability parameters	Local to facility scale (individual emission sources such as coal mines)	Instantaneous or single satellite overpass observations	Estimated methane emission rate (e.g., kg CH_4 h^{-1}) from the detected plume source	Computationally efficient; suitable for quantifying emissions from point sources; can provide facility-level emission estimates	Highly dependent on accuracy of wind data; sensitive to assumptions about plume dispersion and atmospheric conditions; limited temporal coverage	Chauhan and Ravel, (2025)

Studies Estimating Methane Emissions from Coal Mining Activities

There is a variety of literature highlighting the use of aforementioned methods in estimation of GHGs, particularly methane. This section compiles and reviews studies employing different approaches for estimating methane emissions from coal mining in India. Studies were identified using searches on Google Scholar using key words such as *methane emissions, coal mining, remote sensing, satellite based methods, IPCC tier 1/2/3 methodologies.* The search was focused on peer-reviewed articles, institutional publications, and technical reports relevant to coal mine methane emissions and its estimation methodologies. The screening of studies was done based on relevance to coal mine methane emissions, estimating methods and monitoring inventories. The studies were then categorized based on their geographic focus: 'Global-focus' studies analyzed or produced data for the world, including—but not necessarily focusing on—India, while 'India-focus' studies specifically analyzed or produced data for India. The studies were then further categorized based on whether they took a bottom-up or top-down approach.

Global Focus

Bottom-Up Studies

Janssens-Maenhout et al. (2019) constructed the EDGAR, an emissions inventory using a bottom-up methodology that multiplies country-specific activity data (coal production volumes and mining types) with technology-specific emission factors, distinguishing between surface and underground operations. The paper reveals several important implications for coal methane measurement and monitoring in India. As a non-Annex I country, India falls into the category with higher uncertainty ranges (±57% for CH_4, ±93% for N_2O) compared to OECD countries, which complicates verification of emission estimates and any capture efforts. The paper notes that coal mining emissions from abandoned mines and coal waste piles remain significant and poorly constrained, which applies to developing regions including India. While the study revised emission factors for China using local mine data (Peng et al., 2016), India relies more heavily on standardized IPCC emission factors, meaning country-specific variations in mining practices and infrastructure may not be fully captured. The inventory shows that methane recovery abatement is implemented in major mining nations (e.g., U.S., Poland, and China), but the paper does not provide specific details on abatement measures for India, suggesting limited data on capture infrastructure. Additionally, non-Annex I countries like India account for a growing share of global emissions (increasing from less than 40% in 1990 to more than 60% in 2012), yet their statistical infrastructure remains less developed, creating challenges for accurate measurement and monitoring of coal methane emissions over time.

Scarpelli et al. (2020) constructed an inventory of methane emissions from oil, gas, and coal exploitation by spatially downscaling national methane emissions reported to the UNFCCC onto a 0.1° × 0.1° grid, allocating coal emissions to mine locations based on the EDGAR v4.3.2 database. The paper reveals several important implications for coal methane measurement and monitoring in India. As a non-Annex I country, India faces less granular reporting requirements—it's not required to report emissions annually or disaggregate by subsector, which the authors found necessitated manual inspection of National Communications and Biennial Update Reports to extract subsector-level data. This creates challenges for tracking progress on capture initiatives over time. The paper notes that coal emissions are lumped together without partitioning between surface and underground mines or between mining and post-mining activities, limiting the ability to target specific emission sources for monitoring or capture interventions. Additionally, detailed mine location data is more limited for India compared to China, meaning spatial allocation relies more heavily on the EDGAR database with potential displacement errors at fine grid resolution that complicate site-specific monitoring efforts. The paper provides 66-200% uncertainty ranges for coal emission factors based on IPCC guidelines for non-Annex I countries, which significantly complicates verification of any capture efforts.

Top-Down Studies

Shen et al. (2023) conducted a high-resolution inverse analysis of 22 months of TROPOMI satellite observations (May 2018–February 2020), employing Bayesian optimization with the GEOS-Chem atmospheric transport model across 15 regional domains to quantify global fossil fuel methane emissions at up to 50 km resolution. The methodology involved validating results against 24 independent field campaigns and running an ensemble of inversions using multiple prior inventories (GFEI v2, GFEI v1, EDGARv6) to assess uncertainty. Regarding coal specifically, the study estimated global emissions at 32.7 ± 5.2 Tg a^{-1}, which aligns closely with UNFCCC reports but exceeds previous top-down estimates; notable corrections included a 4.8-fold increase for Kazakhstan and a 1.8-fold increase for Australia compared to national reports. Specifically for India, the supplementary data (Supplementary Table 4 and Table 6) reveals that the satellite-derived posterior estimate for coal methane emissions is 1.2 Tg a^{-1} (with a 95% confidence interval of 0.99–1.5 Tg a^{-1}), representing a significant upward revision from the UNFCCC-reported figure of 0.88 Tg a^{-1}.

Frameworks like the IEA's Global Methane Tracker employ a combination of sources to estimate CH4 emissions, including country-level activity statistics, field measurement studies from international partners, and satellite detections from platforms like Sentinel-5P and MethaneSAT (IEA, 2025a). Emissions from abandoned mines are also included in the Tracker, and are calculated by applying production- and nation-specific emission intensities to estimates of legacy infrastructure. However, these estimates come with several uncertainties including limited direct measurements, incomplete reporting, reliance on emission factors, detection challenges for intermittent leaks, and satellite observation constraints. The Tracker regularly compares its top-down estimates with bottom-up national inventories submitted to the UNFCCC and finds that measured data often reveal significantly larger methane emissions than those officially reported (IEA, 2025a). Methane emissions from the fossil fuel sector have been increasing in tandem with energy demand in South and Southeast Asia, with India being the region's largest emitter. Additionally, upstream methane intensity in India is approximately twice the global industry average, highlighting the significance of better measurement, reporting, and mitigation efforts in coal and oil & gas operations (IEA, 2025a).

