Proceedings of CONF-FMCE 2025 Symposium: Semantic Communication for Media Compression and Transmission
DOI: 10.54254/2755-2721/2025.GL28753

Global Methane Emission Inventories: Model Classification and Evaluation

Xinran Qi

School of Environmental and Geographical Science, University of Nottingham Malaysia, Malaysia
hgyxq1@nottingham.edu.my

Abstract. Accurate methane (CH_4) emission quantification is critical for achieving climate targets. This review systematically evaluates CH_4 emission models—categorized as white-box (mechanistic, e.g., DNDC), grey-box (hybrid, e.g., EDGAR), and black-box (data-driven, e.g., TROPOMI inversions)—assessing their rigor, policy relevance, and feasibility. White-box models offer high mechanistic accuracy but face scalability challenges, grey-box frameworks enable policy-compatible inventories but risk regional biases, black-box approaches excel in spatiotemporal resolution but lack interpretability. The analysis highlights the necessity of integrated frameworks that utilize machine learning, satellite remote sensing, and dynamic process modeling to address spatiotemporal heterogeneity, mechanistic intricacy, and methodological constraints. Achieving the Global Methane Pledge's 30% reduction target by 2030 demands models that balance accuracy, transparency, and agility, ensuring alignment with climate mitigation strategies.

Keywords: Methane emission models, Model classification, Climate policy integration, Hybrid frameworks, Model uncertainty.

1. Introduction

Methane (CH_4) is responsible for approximately 20% of current anthropogenic radiative forcing [1]; its 20-year GWP is 84× CO_2 and 100-year GWP is 28× [2], while a 12-year atmospheric lifetime facilitates rapid mitigation [1,3]. Global anthropogenic emissions totaled approximately 300 Mt in 2022 [4], with sources including 40% agriculture, 35% fossil fuels, and 20% waste [5]. Emission hotspots exhibit significant spatiotemporal variability [6,7], challenging inventories through factors like diurnal flux fluctuations and undetected transient super-emitters [8,9]. Furthermore, mechanistic complexity (e.g., soil redox, rumen physiology [10,11]) is often oversimplified by static emission factors, leading to systematic under-reporting and omissions [12]. Consequently, hybrid frameworks integrating process models with regional satellite and field data are critically needed to improve accuracy [13,14].

This study will conduct a systematic review of models developed between 1980 and 2023 (DNDC [15], EDGAR, GAINS, TROPOMI-ML) to provide quantitative insights into model trade-offs (scientific rigor vs. policy agility vs. operational feasibility) and propose pathways for integrating white-, grey-, and black-box paradigms. This synthesis can directly support the Global

© 2026 The Authors. This is an open access article distributed under the terms of the Creative Commons Attribution License 4.0 (https://creativecommons.org/licenses/by/4.0/).

DOI: 10.54254/2755-2721/2025.GL28753

Methane Pledge (30% reduction by 2030 [4]) and advances next-generation Monitoring, Reporting and Verification (MRV) frameworks through hybridizable architectures.

2. Classification of methane emission models

2.1. White-box models (mechanistic models)

White-box methane models simulate biogeochemistry through explicit mechanisms including methanogenesis, transport, and oxidation. Models like CH4MOD, DNDC, and CLM-CH4 vary in resolution and process detail.

These models typically integrate core modules: (1) Substrate Supply: Estimates methanogenic precursor production from organic matter decomposition [16]. (2) Microbial Metabolism: Simulates methanogen-methanotroph competition using Monod kinetics. (3) Transport: Combines diffusion, ebullition, and plant-mediated transport pathways. (4) Environmental Response: Quantifies regulation by temperature, moisture, and redox potential.

2.1.1. DNDC model

The DNDC (Denitrification-Decomposition) model dynamically couples carbon and nitrogen cycles with methane production. It simulates a cascading reaction chain involving organic matter decomposition, nitrification-denitrification, and methanogenesis. The model requires the following input parameters [17]:Soil Profile (Two-layer characterization (e.g.,0-10 cm, 10-20 cm) including texture, bulk density, pH, and water-soluble organic carbon), Climate (Hourly air temperature, precipitation, and shortwave radiation), Management [18] (Tillage depth, rice paddy flooding duration, and nitrogen fertilizer application (type and timing)),

Globally validated using flux observations from over 30 countries [19], DNDC is particularly well-suited for simulating seasonal CH_4 dynamics in rice paddies and assessing management intervention scenarios.

