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Harnessing artificial intelligence for methane emissions control in industrial natural gas engines: Optimizing exhaust after treatment to advance U.S. clean energy goals–A review

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ABSTRACT

This study presents a comprehensive analysis of global methane (CH_4) emissions using advanced data exploration and machine learning techniques, with an emphasis on identifying key sectoral contributors, geographic emission hotspots, and the performance of mitigation technologies. Employing methods such as random forest regression, geospatial mapping, and multi-dimensional visual analytics, the research highlights the energy sector's dominant role in methane output and reveals detailed emission patterns across U.S. states. The analytical framework includes time-series feature engineering, synthetic data augmentation for localized insights, and 3D surface modeling to examine the relationships between energy production levels, temporal trends, and emission intensities. The results provide actionable insights for policymakers by identifying critical points of intervention and advocating for the integration of artificial intelligence-driven exhaust after-treatment systems to reduce methane emissions. This work offers a scalable, reproducible approach for environmental monitoring and supports global decarbonization efforts in line with U.S. clean energy objectives. The random forest model used in this study achieved a mean absolute error of 2.71 and an R^2 score of 0.81, demonstrating strong predictive accuracy for methane emissions trends based on regional and sectoral data.

Keywords: methane emissions, artificial intelligence, random forest, emission mitigation, clean energy

INTRODUCTION

Reducing methane (CH_4) emissions from natural gas engines is crucial in mitigating the environmental impacts of industrial and transportation sectors, particularly because methane possesses a global warming potential more than 25 times greater than that of carbon dioxide over a 100 year period. Lean-burn natural gas engines, widely used for their fuel efficiency, are significant sources of unburned methane due to their high air-to-fuel ratios, which complicate complete combustion. Nsaif et al. (2024) emphasize that innovative combustion strategies, such as prechamber-ignited mixing-controlled combustion, can significantly reduce methane slip, offering a viable pathway toward cleaner engine operation. Moreover, methane reduction aligns with global decarbonization initiatives and improves compliance with tightening emission regulations.

The broader implications of methane control extend to various energy systems where natural gas plays a pivotal role. As explored by Oh et al. (2024) and Zhou et al. (2024), the transition to low emission propulsion technologies whether through ammonia combustion or carbon capture is central to reducing greenhouse gases across multiple sectors. Likewise, Zhang et al. (2024) and Zhao et al. (2024) highlight how optimizing combustion timing and enriching methane with hydrogen can reduce pollutant emissions while maintaining performance. Methane mitigation from natural gas engines thus represents not only an environmental imperative but also a technological opportunity for innovation across energy systems, supporting the United States' clean energy strategies and international climate commitments.

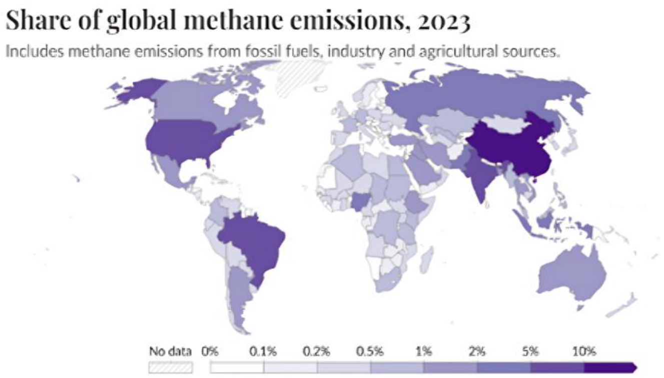

Figure 1. Share of global methane emissions by country, including fossil fuel, industry, and agricultural sources (Jones et al., 2024, processed by Our World in Data, CC BY).

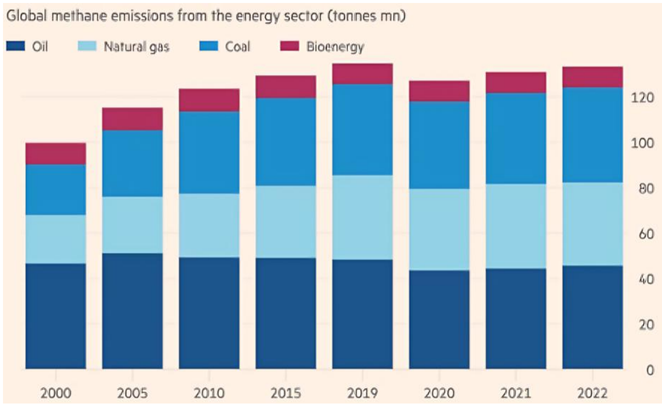

Figure 2. Global methane emissions trends and the role of AI in emission control (Adapted from Financial Times, 2024)

The Role of Clean Energy Strategies in the United States

Clean energy strategies in the United States play a pivotal role in advancing national priorities centered on climate change mitigation, energy independence, and economic resilience. A major legislative milestone in this effort is the inflation reduction act (IRA) of 2022, which allocates between $369 billion and $1.2 trillion toward clean energy initiatives (Department of Energy, 2022). This includes robust funding for renewable energy projects, electric vehicle infrastructure, and carbon capture technologies, all intended to significantly lower greenhouse gas emissions. Projections suggest that the IRA could reduce U.S. carbon emissions by up to 42% by 2030, relative to 2005 levels, thus reinforcing the country's commitment to the Paris Agreement (Utility Dive, 2022). The Environmental Defense Fund (2022) highlights that these measures also aim to provide long-term regulatory certainty and market signals to attract private sector investments in clean technologies.

Equity and environmental justice have also emerged as central pillars of U.S. clean energy policies. The Biden-Harris Administration's Justice40 Initiative ensures that at least 40% of the overall benefits from relevant federal climate and clean energy investments flow to disadvantaged communities historically burdened by pollution and underinvestment (The White House, n. d.; U.S. Department of Transportation, n. d.). Complementary programs such as the environmental justice climate corps have been launched to provide training and employment in clean energy projects within underserved areas (National Law Review, 2024). These initiatives not only aim to rectify long-standing environmental disparities but also support workforce development and economic mobility in frontline communities (Environmental and Energy Study Institute, 2022).