Duren et al. (2025) describes Carbon Mapper, an online data portal designed for high-resolution detection and quantification of methane and carbon dioxide from point sources. Carbon Mapper uses Tanager-1 satellite data and imaging spectroscopy to directly detect and identify emission plumes from specific facilities, including industrial sites, landfills, and oil and gas infrastructure. The study highlights Carbon Mapper's capacity to distinguish discrete and intermittent emitters that are usually overlooked by coarse-resolution satellites and bottom-up inventories. It also explains validation procedures against independent data from airborne hyperspectral instruments (particularly AVIRIS-3 aircraft surveys) and independent controlled release (where known quantities of methane were intentionally emitted). The validation results show a strong agreement between independent measurements and Carbon Mapper estimations indicating that the satellite system can be used as a reliable source for detecting and quantifying methane emissions. The study establishes carbon mapper as an operational measurement-based platform for systematic identification, quantification, and tracking of methane and CO_2 point sources.

While some recent efforts focus on direct plume detection and facility-level quantification, other studies adopt a concentration-based framework to assess regional methane variability using satellite observations. Mostafa and Du (2025) employed a satellite-based observational framework to evaluate the geographical and temporal variability of atmospheric methane utilizing geospatial statistical analysis and column-averaged CH_4 products. Instead of using inverse atmospheric modeling, mass-balance methods, or plume detection to directly measure emission fluxes, the methodology used remotely detected XCH_4 fields to determine regional patterns and trends. This limits source-specific emission estimates but enables large-scale monitoring of methane fluctuation and hotspot screening. Without explicit sectoral separation or validation by ground-based measurements, source attribution is primarily inferential, based on spatial coincidence with recognized anthropogenic and natural activity zones. With respect to CMM, the study mentions coal mining only as a potential contributing source in the background and discussion. No coal-mine-specific methane signal is isolated, quantified, or modeled using the satellite data. Consequently, the paper demonstrates the utility of satellite observations for regional methane assessment but does not provide direct satellite-based estimation of CMM emissions and should be interpreted as descriptive rather than diagnostic for CMM.

Saunois et al. (2025) used a methodology that integrates bottom-up estimates from global emission inventories (such as EDGAR, GAINS, and CEDS) with top-down atmospheric inversion models to quantify methane emissions from coal mining between 2000 and 2020. With regard to coal mining, the study found that global emissions from this sector for the 2010–2019 decade average 40 Tg CH_4 yr^{-1} (with a range of 37–44 Tg CH_4 yr^{-1}). The results indicate a reduced uncertainty range compared to previous assessments, largely due to the harmonization of activity data (primarily from IEA statistics) across different inventories, which corrected previous overestimations in Chinese coal emissions; however, the study notes that emissions from abandoned mines and coal waste piles remain significant and poorly constrained, with recent estimates suggesting they could be substantial contributors to the total global burden. Wang et al. (2019) used these methods to increase consistency between reported emissions and atmospheric observations and refine geographical patterns of methane emissions using a global high-resolution inverse model restricted by national inventories. Similarly, McNorton et al. (2018) separated changes in emissions from changes in atmospheric transport and chemistry using three-dimensional inverse modeling to ascribe recent increases in atmospheric methane to various source categories and geographies.

India Focus

Bottom-Up Studies

Several studies have used a bottom-up approach to estimate methane emissions in India, including using national production data from the DGMS and emission factors derived from field campaigns conducted by the CIMFR. Many of these studies also estimate fugitive emissions from coal mining and handling activities using the IPCC's 2006 methodology: default emission factors based on global average range constitute a tier 1 approach, which is considered to have the highest level of uncertainty. Country-specific or basin-specific emission factors are used in the tier 2 approach, which is associated with a moderate level of uncertainty. Mine-wise measurements are used in the tier 3 approach, which is considered to have the lowest level of uncertainty (IPCC, 2006).

An early study by Garg et al. (2011), for example, estimated methane emissions from coal mining in India at the district level using the IPCC tier2 methodology. By employing mine gassiness categories to map emissions across coal-bearing districts, the study offers spatially disaggregated emission estimates by region, sector and source categories. The study primarily used NATCOM based emission factors[7] for areas where India-specific measurements exist. However, they used default emission factors from IPCC tier 2 methodology for source categories like coal mines where country specific measurements are limited. Also, geological variability, mine depth, and operational practices were not explicitly considered in the estimation. While the study provides valuable estimates of methane emissions at the sub-regional level, uncertainties remain because of limitations in emission factors and available activity data.

Singh and Mallick (2015) also used a bottom-up inventory approach based on activity data and emission factors for CMM emissions. Methane emissions were calculated by multiplying coal production data by mine-specific emission factors expressed in cubic metres of CH_4 per tonne of coal, differentiated according to the degree of gassiness of underground mines (Classes I, II and III). To increase the precision of emission factor estimation, especially for low-concentration VAM streams, direct field measurements of methane concentration in ventilation air were carried out utilizing gas chromatography with a flame ionization detector. Regional and national emission estimates for surface and underground mining operations were then produced by adding the mine-wise emission factors obtained from these data. In order to measure methane emissions from coal mines, this methodology combines production statistics with instrumental monitoring in accordance with an IPCC-consistent framework.

Singh and Sahu (2018) estimated Indian coal-mine methane emissions from 1980-2000 by multiplying emission-factor values with official coal-production statistics for each mining category (underground, open cast, post-mining) and gassiness degree. Emission factors from CIMFR's extensive field activities in the Indian context were compared to IPCC emission factors (IPCC 1997), finding that in the year 2000, India emitted 0.72 Tg methane using the CIMFR methodology and between 0.54–1.69 Tg, based on IPCC emission factors.

Building on earlier national-scale assessments, Singh and Kumar (2016) measured the amount of fugitive methane released by Indian coal mining and post-mining handling operations using time-series data from 1990 to 2012. They estimated emissions using coal production multiplied by category-specific emission factors for

[7] NATCOM (National Communication to the UNFCCC) emission factors for India are country-specific coefficients developed to accurately estimate greenhouse gas (GHG) inventories. Values mentioned in Table 1.

underground and surface mines (see Table 1). Underground emission factors were derived from direct measurements of VAM by measuring airflow (using air velocity and airway cross-sectional area) and methane concentration in return airways. Surface mine emissions were estimated using static flux chamber methods on exposed coal faces. The study found that underground mines produce more emissions than surface mines, and that transporting and handling coal contributes a significant portion to the overall emissions.