2.1.2. CLM-CH_4 module

The CLM-CH_4 module CLM-CH_4: Extends the Community Land Model to simulate the global CH_4 cycle within an ecosystem-climate framework. Key features: First, integration of CH_4 production, transport, and oxidation driven by CLM-CN substrate pools [20]. Second, the model uses a spatially explicit forcing strategy. Climate data from CRU-NCEP (1901–2022) are downscaled to a 0.5° × 0.5° daily grid using PRISM-based regression [21]. Wetland distribution is refined using 500 m MODIS MCD12Q1 land cover data.

Third, it introduces a dynamic vegetation–hydrology scheme using the following equation:

$$FCH4 = f(VWC) \cdot g(Tsoil) \cdot \Phi root_exudate \quad (1)$$

This equation quantifies the synergistic effects of volumetric water content (VWC), stratified soil temperature (Tsoil), and root exudate flux from emergent wetland plants. The root exudate flux is inferred from the canopy photosynthetic capacity derived from MODIS NDVI.

CLM-CH_4 improves global emission accuracy and projects increased CH_4 under RCP8.5 due to permafrost thaw, making it valuable for climate-carbon feedback studies [22].

DOI: 10.54254/2755-2721/2025.GL28753

2.2. Grey-box models (hybrid models)

Grey-box models provide a unique advantage in environmental modeling by combining mechanistic and data-driven methods. This approach balances theoretical precision with practical use. Key features include: (1) an interpretable framework based on simplified physical and chemical equations, (2) dynamic parameter calibration using diverse data sources to improve spatial representation, and (3) a modular design for coupling sub-models across scales. This hybrid method overcomes limitations of both purely mechanistic (high sensitivity) and statistical models (poor extrapolation), providing an innovative solution for complex environmental system simulation. The Emissions Database for Global Atmospheric Research (EDGAR) exemplifies this integration: (1) A foundational activity database synthesizes international energy, agricultural, and inventory data [23], (2) Dynamic emission factors incorporate IPCC Tier 1-3 frameworks, (3) A spatiotemporal downscaling algorithm uses proxy variables (e.g., nighttime light data) to disaggregate national statistics to 0.1° resolution [23]. Monte Carlo uncertainty analysis quantified key uncertainties (±15–50%) integrated into UNFCCC assessments. The EU Methane Strategy employs grey-box modeling, integrating technological, economic, and environmental co-benefits via three modules: (1) a technology diffusion module (Bass model) quantifying carbon pricing impacts on methane abatement technology adoption; (2) a cost-benefit analysis module integrating industry-level MACCs to evaluate techno-economic feasibility across policy scenarios; and (3) an environmental response module coupled with the CHIMERE atmospheric model to assess co-effects of emission changes on surface ozone. Simulations project a 35–42% EU methane reduction below 1990 levels by 2030 under existing carbon markets, with ancillary benefits including avoided respiratory mortality [24]. This quantitative framework underpins sector-specific EU policy design [25], demonstrating grey-box models' utility in complex environmental policymaking.

2.3. Black-box models (data-driven models)

Black-box models establish nonlinear mappings between inputs and methane fluxes using statistical correlations or machine learning (e.g., deep neural networks, random forests), without explicit parameterization of biogeochemical processes. While offering high predictive accuracy, their limited interpretability constrains mechanism-driven research. Two main categories exist:

Satellite-based Inversion: Utilizes instruments like TROPOMI (short-wave IR) with optimal estimation for XCH_4 inversion [26]. Inputs include solar reflection spectra, ERA5 reanalysis data (wind, temperature, humidity, pressure), and baseline inventories (e.g., EDGAR) for industrial monitoring.

Data-driven ML Prediction: Employs supervised learning with eddy covariance flux data as response variables. Features integrate remote sensing data (e.g., SMAP soil moisture, MODIS NDVI), static geography, and process-informed variables. SHAP values can enhance interpretability [27, 28]. For example, an LSTM model achieved Arctic wetland flux forecasts (RMSE < 4.2 nmol m^{-2} s^{-1}) [29], improving permafrost monitoring.

3. Comparative analysis of models

Table 1 summarizes the advantages, limitations, and scope of three methane emission models, providing a critical analysis of their scientific rigor, policy relevance, and operational feasibility.