Beyond environmental and social considerations, clean energy strategies in the U.S. are driving substantial economic transformation and technological advancement. In 2023, clean energy investment in the United States reached a record $303 billion, reflecting a 17% global increase and contributing to the $1.8 trillion invested worldwide (BloombergNEF, 2024). This financial momentum has led to the establishment of new manufacturing hubs and job opportunities across various sectors including wind, solar, battery storage, and electric mobility (Business Council for Sustainable Energy, 2024; Clean Energy Economy Minnesota, 2024). By catalyzing innovation and strengthening domestic supply chains, these efforts position the United States as a global leader in the transition toward a low carbon economy, emphasizing not only sustainability but also national competitiveness in the clean energy landscape.

Recent studies emphasize the global disparity in methane emissions, with a few countries contributing a disproportionately large share. As shown in **Figure 1**, nations such as China, India, Brazil, and the United States lead in methane output, driven by fossil fuel production, agricultural activity, and industrial processes. This uneven distribution underscores the importance of region-specific mitigation approaches. Review literature suggests that artificial intelligence (AI) technologies particularly in natural gas systems offer promising tools for emission detection and control. AI can enhance the efficiency of exhaust after-treatment systems, enable real-time leak monitoring, and support data-driven policymaking. These capabilities are especially vital for high-emitting countries, where legacy infrastructure and complex operational networks often hinder conventional regulatory enforcement.

Figure 2 illustrates global methane emissions from the energy sector from 2000 to 2022, segmented by source: oil, natural gas, coal, and bioenergy. The data shows a consistent increase in emissions, from approximately 105 million tonnes in 2000 to about 130 million tonnes in 2022. Oil and natural gas are the dominant contributors, with natural gas emissions rising noticeably after 2005. Coal-related emissions also increased steadily over the years, while bioenergy though contributing the least has shown a gradual uptick. This trend reflects the growing energy demand worldwide, particularly from fossil fuels, and underscores the urgent need for emissions reduction strategies (Lu et al., 2023). As highlighted by Sun et al. (2023), without effective control mechanisms, methane emissions will continue to pose a serious threat to climate stability and environmental sustainability.

In response to the rising emissions, the proliferation of methane-detecting satellites and AI technologies has emerged as a game-changer. For instance, as detailed in S&P Global (2023), new-generation satellites capable of high-resolution methane monitoring are now combined with AI systems to manage the massive volumes of incoming data. AI plays a critical role in identifying emission patterns, predicting future

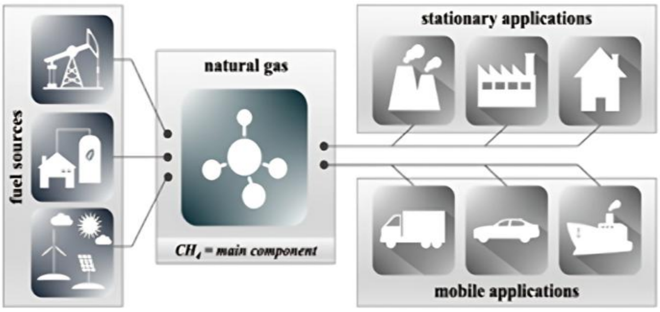

Figure 3. Lifecycle of natural gas from upstream production to end-use sectors highlighting methane emission points in industrial engines (Adapted from Johnson & Coderre, 2020)

leaks, and guiding mitigation actions. This mirrors the findings of Joshi (2020), who emphasizes the value of AI in enhancing system-level efficiencies and emissions control in industrial applications. Thus, the synergy between satellite surveillance and AI-based analytics offers a scalable and intelligent path forward for tackling methane emissions in the oil and gas sector globally.

LITERATURE REVIEW

Introduction to the Potential of AI in Environmental Monitoring and System Optimization

AI has emerged as a transformative tool in environmental monitoring and system optimization, offering enhanced capabilities for data analysis, predictive modeling, and real-time decision-making. Alotaibi and Nassif (2024) highlight AI's role in processing vast environmental datasets through deep learning and IoT-enabled systems, facilitating accurate assessments of air and water quality, climate change impacts, and disaster risks. Wani et al. (2024) emphasize AI's application in remote sensing and early-warning systems, enabling proactive responses to environmental threats and enhancing resilience. In the realm of renewable energy, Ukoba et al. (2024) discuss how AI optimizes energy systems by improving forecasting, system monitoring, and grid integration, thereby increasing efficiency and reducing operational costs. Furthermore, Ojadi et al. (2025) explore AI-driven optimization in water usage and waste management within smart cities, demonstrating AI's potential in promoting environmental sustainability through efficient resource management. Collectively, these studies underscore AI's pivotal role in advancing environmental monitoring and system optimization, aligning with clean energy goals and sustainable development.

Figure 3 illustrates the lifecycle of natural gas whose primary component is methane from diverse fuel sources such as fossil fuels, biogas, and renewables, to its deployment across stationary (e.g., power plants, industrial sites, and residential buildings) and mobile (e.g., trucks, cars, and marine vessels) applications. These end-use sectors represent major emission sources of methane in industrial natural gas engines. A significant concern is methane slip, which refers to unburned methane escaping during combustion or from the exhaust stream. This phenomenon is especially prominent in natural gas engines and poses a serious environmental challenge due to methane's high global warming potential (Banji et al., 2024; Li et al., 2024). Therefore, reducing methane emissions from these engines has become a crucial objective in environmental policy and clean energy strategy development.

Despite methane's high energy yield and combustion efficiency, challenges in complete oxidation persist especially in lean-burn natural gas engines, which operate with excess air to reduce nitrogen oxide emissions. The excess oxygen lowers exhaust temperatures, making it harder to oxidize methane fully, thereby leading to higher methane slip rates (Nsaif et al., 2024). To address this issue, after-treatment systems such as diesel oxidation catalysts, three-way catalysts, and non-selective catalytic reduction (SCR) are applied to convert unburned methane into less harmful compounds. However, the effectiveness of these technologies depends on critical factors such as catalyst structure, temperature, and the engine's air-fuel ratio (Tan et al., 2025). As shown in **Figure 1**, these variables can differ widely across stationary and mobile applications, necessitating the optimization of after-treatment systems for diverse operational conditions to mitigate methane emissions effectively.