The significance of employing mine-specific or region-specific factors rather than uniform national averages was emphasized by the fact that mine-wise variations in gas content and degree of gassiness have a significant impact on emission levels (IPCC, 2019). Using ventilation-air measurements for underground mines and static-flux-chamber measurements for surface mines, Singh and Kumar (2016) quantified methane emissions with an activity-data × emission-factor approach that follows the IPCC methodology. However, the emission factors themselves were derived from extensive field measurements in India (the CIMFR national factors) rather than the generic IPCC default factors, which are presented only for benchmarking purposes. Moreover, the national emission factors developed in this study informed India's national communications and biennial update reports to UNFCCC. A key strength of the study lies in its reliance on primary field measurements across multiple mines and its distinction between mine categories based on gassiness. However, the sample size (25 surface and 67 underground mines) was limited relative to India's total active mines, raising concerns about representativeness.

Subsequent methodological refinements have further strengthened emission estimates. Singh et al. (2022) used the published—but not yet required for reporting–2019 IPCC refinements and a substantially larger field-measurement campaign (108 underground mines, representing ~31 % of degree-I, 20 % of degree-II and ~100 % of degree-III mines). The study used region-specific, degree-based emission factors to show that previous inventories likely overestimated emissions for the most gassy mines, and that the use of a default, deterministic emission factor likely ignores variabilities at the level of the coalfield. Its methodological advance lies in capturing heterogeneity: emission factors are reported separately for each gassiness degree and for individual coalfields, revealing that a small subset of high-gas coalfields (primarily in Raniganj, Jharia, East Bokaro, Makum) dominate the CH_4 budget. In doing so, Singh et al. (2022) provide a clearer picture of where mitigation (e.g., CMM capture, ventilation-air methane utilisation) would be most effective. Some limitations of the study include the analysis being limited to a subset of underground mines, and the use of spot measurements, which can lead to +/-20% error as emissions vary across time scales.

Wright et al. (2024) analyzed India's CMM emissions using the national emissions inventory methodology with tier 3 emission factors, drawing on data from UNFCCC, India's Coal Ministry, DGMS, IEA, and academic research. The analysis combined historical coal production data (2010–2022) with government projections to model future emissions through 2029, accounting for mine type (surface vs. underground) and degree of gassiness. The study found that India's coal mine methane emissions could more than double by 2029—from 812 kt in 2019 to over 1,670 kt—driven by planned expansion of underground mining (projected to triple to 100 million tonnes annually) and total domestic coal production reaching 1.5 billion tonnes by 2030. The report estimated that a moderate rollout of mitigation technologies could capture over 1,600 kt of methane between 2025-2030, equivalent to 44.5 million tonnes of CO_2e, with potential economic benefits of up to USD 980 million by displacing imported gas. The authors conclude that without proactive mitigation, these fugitive emissions will have a short-term warming impact comparable to all of India's trucks and buses combined, representing both a significant climate risk and a "low-hanging opportunity" for emissions reduction through existing technology.

Mishra et al. (2026) developed a 0.1° × 0.1° gridded methane emission dataset for India for the year 2023 using a bottom-up spatial disaggregation framework integrated with national activity data and sector-specific emission factors. Using publicly reported data from national coal production statistics by the MoC and peer-reviewed emission factors in accordance with IPCC tier 2 and 3 recommendations, the study created a national methane inventory by source sector. Then, using proxy variables that reflect emission intensity, such as coal mine locations and production data for fossil fuel sources, the sectoral totals (energy, agriculture, waste, and other minor sources) were spatially allocated onto a uniform grid. Geographic information systems (GIS) methods were applied to harmonize all proxies to a common resolution and projection, ensuring consistency across sectors. The study found that methane emissions in India are strongly controlled by agriculture, and coal-related activities and are highly localized into identifiable hotspots which are inadequately captured by coarse global inventories.

Sadavarte et al. (2022) combines mine-level production data with satellite-based geographic characterisation to enhance the representation of CMM emissions, positioned between top-down atmospheric inference and bottom-up inventory estimation. The work improved Indian CMM estimation by creating a spatially explicit gridded inventory at 0.1° resolution utilizing mine-wise production data and emission parameters unique to India. By combining GIS-based mine boundary mapping with Sentinel-2 imagery and official production statistics, it enhances spatial attribution as compared to national-level inventories. The combination of bottom-up mine-level data with spatial allocation, which enables regional comparison and atmospheric modeling, is the methodological strength. The study does not include emissions from abandoned mines. In this study, satellite data were only used for boundary detection, not methane measurement and validation. As a result, even while the study increases geographical resolution, it still primarily relies on emission parameters instead of actual atmospheric observation, thereby classified as a bottom-up approach.

Top-Down Studies

Romana et al. (2022) used satellite-derived atmospheric observation (using the AIRS, for CH_4) and ground-based soil sampling to conduct a time series (2003–2020) analysis of CO_2, CH_4, NO_2, and SO_2 concentration over Singrauli coal power cluster in Madhya Pradesh, India. Using a multiplicative model and linear regression, the study also forecast concentrations up to the year 2025. The analysis showed an increased trend in methane concentrations as well as an increase in coal mining and thermal power production. Based on these results the study suggests that in the absence of mitigation and utilization strategies, India will struggle to meet the Paris agreement goals to curb emissions by 2030.

Similarly, Siddiqui et al. (2024) used data from Sentinel-5P (TROPOMI) for regional observation and data from EMIT for high-resolution plume detection. This approach enables both point-source detection and wider spatial coverage, and the matched-filter algorithm combined with the integrated methane enhancement approach for flux calculation adheres to standard procedure in methane plume remote sensing. The process includes geospatial overlay analysis with layers of anthropogenic activity, quality assurance screening, and spatiotemporal filtering. The methodology does not incorporate atmospheric transport or inverse modeling approaches. The study identifies coal mines as a major source of methane but does not estimate the methane concentration from any actual coal mines. Rather, it gives a methodological understanding of employing satellite-based methods in atmospheric methane estimation.