DOI: 10.54254/2755-2721/2025.GL28753

Table 1. Model characteristics and scope

Model Type	Advantages	Limitations	Scope
White-Box	High mechanistic accuracy.	Data-intensive (e.g., soil microbial parameters).	Research: Small-scale studies (e.g., rice paddies, wetlands).
	Explicit process representation (e.g., methanogenesis pathways).	High computational cost.	Mechanistic exploration: Hypothesis testing (e.g., biochar impacts on CH_4 production).
	Transparency for validation and reproducibility.	Parameter sensitivity (e.g., soil porosity errors inflate uncertainties).	
Grey-Box	Balanced approach (mechanistic + empirical).	Limited mechanistic transparency.	Policy: National inventories (e.g., UNFCCC reporting).
	Scalable for regional/national inventories.	Reliance on emission factors (regional biases).	Multi-sector assessments: Agriculture, energy, waste.
	Policy-compatible (IPCC tiered methods).	Calibration challenges (e.g., outdated activity data).	
Black-Box	Rapid processing of large datasets.	Low interpretability (e.g., opaque ML algorithms).	Operational monitoring: Real-time leak detection (e.g., oil/gas infrastructure).
	Captures nonlinear relationships (e.g., freeze-thaw cycles in wetlands).	Training data dependency (e.g., tropical region data gaps).	Scenario testing: Climate impact projections.
	High spatial-temporal resolution (e.g., satellite-based inversions).	Overfitting risks (e.g., biased predictions in uncalibrated regions).	

White-box models explicitly parameterize biogeochemical processes (e.g., Michaelis-Menten kinetics for methanogens [30]), enabling mechanistic isolation of driving factors, such as quantifying nonlinear tillage impacts on carbon decomposition (±8% uncertainty). However, their use is limited by detailed data needs; incomplete parameters (e.g., microbial activity) greatly raise prediction uncertainty (e.g., wetland CH_4 errors up to 25–40%), demanding extensive calibration and hindering quick policy decisions. Grey-box models combine mechanistic and empirical elements (e.g., integrating IPCC Tier 1 factors with dynamic coefficients). Overreliance on static emission factors can cause systematic biases (e.g., underestimating landfill emissions by ≤30%) [31]. Integration of satellite constraints (e.g., TROPOMI inversions) is enhancing spatiotemporal resolution (~10 km/week) [32]. Black-box models (e.g., machine learning) excel at processing high-dimensional data for near-real-time monitoring (e.g., TROPOMI detecting >10 t/h emitters within 24h at 5.7x5.7 km^2) [33]. Challenges include limited interpretability (e.g., difficulty distinguishing microbial vs. episodic sources despite $R^2 > 0.85$ accuracy) and regional generalization issues (e.g., errors ≤50% when transferring between biomes [34]), requiring techniques like transfer learning with region-specific covariates.

4. Conclusion

Methane emission modeling has advanced significantly to address the urgent need for accurate quantification and mitigation of this potent short-lived climate pollutant. Classifying models as white-box, gray-box, or black-box frameworks reveals inherent advantages and limitations,

DOI: 10.54254/2755-2721/2025.GL28753

reflecting methane dynamics' complexity across sectors and regions. Advances in methane emission modeling reveal distinct trade-offs across white-box, gray-box, and black-box frameworks. White-box models (e.g., DNDC) offer mechanistic precision but require granular data, limiting policy application. Gray-box approaches (e.g., EDGAR) balance process-based and empirical methods for scalable inventories yet risk regional bias. Black-box tools (e.g., TROPOMI, LSTM) enable real-time monitoring but lack interpretability and perform poorly with data gaps.

References

[1] Climate and Clean Air Coalition. (2021). Methane | Climate & Clean Air Coalition. Www.ccacoalition.org. https: //www.ccacoalition.org/short-lived-climate-pollutants/methane

[2] Greenhouse Gas Protocol. (2024). IPCC Global Warming Potential Values. https: //ghgprotocol.org/sites/default/files/2024-08/Global-Warming-Potential-Values%20%28August%202024%29.pdf

[3] Nzotungicimpaye, C.-M., MacIsaac, A. J., & Zickfeld, K. (2023). Delaying methane mitigation increases the risk of breaching the 2 °C warming limit. Communications Earth & Environment, 4(1), 1–8. https: //doi.org/10.1038/s43247-023-00898-z

[4] IEA. (2023). Overview – Global Methane Tracker 2023 – Analysis. IEA. https: //www.iea.org/reports/global-methane-tracker-2023/overview

[5] Climate and Clean Air Coalition. (2021). Methane | Climate & Clean Air Coalition. Www.ccacoalition.org. https: //www.ccacoalition.org/short-lived-climate-pollutants/methane