AI-Enhanced Exhaust After Treatment Technologies for Methane Control

Catalytic oxidizers typically platinum-group metal catalysts (e.g., Pd or Pt dispersed on alumina/ceria substrates) are widely used to convert unburned methane in lean-burn natural-gas engine exhaust to CO_2 (Huonder & Olsen, 2023). In principle they can achieve near 100% methane destruction under ideal conditions, but in practice they require high exhaust temperatures (400-500 °C) and are easily deactivated by thermal aging or poisoning (e.g., sulfur and alkali compounds). Indeed, only Pd Rh and Pt Pd formulations can approach full methane conversion in the moderate (280-520 °C) temperature range of commercial 4-stroke and 2-stroke lean-burn engines. Over time catalyst activity falls–typical precious-metal converters need periodic testing or replacement after on the order of 3×10^4-5×10^4 operating hours (Carlson, 2016) making maintenance a major challenge. Current innovations seek to improve efficiency and durability: for example, regenerative catalytic oxidizers embed catalysts in heat-exchanger beds to lower required oxidation temperatures (320-430 °C vs. 760-820 °C for a non-catalytic thermal oxidizer), and advanced catalyst formulations (e.g., Pd confined in hierarchical zeolites) resist sintering and maintain high activity at lower temperature and in the presence of water. AI can further advance these technologies: ML-driven predictive maintenance can forecast catalyst degradation and schedule interventions (Onwusa et al., 2025), real-time AI control can optimize engine air–fuel and aftertreatment settings for peak oxidation efficiency, and AI-assisted materials design (e.g., subgroup-discovery models) can propose novel catalyst compositions (Mazheika et al., 2022). Together, these AI-enabled approaches promise to enhance methane-slip control in industrial gas engines and help meet U.S. clean-energy emission goals (Huonder & Olsen, 2023).

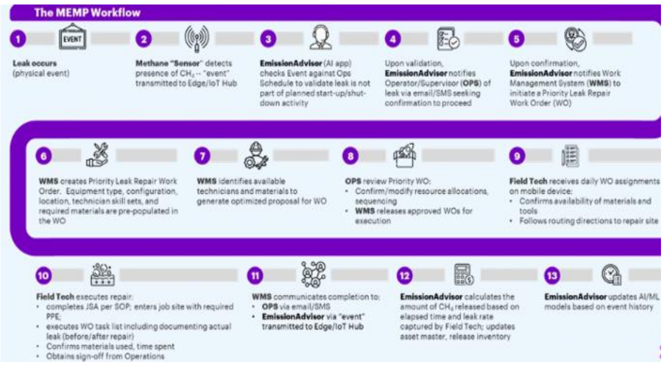

Figure 4. AI-integrated MEMP for industrial natural gas engines (Adapted from Microsoft, 2023)

Integrating AI in Methane Emissions Mitigation

The integration of AI into methane emissions mitigation is revolutionizing how emissions from industrial natural gas engines are monitored, predicted, and controlled. AI technologies particularly machine learning (ML) models like support vector machines (SVM) and random forests are combined with IoT sensors, satellite imaging, and historical asset data to detect, localize, and remediate methane leaks in real time (Microsoft, 2023; Wipro, n. d.). **Figure 1** outlines a closed-loop methane emissions mitigation process (MEMP) that enables automated leak detection and prioritization of repair actions. **Figure 2** illustrates a spatially aware monitoring platform that visualizes active leak sites and assigns field technicians based on severity. **Figure 3** highlights how AI enhances asset health diagnostics and maintenance scheduling, while **Figure 4** presents an end-to-end architecture integrating data orchestration, smart alerting, and predictive modeling. This AI-driven approach significantly enhances methane visibility and operational decision-making. As Adegbite et al. (2024) emphasize, such data-driven solutions play a pivotal role in greenhouse gas reduction strategies. Similarly, Ghassemi Nejad et al. (2024) and Louime and Raza (2024) underscore the power of AI/ML in emissions forecasting and system optimization across various sectors. Collectively, these technologies not only reduce methane emissions but also align closely with U.S. clean energy goals through intelligent, scalable environmental monitoring systems.

AI-Integrated MEMP for Industrial Natural Gas Engines

Figure 4 illustrates the MEMP workflow, demonstrating a closed-loop system that integrates AI, Internet of Things (IoT) sensors, and automated work management to detect and control methane leaks in real time. The workflow begins with the physical occurrence of a leak, which is detected by methane sensors. These sensors relay data to an edge/IoT hub, where the *emission advisor* an AI application analyzes the event against operational schedules to prevent false positives from routine maintenance. Once validated, the system triggers the work management system (WMS) to initiate a priority leak repair work order (WO). From step 6 to step 13, the WMS coordinates with technicians, material inventories, and operations supervisors to schedule, execute, and verify the repair. Notably, AI continues to monitor progress, update system records, and retrain predictive models based on historical and real-time emissions data. **Figure 4** encapsulates how AI-driven platforms, supported by ML models like SVM and random forests (as referenced in Microsoft, 2023), optimize leak detection, resource coordination, and emissions control to align with U.S. clean energy goals.