Dangeti et al. (2024) used satellite-based observations of column-averaged methane (XCH_4) from GOSAT and Sentinel-5P/TROPOMI to conduct a spatiotemporal analysis of atmospheric methane (XCH_4) across South Asia (with a focus on India). The study found strong correlations between the remote sensing data and bottom-up EDGAR inventories but also revealed that satellite-based data capture hotspots and point-source variability that inventory-based methods typically do not. With regard to thermal power plants and coal mines, the study found that the release of methane into the atmosphere is commensurate with the production of the power and mining capacity.

Lama et al. (preprint) used satellite-based data (TROPOMI) and Bayesian inversion via the Integrated Methane Inversion framework (IMI) to assess methane emissions over

India at the national, state, and urban scales. The study combined posterior (top-down) estimations with cutting-edge bottom-up inventories including EDGAR, GHG platform India and BUR of India to UNFCCC, quantifying the country's methane emissions in 2021 at a resolution of up to 0.25° x 0.3125°. Although the national posterior estimate (34.4 Tg yr^{-1}) was 68% larger than India's UNFCCC inventory, it was generally consistent with India's UNFCCC inventory, though lower than global bottom-up priors (EDGAR/GFEI). The sectoral data showed that coal emissions were 57% lower than the prior global inventories (EDGAR/GFEI) used in the study, but landfill and oil and gas emissions were almost 30% higher. The study further identified pronounced methane hotspots over urban centers and coal- and energy-intensive regions that were weakly represented in bottom-up inventories relying on activity data and generalized emission factors. These discrepancies were attributed to incomplete accounting of diffuse and episodic sources, spatial aggregation errors, and uncertainties in emission factors.

Range of Methane Emission Estimates for India's Coal Mining Activities

Methane emission estimates from India's coal mining sector exhibit substantial variability across studies due to differences in methodological approaches, data inputs, and sectoral scope. It should be noted that discrepancies in methane emission estimates may partly reflect real increases in emissions over time, driven by changes in coal production and mining practices, in addition to methodological differences. The use of consistent, time-resolved datasets, including satellite observations, is therefore essential to distinguish actual emission trends from methodological improvements.

Estimates of coal mine methane (CMM) emissions for India show substantial variation, ranging from ~0.05 to ~2.87 Tg CH_4 yr^{-1}, largely due to differences between bottom-up and top-down methodological approaches. Bottom-up studies rely on activity data such as coal production, mine type, and emission factors, and therefore reflect assumptions about the physical characteristics of coal seams and mining practices. India-specific bottom-up inventories, including Sadavarte et al. (2022), the Government of India's BUR-4 (2024), and Mishra et al. (2026), consistently report emissions in the range of ~0.78–0.83 Tg CH_4 yr^{-1}. Notably, the official BUR-4 (2024) estimate of 0.79 Tg CH_4 yr^{-1} aligns closely with these independent studies, suggesting that the official inventory's best estimate is consistent with recent high-resolution national inventories. These estimates incorporate country-specific activity data and, in the case of BUR-4 and Mishra et al. (2026), reflect emission factors broadly representative of Indian mining conditions, including relatively low gas content. Sadavarte et al. (2022) similarly apply IPCC Tier 2 emission factors derived from Indian mine measurements, although such approaches may still be limited in representing spatial heterogeneity and mine-level variability across India.

However, bottom-up estimates can vary significantly depending on sectoral coverage. For instance, Singh et al. (2022) report much lower emissions (~0.05–0.08 Tg CH_4 yr^{-1}) because their analysis is limited strictly to underground mining, excluding surface and post-mining emissions which dominate India's coal sector. In contrast, global inventories such as CEDS (Hoesly et al., 2025) and EDGAR v7 (Crippa et al., 2023) report significantly higher estimates (~2.85–2.87 Tg CH_4 yr^{-1}). These global models likely reflect differences in underlying assumptions, including the use of harmonized emission factors that may not fully account for country-specific characteristics of the Indian coal sector, or potentially include broader fugitive sources not captured in national inventories.

Top-down approaches, which use satellite observations and atmospheric inversion models, generally produce higher and more variable estimates for India, ranging from ~0.50 to ~1.38 Tg CH_4 yr^{-1}. Studies such as Shen et al. (2023), Janardanan et al. (2024), and Lama et al. (preprint) infer emissions based on observed atmospheric methane concentrations and transport modeling. Top-down approaches capture total, observation-based emissions that inherently include contributions from all sources within a region, including those not explicitly represented in inventories, though separating coal-specific emissions from other regional sources (like agriculture) remains a significant challenge. As a result, top-down estimates are frequently higher than inventory-based values. However, they are also subject to significant uncertainties, particularly in attributing emissions to specific sectors. In regions like India, where coal mining coexists with other major methane sources such as agriculture and waste, separating coal-related emissions from total atmospheric methane remains challenging, contributing to the wide spread in estimates (e.g., Lama et al. (preprint) reporting 0.50 Tg vs. Janardanan et al. (2024) reporting 1.38 Tg).

Finally, the IEA's (2025b) hybrid approach, which combines satellite data with measurement campaigns and includes abandoned mines and super-emitters, yields an estimate of ~2.1 Tg CH_4 yr^{-1}. This value sits between the independent bottom-up estimates (~0.8 Tg) and the global inventories (~2.9 Tg), suggesting that unreported sources such as abandoned infrastructure and episodic super-emissions may account for a significant portion of the discrepancy between national inventories and global models.

Table 3 compiles methane estimates by various studies from 2022 to 2026. The table was created by reviewing each study, extracting comparable information on geographic scope, data year, approach, method, and uncertainty. Reported methane estimates for each study were standardized into common units (Tg CH_4 yr^{-1}) and summarized alongside methodological notes to enable comparison across different approaches, methods, and scopes. Figure 1 represents this information graphically.