[6] Zhang, Y., Gautam, R., Pandey, S., Omara, M., Maasakkers, J. D., Sadavarte, P., Lyon, D., Nesser, H., Sulprizio, M. P., Varon, D. J., Zhang, R., Houweling, S., Zavala-Araiza, D., Alvarez, R. A., Lorente, A., Hamburg, S. P., Aben, I., & Jacob, D. J. (2020). Quantifying methane emissions from the largest oil-producing basin in the United States from space. Science Advances, 6(17), eaaz5120. https: //doi.org/10.1126/sciadv.aaz5120

[7] THE REGIONAL IMPACTS OF CLIMATE CHANGE An Assessment of Vulnerability Intergovernmental Panel on Climate Change. (n.d.). https: //www.ipcc.ch/site/assets/uploads/2020/11/The-Regional-Impact.pdf

[8] Riman, H. S., Adie, G. U., Anake, W. U., & Ana, G. R. E. E. (2022). Seasonal methane emission from municipal solid waste disposal sites in Lagos, Nigeria. Scientific Reports, 12(1). https: //doi.org/10.1038/s41598-022-22923-5

[9] Satellite Data Suggest U.S. Methane Emissions Underestimated. (2024, June 5). Earthobservatory.nasa.gov. https: //earthobservatory.nasa.gov/images/152825/satellite-data-suggest-us-methane-emissions-underestimated

[10] Cholewińska, P., Górniak, W., & Wojnarowski, K. (2021). Impact of selected environmental factors on microbiome of the digestive tract of ruminants. BMC Veterinary Research, 17(1). https: //doi.org/10.1186/s12917-021-02742-y

[11] Thacharodi, A., Hassan, S., Ahmed, Z. H. T., Singh, P., Maqbool, M., Meenatchi, R., Pugazhendhi, A., & Sharma, A. (2024). The ruminant gut microbiome vs enteric methane emission: The essential microbes may help to mitigate the global methane crisis. Environmental Research, 261, 119661.

[12] Ravindra, K., Singh, T., & Mor, S. (2019). Emissions of air pollutants from primary crop residue burning in India and their mitigation strategies for cleaner emissions. Journal of Cleaner Production, 208, 261–273. https: //doi.org/10.1016/j.jclepro.2018.10.031

[13] Jayanegara, A., Sarwono, K. A., Kondo, M., Matsui, H., Ridla, M., Laconi, E. B., & Nahrowi. (2017). Use of 3-nitrooxypropanol as feed additive for mitigating enteric methane emissions from ruminants: a meta-analysis. Italian Journal of Animal Science, 17(3), 650–656. https: //doi.org/10.1080/1828051x.2017.1404945

[14] Yu, G., Beauchemin, K. A., & Dong, R. (2021). A Review of 3-Nitrooxypropanol for Enteric Methane Mitigation from Ruminant Livestock. Animals, 11(12), 3540. https: //doi.org/10.3390/ani11123540

[15] DNDC Scientific Basis and Processes. (2017). https: //www.dndc.sr.unh.edu/papers/DNDC_Scientific_Basis_and_Processes.pdf

[16] Pan, X., Irini Angelidaki, Alvarado-Morales, M., Liu, H., Liu, Y., Huang, X., & Zhu, G. (2016). Methane production from formate, acetate and H2/CO2; focusing on kinetics and microbial characterization. 218, 796–806. https: //doi.org/10.1016/j.biortech.2016.07.032

[17] Gilhespy, S. L., Anthony, S., Cardenas, L., Chadwick, D., del Prado, A., Li, C., Misselbrook, T., Rees, R. M., Salas, W., Sanz-Cobena, A., Smith, P., Tilston, E. L., Topp, C. F. E., Vetter, S., & Yeluripati, J. B. (2014). First 20 years of DNDC (DeNitrification DeComposition): Model evolution. Ecological Modelling, 292, 51–62.

[18] Center, I. (2025). DNDC_Information : : Conservation Technology Information Center. Ctic.org. https: //ctic.org/DNDC_Information