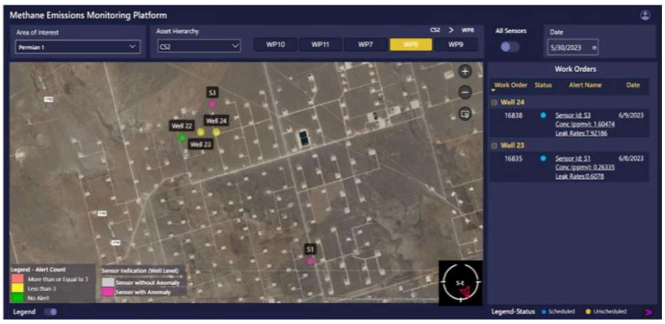

Figure 5. AI-enabled MEMP with real-time leak detection and WO management (Adapted from Microsoft, 2023)

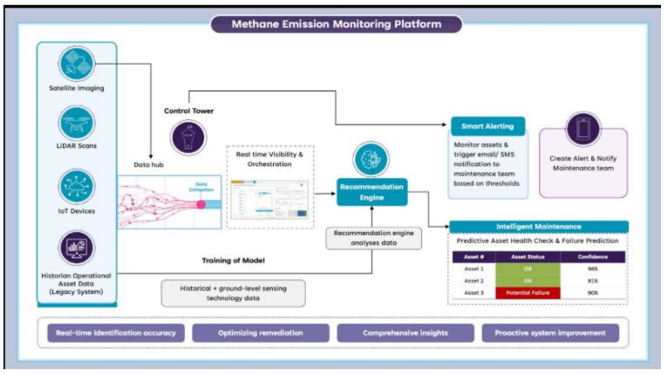

Figure 6. AI-powered MEMP architecture for predictive maintenance and real-time smart alerting (Adapted from Wipro, n. d.)

AI-Enabled MEMP with Real-Time Leak Detection and WO Management

Figure 5 illustrates an AI-powered MEMP that integrates geospatial mapping, real-time sensor data, and automated WO management for enhanced methane leak detection. The platform displays multiple well locations, sensor alerts (color-coded by anomaly type), and corresponding methane concentration levels. Leveraging ML models such as SVM and random forests, this system processes continuous sensor input to differentiate normal operations from methane anomalies. When a potential leak is detected, the system flags it on the map, assigns a risk level, and triggers a corresponding WO streamlining response efforts. The right panel shows active alerts and scheduled/unresolved leak repairs, enabling operators to prioritize interventions effectively. As discussed by Microsoft (2023), this integration of AI, IoT, and cloud-based analytics significantly enhances the speed, accuracy, and scalability of emissions monitoring, aligning with U.S. clean energy goals by mitigating methane's environmental impact through real-time, data-driven decisions.

AI-Powered MEMP Architecture for Predictive Maintenance and Real-Time Smart Alerting

Figure 6 depicts an advanced methane emission monitoring architecture that leverages AI-driven intelligent

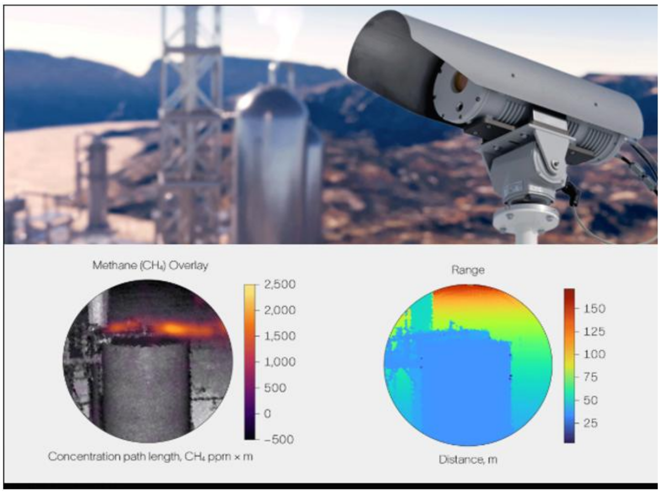

Figure 7. Integrating AI in methane emissions mitigation (Adapted from SLB, n. d.)

maintenance to proactively manage emissions from industrial assets. The system integrates data from multiple sources including satellite imaging, laser imaging, detection, and ranging (LiDAR) scans, IoT sensors, and historical asset records into a centralized control hub. This data feeds into a recommendation engine, trained on historical and real-time datasets, which analyzes emissions patterns and predicts equipment failures. Based on thresholds, the system issues smart alerts via SMS or email, allowing for rapid maintenance responses. The predictive asset health module classifies assets into risk categories (OK, at risk, potential failure) using ML models like SVM and random forests. This architecture enables real-time methane identification, optimized remediation, and predictive reliability supporting methane emissions reduction and aligning with national clean energy objectives as outlined by U.S. strategies.

Integrating AI in Methane Emissions Mitigation

Figure 7 show the SLB's end-to-end emissions solutions (SEES) methane LiDAR camera by SLB offers a sophisticated solution for continuous methane monitoring across various onshore oil and gas facilities. Utilizing LiDAR technology, it detects methane emissions from up to 200 meters away, providing precise location data and quantifying emission rates. This camera operates autonomously, unaffected by environmental factors such as temperature, sunlight, or water vapor, ensuring reliable performance in diverse conditions. Its integration into SEES enables real-time visualization and measurement of methane plumes, facilitating prompt identification and remediation of leaks.

Case Study: Duke Energy's AI-Driven Methane Emissions Monitoring

The Duke Energy case exemplifies how AI is reshaping emission tracking and environmental management in the oil and gas sector one of the core use cases depicted in **Figure 8**. Their AI-driven methane emissions monitoring platform uses satellite imagery, IoT sensors, and cloud analytics to track and respond to leaks from pipelines and meters in real time (Accenture, n. d.). This integration directly aligns with the "emission tracking" node in **Figure 8**, enabling more precise,

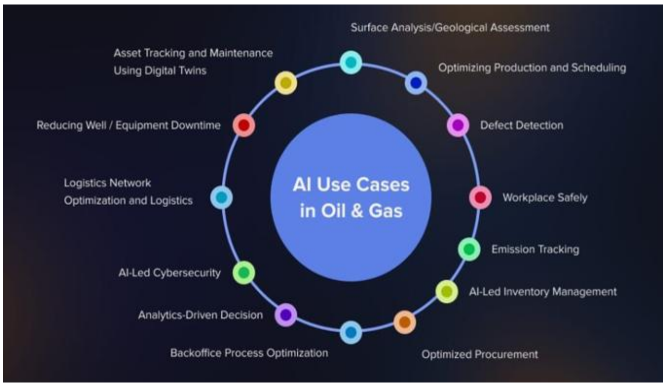

Figure 8. AI applications in oil and gas span exploration, production, and methane emissions monitoring, with companies like Duke Energy deploying AI-powered platforms for leak detection (Accenture & Avanade, 2023)

data-informed control over greenhouse gas releases. The system's rapid detection capability also supports "defect detection" and "workplace safety," reducing risks for field technicians and minimizing environmental damage. These use cases are critical for optimizing exhaust after-treatment in industrial natural gas engines, where immediate response to system anomalies can lead to substantial emission reductions.