Table 3: Comparison of estimated annual methane emissions from the Indian coal sector across recent studies. Table in ascending order by estimate year.

Study (Year)	Estimate Year	Approach	Method	Scope	Key Notes	Estimated CH_4 (Tg/yr)	Uncertainty / Range (Tg/yr)	Data Source	Uncertainty Source
Janardanan et al. (2024)	2015*	Top-down	Inverse Atmospheric Modeling	Coal Sector (National)	2009-2020 average; GOSAT-based.	1.38	1.32 – 1.44	Page 6, Table 1: Row "Coal" = 1.38 ± 0.06.	Page 6, Table 1: Uncertainty provided as ±0.06.
Sadavarte et al. (2022)	2018	Bottom-up	Local Gridded Inventory	Coal Mining (Surface + UG)	High-res grid; excludes abandoned.	0.83	0.17 – 1.48	Page 1 (Abstract): "CH_4 emissions: 825 [min: 166 – max: 1484] Gg yr^{-1}"	Page 8: "combined uncertainty of ±80%"
Singh et al. (2022)	2019	Bottom-up	National Bottom-up	UG Coal Only	Only UG mines. Derived from total GHG inventory (60% of 1.3–3.6 Mt-CO_2e).	0.053	0.028 – 0.077	Page 7 & 14: "Total GHG... 1.3–3.6 Mt-CO_2e... 60% CH_4... GWP 28".	Page 4: 90% CI for total GHG. Derived: Range calculated by applying 60% share and GWP=28 to bounds.

Shen et al. (2023)	2019*	Top-down	Inverse Atmospheric Modeling	Coal Sector (National)	Global study using TROPOMI; high confidence for India due to satellite coverage.	1.2	0.99 – 1.5	Supp. Table 4 & Table 6: Annual estimate for India.	Supp. Table 4 & Table 6 (<30% uncertainty).
BUR-4 (2024)	2019	Bottom-up	Official National Inventory	Coal Mining + Handling	Derived from 62% of total fugitive (16,656 Gg CO_2e). Converted using AR2 (GWP=21).	0.79	0 – 1.58	MOEFCC [2024], Table 2.35 & Fugitive Emissions Data.	Page: Table 2.35 (Combined Uncertainty = 100.12%).
Lama et al. (preprint)	2021	Top-down	Inverse Atmospheric Modeling	Coal Sector (National)	57% lower than prior; separates waste/coal well. TROPOMI+GOSAT.	0.50	0.40 – 0.64	Page 7, Table 1: Row "Coal", Posterior = 0.5 (0.4 – 0.64).	Page 7, Table 1: Range provided in parentheses.
Crippa et al. (2023)	2022	Bottom-up	Global Gridded Inventory	Coal Sector (Global Model)	Global study; India subset. Coal Only.	2.87	Unknown	IEA (2025b) Chart, Page 23: "Methane emissions from the fossil fuel sector" (Coal segment).	N/A

Mishra et al. (2026)	2023	Bottom-up	Local Gridded Inventory	Coal Mining (Surface + UG)	Uses country-specific EFs; 0.78 Tg for coal mining only (excludes post-mining activity); high uncertainty (up to ±161% per Fig 5).	0.78	0.53 – 2.03	Page 1374: "0.78 Tg yr^{-1} specifically attributed to coalmines."	Page 1375: "uncertainty... lies in the range of ±32 %–161 %"
Hoesly et al. (2025)	2023	Bottom-up	Global Gridded Inventory	Coal Sector (Global Model)	Global study; India subset. Coal Only.	2.85	Unknown	IEA (2025b) Chart: "India methane emissions from energy sources" (Coal segment).	N/A
IEA (2025b)	2024	Hybrid	Hybrid	Coal Sector (Includes abandoned)	Combines UNFCCC inventories with satellite observations (for super-emitters) and atmospheric modeling.	2.1	High (Qualitative)	Page 23, Figure 1: Bar chart for India "Coal" in Mt).	Not reported (uncertainty described qualitatively as "high")

**Note: the estimate year for Janardanan et al. (2024) is the midpoint of 2009–2020, while the estimate year for Shen et al. (2023) is the midpoint of 2018–2020 (see those studies for details on data collection).*