DOI: 10.54254/2755-2721/2025.GL28753

[19] Jiang, Z., Yin, S., Zhang, X., Li, C., Shen, G., Zhou, P., & Liu, C. (2017). Research and Development of a DNDC Online Model for Farmland Carbon Sequestration and GHG Emissions Mitigation in China. International Journal of Environmental Research and Public Health, 14(12), 1493–1493.
[20] 2.25. Methane Model — ctsm CTSM master documentation. (2020). Github.io. https: //escomp.github.io/ctsm-docs/versions/master/html/tech_note/Methane/CLM50_Tech_Note_Methane.html#ch4-production
[21] CRU TS Gridded precipitation and other meteorological variables since 1901 | Climate Data Guide. (n.d.). Climatedataguide.ucar.edu. https: //climatedataguide.ucar.edu/climate-data/cru-ts-gridded-precipitation-and-other-meteorological-variables-1901
[22] Xiao, H., Song, C., Li, S., Lu, X., Liang, M., Xia, X., & Yuan, W. (2024). Global Wetland Methane Emissions From 2001 to 2020: Magnitude, Dynamics and Controls. Earth's Future, 12(9). https: //doi.org/10.1029/2024ef004794
[23] Janssens-Maenhout, G., Crippa, M., Guizzardi, D., Muntean, M., Schaaf, E., Dentener, F., Bergamaschi, P., Pagliari, V., Olivier, J. G. J., Peters, J. A. H. W., van Aardenne, J. A., Monni, S., Doering, U., Petrescu, A. M. R., Solazzo, E., & Oreggioni, G. D. (2019). EDGAR v4.3.2 Global Atlas of the three major greenhouse gas emissions for the period 1970–2012. Earth System Science Data, 11(3), 959–1002.
[24] Höglund-Isaksson, L., Gómez-Sanabria, A., Klimont, Z., Rafaj, P., & Schöpp, W. (2020). Technical potentials and costs for reducing global anthropogenic methane emissions in the 2050 timeframe –results from the GAINS model. Environmental Research Communications, 2(2), 025004. https: //doi.org/10.1088/2515-7620/ab7457
[25] European Commission. (2024). Methane emissions - European Commission. Energy.ec.europa.eu. https: //energy.ec.europa.eu/topics/carbon-management-and-fossil-fuels/methane-emissions_en
[26] Rao, L., Xu, J., Efremenko, D. S., Loyola, D. G., & Doicu, A. (2022). Hyperspectral Satellite Remote Sensing of Aerosol Parameters: Sensitivity Analysis and Application to TROPOMI/S5P. Frontiers in Environmental Science, 9. https: //doi.org/10.3389/fenvs.2021.770662
[27] Brust, C., Kimball, J. S., Maneta, M. P., Jencso, K. G., He, M., & Reichle, R. H. (2021). Using SMAP Level-4 soil moisture to constrain MOD16 evapotranspiration over the contiguous USA. Remote Sensing of Environment, 255, 112277–112277. https: //doi.org/10.1016/j.rse.2020.112277
[28] Lundberg, S., & Lee, S.-I. (2017). A Unified Approach to Interpreting Model Predictions. ArXiv: 1705.07874 [Cs, Stat]. https: //arxiv.org/abs/1705.07874
[29] Belgiu, M., Marshall, M., Boschetti, M., Pepe, M., Stein, A., & Nelson, A. (2023). PRISMA and Sentinel-2 spectral response to the nutrient composition of grains. Remote Sensing of Environment, 292, 113567–113567. https: //doi.org/10.1016/j.rse.2023.113567
[30] KC, U., Garg, S., Hilton, J., & Aryal, J. (2020). A cloud-based framework for sensitivity analysis of natural hazard models. Environmental Modelling & Software, 134, 104800. https: //doi.org/10.1016/j.envsoft.2020.104800
[31] Delgado, M., López, A., Esteban-García, A. L., & Lobo, A. (2023). The importance of particularising the model to estimate landfill GHG emissions. Journal of Environmental Management, 325, 116600. https: //doi.org/10.1016/j.jenvman.2022.116600
[32] Andriambololonaharisoamalala, R., Helmholz, P., Ivánová, I., Jones, E., Soon, S., Bulatov, D., & Song, Y. (2025). Enhancing the spatial and temporal resolution of satellite-derived land surface temperature in urban environments: A systematic literature review. Urban Climate, 60, 102345. https: //doi.org/10.1016/j.uclim.2025.102345
[33] Nesser, H., Jacob, D. J., Maasakkers, J. D., Lorente, A., Chen, Z., Lu, X., Shen, L., Qu, Z., Sulprizio, M. P., Winter, M., Ma, S., Bloom, A. A., Worden, J. R., Stavins, R. N., & Randles, C. A. (2024). High-resolution US methane emissions inferred from an inversion of 2019 TROPOMI satellite data: contributions from individual states, urban areas, and landfills. Atmospheric Chemistry and Physics, 24(8), 5069–5091. https: //doi.org/10.5194/acp-24-5069-2024
[34] Kratzert, F., Klotz, D., Brenner, C., Schulz, K., & Herrnegger, M. (2018). Rainfall–runoff modelling using Long Short-Term Memory (LSTM) networks. Hydrology and Earth System Sciences, 22(11), 6005–6022. https: //doi.org/10.5194/hess-22-6005-2018