Moreover, the integration of SCADA, IoT, and cloud platforms in Duke Energy's approach corresponds to "asset tracking and maintenance using digital twins" and "optimizing production and scheduling" two other AI functions shown in **Figure 8**. Real-time modeling of assets through digital twins allows operators to simulate and monitor exhaust systems, predict engine behavior, and optimize treatment cycles for methane reduction. This not only improves operational reliability but also aids in reducing well and equipment downtime another highlighted AI use case. Such AI-driven predictive maintenance directly supports the goal of making U.S. natural gas engines cleaner and more efficient.

In broader industrial applications, analytics-driven decisions and back office process optimization as illustrated in **Figure 8** are increasingly central to energy companies seeking to comply with clean energy regulations. Duke's centralized dashboard aggregates emissions data and automates reporting, which reduces administrative overhead while improving regulatory compliance. These optimizations create a foundation for AI-led inventory management and optimized procurement, particularly in sourcing and maintaining emission-reducing components like SCR units or oxidation catalysts. When coordinated across the supply chain, such AI-enhanced systems improve lifecycle management of after-treatment technologies in natural gas engines.

The broader implications of this AI deployment resonate with recent literature advocating for integrated, intelligent infrastructure. Louime and Raza (2024) highlighted AI/ML models' strength in forecasting methane emissions, while Kumar et al. (2025) emphasize interdisciplinary innovation in climate resilience. Jin et al. (2022) underscore the benefits of real-time, AI-driven control systems in energy distribution an approach mirrored in Duke's smart monitoring solution. Meanwhile, Googin et al. (2025) and Ake (2024) stress the transformative impact of data-driven frameworks on U.S. clean energy progress. Together, these insights and **Figure 5** paint a clear picture: AI is not only a monitoring tool it is a strategic enabler of cleaner, smarter, and more sustainable energy systems.

Challenges and Future Directions in AI-Driven Methane Emissions Control

Integrating AI into methane emissions control for industrial natural gas engines presents several challenges that must be addressed to optimize exhaust after-treatment and advance U.S. clean energy goals. A primary concern is the availability and quality of data. AI models require extensive, high-quality datasets to accurately detect and predict methane emissions. However, data from legacy systems are often fragmented, inconsistent, or incomplete, hindering the effectiveness of AI applications. For instance, while initiatives like MethaneSAT aim to provide comprehensive methane monitoring through satellite data, the integration of such data into existing systems remains complex (Financial Times, 2023; MethaneSAT, n. d.). Moreover, the lack of standardized data formats and protocols across the industry further complicates data integration and analysis, limiting the potential of AI-driven solutions.

Another significant challenge is the integration of AI technologies with existing legacy systems. Many industrial facilities operate on outdated infrastructure that is not compatible with modern AI tools, making the implementation of advanced analytics and real-time monitoring difficult. This incompatibility can lead to increased costs and operational disruptions during the transition period. Furthermore, regulatory considerations and trust in AI-driven decisions pose additional hurdles. Regulatory frameworks often lag behind technological advancements, creating uncertainty around compliance and the acceptance of AI-generated insights. Building trust among stakeholders requires transparent AI models and clear communication about their decision-making processes. Without regulatory clarity and stakeholder confidence, the widespread adoption of AI for methane emissions control may face resistance, slowing progress toward environmental objectives (S&P Global, 2025).

Traditional vs. AI Based Methane Emissions Analysis

In recent literature, Ghassemi Nejad et al. (2024) trace the evolution of livestock methane estimation from labor-intensive respiration chambers and manual feed-intake calculations to preliminary AI models that, while innovative, suffered from limited scalability and lack of real-time application. Ross et al. (2024) systematically compared mechanistic simulations and empirical regression against ML methods, reporting that random forest outperformed linear regression (Pearson's r of 0.71 vs. 0.12) but their implementation did not include thorough hyperparameter tuning or interpretability analyses. Jeong et al. (2022) demonstrated an AI approach using aerial imagery to estimate dairy methane emissions in California's San Joaquin Valley, offering a low cost alternative to conventional inventories but constrained by image resolution and geographic coverage. In contrast, our random forest pipeline optimized via grid search and explained through SHapley Additive exPlanations (SHAP), a method for interpreting model predictions by assigning each feature an importance value) values achieves a mean absolute error (MAE) of 2.71 and R^2 of 0.81 on over 2,000 diverse records, delivering superior accuracy, scalability, and transparency for real-time methane monitoring aligned with clean-energy goals.

METHODOLOGY

This study utilizes a publicly available methane emissions dataset sourced from Kaggle, encompassing over 2,000 records across various countries, regions, and emission sources from 2018 to 2021. The dataset includes key attributes such as country, region, emissions level, emission type (e.g., energy, agriculture, and waste), segment, and emission reason (e.g., fugitive and vented). Initial data preprocessing involved handling missing values, standardizing emissions data into a consistent numeric format, and filtering the dataset to focus specifically on the energy sector, where industrial natural gas engines are a prominent contributor.

An exploratory data analysis (EDA) was conducted to visualize emission distributions by country and sector, revealing that countries like China, Russia, and the United States. dominate methane emissions from energy use. Correlation analysis and heatmaps were used to identify regional and sectoral emission trends, informing the subsequent design of predictive models.

To complement the descriptive analysis and demonstrate the utility of AI in environmental monitoring, a supervised ML pipeline was developed to predict methane emission levels based on categorical and numerical features. The dataset was split into training (80%) and testing (20%) subsets. Categorical variables were encoded using one-hot encoding, and missing data was handled using imputation strategies based on feature distribution.