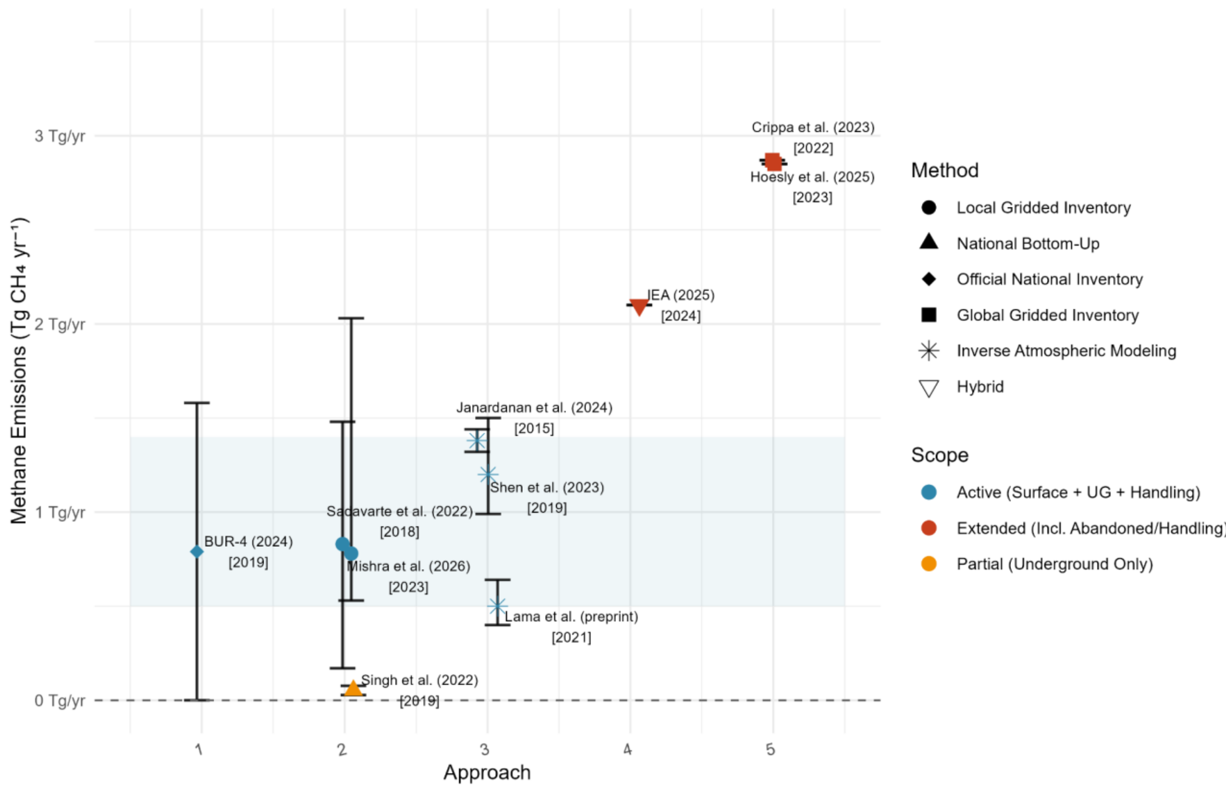

Figure 1. Methane emission estimates from India's coal mining sector by approach, method, and scope. The shaded blue band (0.5–1.4 Tg yr⁻¹) represents the consensus range among studies focusing on active mining operations and handling, excluding abandoned mines. Error bars represent reported uncertainty ranges of each estimate. The parentheses indicate the study year and the square brackets indicate the estimate year. Note that the estimate year for Janardanan et al. (2024) is the midpoint of 2009–2020, while the estimate year for Shen et al. (2023) is the midpoint of 2018–2020. Plotted points and error bars have been 'jittered' slightly to avoid visual overlap. 'B-up' = Bottom-up. 'UG' = Underground.

Overall, the wide range of estimates (~0.05 to ~2.87 Tg CH_4 yr^{-1}) underscores the profound influence of methodological choices and sectoral scope. Contrary to the assumption that national inventories systematically underreport emissions, the Government of India's BUR-4 (2024) estimate (0.79 Tg) aligns closely with independent, high-resolution bottom-up studies (Mishra et al., 2026; Sadavarte et al., 2022), suggesting that the "official" best estimate is robust. The primary discrepancies arise instead from global Inventories (e.g., Hoesly et al., 2025; Crippa et al., 2023), which report values nearly four times higher (~2.85–2.87 Tg), likely due to the application of harmonized emission factors that may not fully capture country-specific mining conditions, such as the relatively low gas content of Indian coal seams.

At the source level, emission factors for underground coal mines exhibit substantial variability due to heterogeneity in coal seam properties, including gas content, depth, permeability, and mining practices. The use of generalized emission factors and limited mine-specific measurements introduces significant uncertainty, as evidenced by the wide confidence intervals in Singh et al. (2022) (0.05–0.08 Tg for underground only) and Mishra et al. (2026) (0.53–2.03 Tg). These uncertainties can span an order of magnitude, making precise attribution difficult without mine-level data.

At the regional scale, the challenge of separating coal-related emissions from the total atmospheric signal is highlighted by the widespread in top-down estimates, which range from 0.50 Tg in Lama et al. (preprint) to 1.38 Tg in Janardanan et al. (2024). This divergence suggests that atmospheric observations are influenced by multiple co-located sources such as thermal power plants, agriculture, and wetlands, complicating source attribution. Furthermore, uncertainties in meteorological inputs and the spatial resolution of the inversion models contribute to the discrepancies between the observed and modeled methane fields.

Together, these studies underscore that uncertainties in coal mine methane estimates are driven by a dual challenge: bottom-up limitations in capturing spatial heterogeneity and unreported sources (e.g., abandoned mines and super-emitters, as noted in IEA, 2025), and top-down limitations in source attribution amidst complex regional backgrounds. This necessitates integrated frameworks that combine high-resolution, country-specific activity data (as in Mishra et al., 2026) with observational constraints from satellite inversions (as in Lama et al., preprint; Janardanan et al., 2024) to refine the "true" emission budget.

Mitigation and Utilization Pathways

India's CBM and CMM resources (especially in areas such as Jharia, East Bokaro and Raniganj) represent critical transitional energy resources for India, offering opportunities to diversify India's natural gas supply, bolster energy security, and support the country's longer climate change goals (Joshi et al., 2023; Hummel et al., 2018; Adsul et al., 2023). Singh and Sahu (2018), for example, note that capturing CBM/CMM can simultaneously enhance underground safety and offset a portion of India's conventional fossil-fuel consumption in industrial and power-generation settings. The following sections review the literature on the methods and viability of CBM and CMM/VAM in India.

CBM

CBM has emerged as an important unconventional energy resource in India in response to increasing energy demand and declining conventional gas reserves. CBM is produced during the coalification process and stays adsorbed in coal seams, which if successfully recovered, acts as a potential source of cleaner energy. In India, CBM exploration activity began in the mid-1990s and commercial-scale production of CBM commenced in July 2007 in Raniganj coalfield (Singh, 2022) . There is significant potential for CBM in India: approximately 2600 billion cubic meters (bcm) of CBM reserves are available, and out of the total 33 CBM blocks identified in India, the estimated available reserves amount to approximately 1,767.07 bcm (Directorate General of Hydrocarbons, 2024). The majority of CBM reserves are concentrated in Jharkhand (720 bcm), followed by Rajasthan (360 bcm), Gujarat (350 bcm), Orissa (240 bcm) and Chattisgarh (240 bcm) (Vedanti et al., 2020).

Panwar et al. (2022) examined CBM potential in the Raniganj coalfield using time series forecasting and reservoir modeling. They combined geological and production data to simulate reservoir behavior and created forecasting scenarios, revealing substantial recoverable methane despite declining production rates. The study emphasizes the need for accurate reservoir characterization to ensure reliable long-term recovery projections. Similarly, Ojha et al. (2023) assessed CBM in the Cambay basin through geochemical analysis of stable isotopes and molecular composition. Their findings indicate that CBM primarily develops through biogenic processes, suggesting a strong potential for long-term methane accumulation in shallow coal seams.