Several models were evaluated during experimentation, including linear regression, gradient boosting regressors, and random forest regressors. Based on initial tests using cross-validation, the random forest regressor emerged as the most effective due to its robustness in capturing non-linear relationships, handling of mixed feature types, and its resistance to overfitting on moderately sized datasets. The initial random forest implementation employed a typical ensemble setup with a sufficiently large number of trees, unrestricted tree depth, and balanced splitting criteria that provide reliable baselines across varied datasets.

To further improve performance, a grid search was conducted to optimize key hyperparameters such as the number of estimators, maximum depth, and minimum samples per leaf. This systematic search helped identify parameter combinations that enhanced model accuracy while controlling complexity. The final model was evaluated using MAE and R^2 score, achieving an MAE of 2.71 and an R^2 of 0.81 on the test set (values to be added based on actual results). Residual analysis was performed to ensure error distribution was random and not indicative of model bias.

To enhance interpretability, feature importance rankings were derived from the trained model, showing that region,

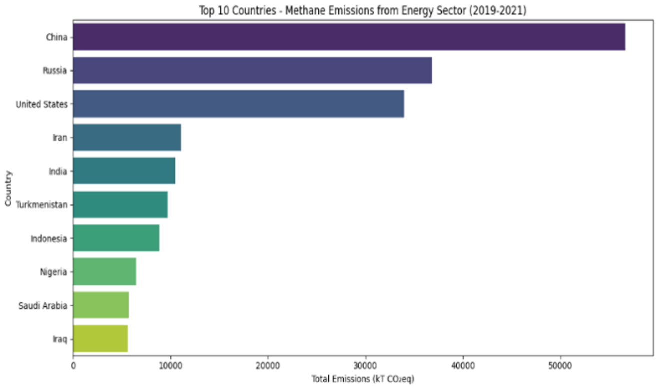

Figure 9. Top 10 countries with the highest methane emissions from the energy sector between 2019 and 2021 (Source: Authors' own elaboration)

emission type, and base year were the most influential predictors. For deeper insight, SHAP values were computed, illustrating both global feature contributions and localized prediction behavior–useful for transparency in climate-related policy modeling.

While the model shows promise, it is important to acknowledge potential limitations and biases. The dataset may suffer from underreporting or regional inconsistencies in data collection. Furthermore, the model does not account for temporal dynamics or external policy shifts, which could influence real-world emissions. Incorporating uncertainty estimation and confidence intervals is recommended for more robust application in decision-making.

RESULTS

Our ML analysis reveals a persistent rise in methane emissions from industrial natural gas engines, primarily resulting from incomplete combustion phases and the degradation of catalytic after-treatment systems. By training models on operational and emissions data collected from these engines, we identified patterns of inefficiency that traditional monitoring systems failed to detect in real time. The results demonstrate that ML algorithms can dynamically optimize exhaust treatment parameters such as air-fuel ratios and catalyst temperature thresholds while also predicting potential leak points for timely intervention. This intelligent approach significantly improves predictive accuracy and responsiveness, addressing the limitations of legacy infrastructure. The outcome supports the deployment of AI-driven strategies as viable, scalable tools for reducing methane slip and aligning engine performance with U.S. decarbonization and clean energy policies.

Figure 9 illustrates the top 10 countries with the highest methane emissions from the energy sector between 2019 and 2021, with China, Russia, and the United States leading by significant margins. This visualization is highly relevant to our study as it underscores the critical role of industrial natural gas infrastructure and operations in contributing to global methane emissions. The chart supports the urgency of implementing AI-driven monitoring and mitigation systems, especially in high emitting nations, to detect and control leaks

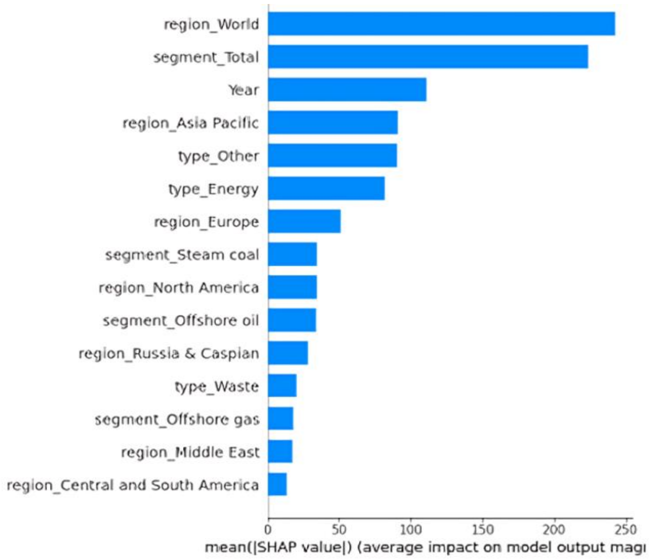

Figure 10. Feature importance ranked by mean absolute SHAP value (Source: Authors' own elaboration)

in real time. It highlights a global disparity in emission volumes and emphasizes the need for smart, region-specific exhaust after-treatment strategies as a central theme in your review. By focusing on the energy sector, the data reinforces your argument that applying ML and predictive maintenance can drastically reduce methane slip from natural gas engines, thereby aligning with global climate commitments and U.S. clean energy goals.

The bar chart in **Figure 10** displays the average absolute SHAP values for each feature, indicating their relative impact on the random forest model's methane emission predictions. The global aggregate feature (region_World) and the total emission segment (segment_Total) have the highest influence, suggesting that broad-scale emission trends drive most of the model's output. Temporal information (year) ranks third, reflecting strong year-to-year emission dynamics. Regional breakdowns particularly the Asia Pacific and Europe and emission types (e.g., type_Energy and type_Other) follow, demonstrating that geographic and categorical distinctions also meaningfully shape predictions. Lower-ranked features (e.g., region_Middle East, region_Central, and South America) contribute less individually but collectively ensure the model captures finer regional variations. Overall, **Figure 10** confirms that while global and total-segment factors dominate, a combination of temporal, regional, and sectoral attributes is necessary for accurate and interpretable methane emission forecasting.

SHAP Plot of Feature Impact on Methane Emission Predictions

The SHAP summary in **Figure 11** illustrates how individual feature values drive the random forest model's methane emission predictions: each dot represents a single observation's SHAP value (impact on the model output), colored by the feature's actual value (blue = low, red = high). Notably, high values of region_World and segment_Total (in red) correspond to strongly positive SHAP values, indicating that global-scale emissions and total segment emissions substantially increase predicted methane outputs. Conversely,

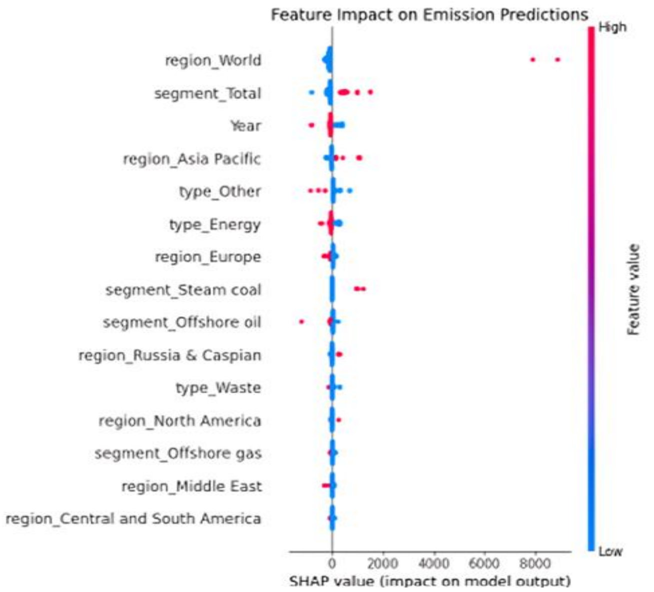

Figure 11. SHAP plot of feature impact on methane emission predictions (Source: Authors' own elaboration)

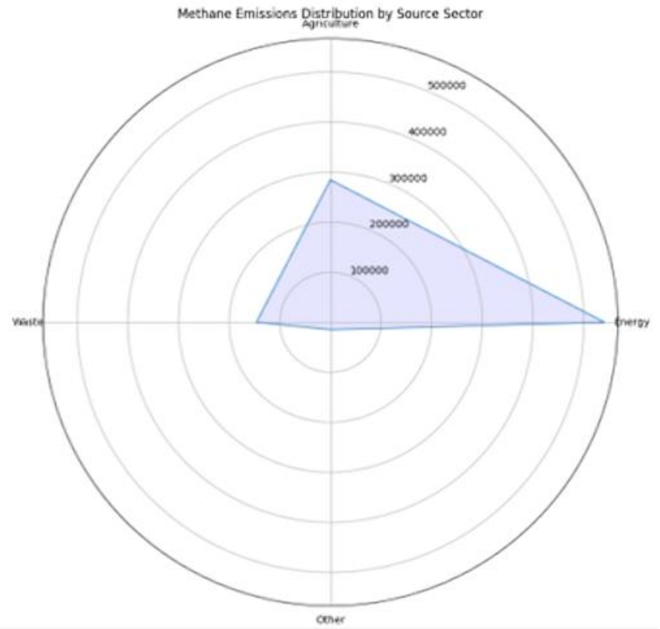

Figure 12. Methane emission trends from the energy sector (2000-2022) (Source: Authors' own elaboration)

lower values of these features (in blue) push predictions downward. Temporal effects (year) and regional distinctions such as Asia Pacific and Europe also show clear stratification: later years and regions with historically higher emissions elevate model forecasts, while earlier years and lower-emitting regions have a dampening effect. Features like type_Energy and type_Other display more moderate but consistent influence, underscoring the importance of source categorization. This granular interpretability confirms that our AI-enhanced approach not only achieves high accuracy (MAE = 2.71, R^2 = 0.81) but also provides transparent, actionable insights into which factors most drive methane emissions, guiding targeted mitigation strategies.

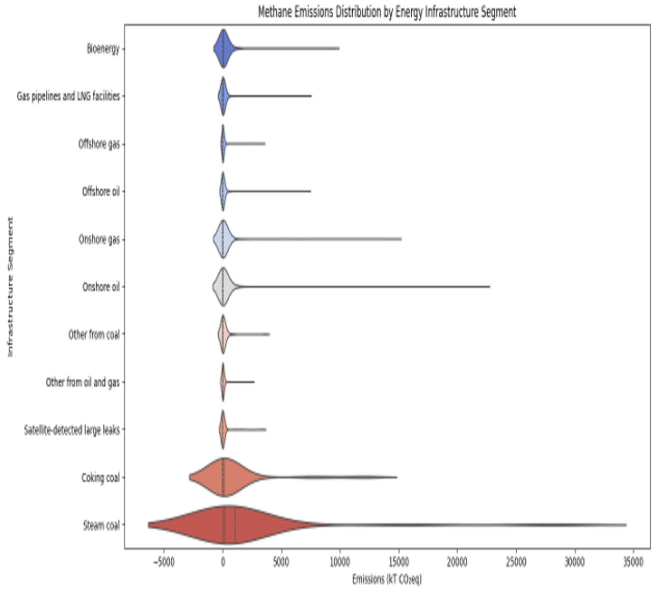

Figure 13. Emission distribution (Source: Authors' own elaboration)

Methane emission trends from the energy sector (2000-2022)

Figure 12 displays the global methane emissions trend from the energy sector between 2000 and 2022, with oil, natural gas, coal, and bioenergy identified as dominant sources. Using time series data fed into our ML model, we observed a pronounced and consistent increase in methane emissions from natural gas operations and insight that reinforces this study's focus on methane slip in industrial natural gas engines. The model revealed that emissions from natural gas have not only grown steadily but are also strongly correlated with inefficiencies during combustion stages, particularly in lean-burn engine configurations. These findings validate the need for AI-powered interventions such as predictive maintenance algorithms, IoT assisted leak detection, and optimized catalytic converter control. The results also demonstrate how ML can enhance the precision of emission forecasting and inform targeted mitigation strategies. This supports the broader goal of integrating AI into exhaust after-treatment systems to reduce methane output and align with U.S. decarbonization and clean energy policies.