Prabu and Mallick (2015) evaluated CBM resources and CO_2 sequestration potential using a correlation-based desk assessment, employing Kim's correlation and Langmuir-type models. They estimated methane content and potential CO_2 storage in Indian coal and lignite reserves. However, this approach is limited by generalized correlations, introducing uncertainty at finer scales. Adsul et al. (2023) focused on the geological and biogeochemical controls on CBM production and storage. Their analysis, incorporating laboratory data and isotopic studies, concluded that Indian coal basins possess a mixed-origin methane system, influenced significantly by biogeochemical conditions. This suggests that enhancing microbial CBM recovery could boost India's domestic gas resources and energy security.

As of FY 2025−2026, CBM exploration & production spans ~7010 sq.km in India, with 15 CBM blocks under operation (7 are in exploration, 3 in development and 5 are in production stage). The cumulative CBM production up to FY 24–25 is 7.14 bcm. CBM activities have contributed USD 148 million as royalties for State Governments and USD 7 million to the Central Government (Directorate General of Hydrocarbons, 2025). Among the five producing CBM blocks in India, RG(E)-CBM-2001/I (cumulative production of 89.98 billion cubic feet (bcf), awarded to Essar Oil Limited, is the largest producing block in India (covering an area of approximately 500 sq. km), has been operational since July 2016, and comprising more than 400 wells (Vedanti et al., 2020; DGMS, 2024). A consistent upward trend is observed in all CBM production blocks from 2024–2025 to 2029–2030, with significant contribution from Raniganj East and the NK-CBM-2001/I block (Joshi et al., 2023).

Despite these advancements, India currently only produces about 2.8 MMSCMD, while other coal economies like the United States and Australia produce 48.2 MMSCMD and 30.1 MMSCMD, respectively (Meel & Lokhande, 2026) . The sector faces several obstacles to growth including low flow rates in many seams, insufficient drilling and processing infrastructure, and weak policy and financial incentives, which have kept the number of operational CBM projects modest (Singh & Sahu, 2018). Several technical, policy, and commercial challenges persist in scaling up CBM production, with many awarded contracts relinquished due to technical or financial complications (Bajpai et al., 2024). Geologically, Indian coal seams are highly heterogeneous, varying in rank, thickness, faulting and cleat development, making it difficult to predict gas-in-place and to design wells that consistently produce. Many of these seams also suffer from low permeability, so conventional drilling yields little gas and requires costly stimulation methods such as multi-stage hydraulic fracturing (R. Singh et al., 2025). This is compounded by the fact that India currently lacks widespread expertise in advanced directional drilling, multi-stage fracking and sophisticated water-treatment technologies (e.g., reverse-osmosis, forward-osmosis, constructed wetlands), limiting rapid commercial roll-out (Meel & Lokhande, 2026).

Extracting the gas necessitates large volumes of de-watering, producing highly saline water containing heavy metals, creating significant disposal, treatment and reuse challenges and risk of contaminated groundwater or surface soils (Sharma et al., 2024) . High upfront capital for drilling, hydraulic fracturing, building extensive surface facilities, and land acquisition, and uncertain revenue due to government-regulated gas prices subject to exchange-rate swings and royalty obligations, challenge the economics of scaling up commercial CBM (Singh & Hajra, 2018).

Further, a fragmented regulatory where licences involve the MoPNG, DGH, and the India Ministry of Coal, leading to overlapping approvals, procedural delays and inconsistent incentives across states, slow environmental and mining clearances, and an under-developed CBM-specific legal framework. These technical and regulatory issues are further amplified by socio-political challenges (insurgent activity, local opposition, encroached government lands), and uncertain gas pricing/incentives that make commercial projects financially risky (Singh & Hajra, 2018). CBM blocks often intersect inhabited or tribal lands, so without clear benefit-sharing, revenue-sharing or employment guarantees, projects can encounter community resistance, land-acquisition disputes and difficulty obtaining a social licence to operate.

CMM

While multiple (pre-) feasibility studies assessing the technical and economic viability of CMM utilization projects have been undertaken in eastern India, there are no active commercial projects thus far. In partnership with the EPA, India previously undertook pre-feasibility studies and pilot projects (in the mid-2010s) in gassy coalfields like Moonidih, Sawang, and Chinakuri (EPA, 2019). The studies examined the economics of utilizing long, in-seam boreholes to drain gas from deeper portions of the mines, though these efforts were hindered by constraints pertaining to funding and acquiring the appropriate technology.

In 2009, a CMM demonstration project implemented at Sudamdih and Moonidih mines was funded by the UNDP, the GEF, and the MoC (EPA, 2019). India has only implemented one operational CMM project, a 500 kW power generation pilot project at Moonidih UG mine (funded for implementation by GEF, UNDP, and the Government of India Ministry of Science and Technology). The project captured CMM, which was fed into a local pipeline leading to two 250 kW gas generators to produce electricity for local consumption. Ownership of the project was officially turned over to BCCL in 2010. However, Sudamdih is still categorized as a "favourable site" for potential CMM recovery in the Jharia Coalfield due to its high gas content, though commercial-scale drainage has not yet been established (Singh and Kumar, 2016).

Hummel et al. (2018), for example, demonstrated that the use of in-mine horizontal boreholes for pre-drainage, capture, and utilization of CMM is both technically and economically feasible. Using a combined engineering-economic modeling framework, they investigated the viability and advantages of CMM recovery at two Degree-III gassy underground coal mines in India (Sawang and Chinakuri). In order to estimate methane drainage from in-seam horizontal pre-drainage boreholes under various borehole spacings and drainage durations, the study used reservoir simulation (COMET3®). To predict gas production and residual in-situ methane reduction, a number of scenarios (18 in all) were simulated by altering drill spacing (15–152 m) and pre-drainage periods (1, 3, and 5 years). These production profiles were then linked to a discounted cash-flow economic model to estimate NPV, IRR, and payback period for power generation using drained methane, and to a carbon accounting method based on IPCC global warming potential factors to quantify CO_2-equivalent emission reductions.

More recently, in 2021, a pilot was developed with BCCL and Prabha Energy in partnership with the US-based consultant Advanced Resources International, to extract CMM from the coal mine Jharia CBM Block-I representing the first time the extraction of CMM has been allowed within a designated coal mining block (GMI, 2024). However, no further information about the status of this project is publicly available at this time. Additionally, the MoC made CMPDI a Nodal Agency for development of CMM in India, and established the "CMM/CBM Clearinghouse" in association with EPA & Coal India Limited under the aegis of the MoC. While the CMM/CBM Clearinghouse produced a technical guide on CBM opportunities and partnered on feasibility studies of CMM and CBM projects in different Indian coalfields their website has been inactive since 2021.

Substantial barriers to commercializing CMM remain, however. A recent study of the perception of Indian stakeholders indicates a perception that CMM recovery opportunities in India are limited, due to a lack of substantial gassy coalfields and inadequate pipeline infrastructure near coalfields (U. Singh et al., 2025). Furthermore, the volume and gas purity may mean lower capacity factors and the need for additional gas upgrading, which might make the process cost-prohibitive (Hummel et al., 2018; Sinha & Panigrahi, 2019). Moreover, Singh & Mallick (2015) concluded that although ventilation air methane represents the largest share of methane emitted from underground mines, its extremely low concentrations (<0.02%) poses major technological and economic challenges for energy recovery. These include technological challenges related to low methane concentrations and variable airflow, as well as economic constraints such as high capital costs, low energy recovery potential, and limited policy incentives (Singh & Mallick, 2015).

Singh (2022) and Singh & Hajra (2018) nevertheless identify examples of potential case studies for potential CMM projects in India. Kalidaspur Colliery in the Raniganj coalfield (Degree III) records methane emissions of 8.8 – 19.3 m^3 per tonne of coal, with an estimated 1.274 bcm of gas in the lease area and an additional 2.509 bcm in the adjacent virgin Bakulia block; the high-purity gas (> 96 % combustible) could feasibly supply the mine's ~1 MW power demand and support a small-scale CMM project.

Ghusick Colliery in the Jharia coalfield (also Degree III) produces only 70 t day^{-1} because of severe gas outbursts, yet still releases 11 – 14 $m^3 min^{-1}$ of methane, indicating strong CMM potential that would require targeted drainage methods such as inseam drilling. Mines in the Mohuda sub-basin (Degree III at Bhatdih, lower grades elsewhere) illustrate how high ventilation can mask substantial emissions—measured at 4.66 $m^3 t^{-1}$ overall, with localized blow-outs up to 5.61 $m^3 t^{-1}$—yielding an estimated 1.52 bcm of recoverable CMM across the basin and suggesting spot-drainage could be economically viable. Finally, Amlabad Colliery (Degree III) exhibits the highest emission rate at 23 $m^3 t^{-1}$ and ventilation-air methane concentrations of 0.3 %–0.5 %; despite a modest production of ≤ 70 t day^{-1}, the mine holds roughly 0.76 bcm of gas, with nearby Sudamdih mines adding another 1.47 bcm, making CMM extraction attractive for both safety improvement and energy recovery, especially if existing UNDP-funded drilling rigs are repurposed. Across all sites, the studies underscore that high-gassiness mines pose serious explosion risks, but contain sufficient methane (0.5 – 2.5 bcm per collieries) to justify dedicated capture infrastructure, integration with regional gas grids, and coordinated policy support for drilling, processing, and potential carbon-capture pairing.

Conclusions

This report synthesized evidence on methane emissions from coal mining in India by examining estimation methodologies, the range and divergence of reported emission values, and the status of mitigation and utilization pathways. It shows that bottom-up inventories and satellite-based approaches offer complementary but often divergent perspectives, reflecting differences in assumptions, data inputs, and system boundaries. Reported estimates span from less than 1 Tg CH_4 yr^{-1} in earlier inventories to approximately 2.9 Tg CH_4 yr^{-1} in more recent assessments, indicating substantial variability that arises not only from methodological differences but also potentially from temporal changes in emissions. Variations within bottom-up studies themselves further underscore the influence of emission factors, methodological tiers, spatial coverage, and inclusion of emission sources such as post-mining activities, degasification, and abandoned mine methane.

The review of Indian studies highlights a clear methodological progression from generalized emission factors toward more measurement-based and region-specific approaches, improving representation of geological and operational heterogeneity. At the same time, top-down studies provide valuable insights into spatial patterns and emission hotspots, though their application in India remains limited in terms of deriving consistent national-scale estimates. The continued divergence between inventory-based and observation-based estimates points to a fundamental gap in reconciling these approaches, suggesting that current frameworks do not fully capture the spatial and temporal variability of methane emissions from coal mining.

Several knowledge gaps emerge from this assessment. There remains limited availability of consistent, mine-level measurements across different coal basins, constraining the development of robust, representative emission factors. Differences in system boundaries and incomplete inclusion of emission sources reduce comparability across studies. In gridded and satellite-based approaches, uncertainties related to spatial allocation, atmospheric transport, and source attribution persist, particularly in regions with overlapping emission sources. Moreover, the absence of long-term, harmonized datasets limits the ability to distinguish methodological differences from actual emission trends over time.

The review also indicates that while CBM and CMM offer significant potential for methane mitigation and energy recovery, their deployment in India remains limited due to geological and technical constraints such as low permeability, heterogeneous coal seams, and low methane concentrations. This is compounded by infrastructure gaps, high costs, regulatory complexities, and environmental challenges, along with limited commercial experience and stakeholder perceptions of low recovery potential.

Addressing these gaps will require greater integration between bottom-up and top-down methodologies, expanded measurement campaigns to improve emission factor accuracy, and more consistent treatment of emission sources and system boundaries. Strengthening the linkage between observational data and inventory frameworks, along with improved data transparency and long-term monitoring, is critical for reducing uncertainties and developing more reliable national methane estimates for India.

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