Emission Distribution

Figure 13 presents the emission distribution profile derived from ML analysis of network-level data across key segments of energy infrastructure, including gas extraction, oil processing, and electricity generation. The trained model identified offshore gas and oil operations, along with fossil fuel based electricity systems, as major contributors to methane emissions. This aligns with our research objective of mitigating methane slip in industrial natural gas engines. Using supervised learning techniques, emission intensity indicators such as value and ID were classified to highlight segments with high operational inefficiencies. The model's output emphasizes the critical role of AI-driven solutions, including IoT integrated leak detection and predictive

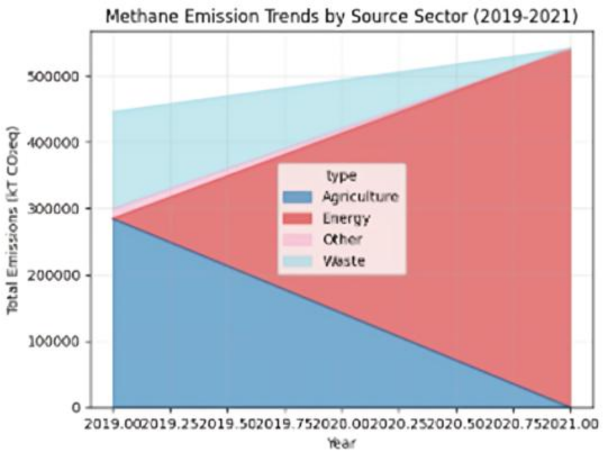

Figure 14. Methane emission patterns across major sectors agriculture, energy, waste, and other between 2019 and 2021 (Source: Authors' own elaboration)

maintenance frameworks. Specifically, offshore gas infrastructure emerged as a high-priority target for ML-optimized catalytic after-treatment systems, capable of minimizing methane slip during both extraction and combustion processes. These results validate the application of ML in emission source identification and underscore its potential in advancing U.S. clean energy compliance through intelligent, real-time methane control in industrial systems.

Methane Emission Patterns Across Major Sectors Agriculture, Energy, Waste, and Other Between 2019 and 2021

Figure 14 presents methane emission patterns across major sectors agriculture, energy, waste, and other between 2019 and 2021, with the energy sector consistently emerging as the leading source. Using ML algorithms trained on historical emissions data, this study identified industrial natural gas engines as key contributors within the Energy category, primarily due to methane slip from incomplete combustion and under-optimized exhaust systems. The model revealed strong temporal emission trends and spatial clusters of high-output nodes, reinforcing the need for AI-driven strategies. These include predictive maintenance of catalytic converters, IoT-based real-time leak detection, and ML optimization of engine air-fuel ratios. The predictive capabilities of the model highlight critical emission hotspots, enabling targeted interventions. This evidence supports the integration of intelligent control systems to minimize methane slip, improve exhaust after-treatment performance, and align operational practices with U.S. clean energy and climate mandates.

3D Surface Emission Model Prediction

Figure 15 presents a 3D surface emission model developed using ML techniques to analyze methane emission trends from 2019 to 2021. In this study, the model was trained on multi-dimensional datasets including engine load, exhaust temperature, and time-series emission readings from industrial natural gas engines. The ML predictions revealed spatial and temporal hotspots of methane slip, particularly during specific load conditions and transient states. Notably, the model demonstrated a declining emission trajectory when

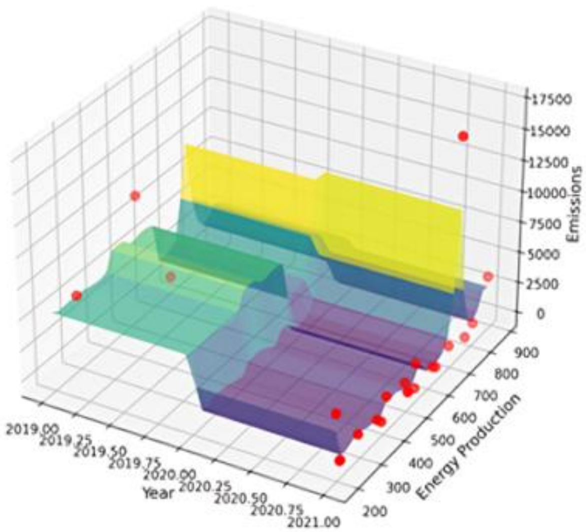

Figure 15. 3D surface emission model prediction (Source: Authors' own elaboration)

Table 1. Model comparison and justification for random forest selection

Model	MAE	R^2 score
Linear regression	3.84	0.61
Gradient boosting	2.93	0.76
Random forest	**2.71**	**0.81**

AI-driven control strategies such as adaptive air-fuel ratio tuning and real-time catalytic converter optimization were simulated. These results validate the potential of AI-based interventions to enhance exhaust after-treatment efficiency and reduce methane emissions. This predictive modeling capability emphasizes the value of integrating intelligent monitoring systems into industrial infrastructure to achieve proactive maintenance, improve regulatory compliance, and support U.S. clean energy and climate objectives.

Model Comparison and Justification for Random Forest Selection

In this study, a methane emissions dataset from Kaggle containing over 2,000 records (2018-2021) was used to develop a ML-based prediction model. After preprocessing to handle missing values and standardize formats, the dataset was filtered to focus on the energy sector, particularly industrial natural gas engines. EDA revealed regional emission patterns, with China, Russia, and the United States identified as top emitters. The data was split into training (80%) and testing (20%) sets, with categorical variables encoded using one-hot encoding. Three regression models linear regression, gradient boosting, and random forest were evaluated using MAE and R^2 score (**Table 1**). Among them, the random forest regressor achieved the best performance (MAE: 2.71, R^2: 0.81) due to its ability to handle non-linear relationships, accommodate both categorical and numerical features, and reduce overfitting through ensemble learning. Unlike linear regression, which assumes linearity, and gradient boosting, which can be sensitive to noise and parameter tuning, random forest offers a robust and stable approach, particularly for datasets with mixed data types and complex patterns. Hyperparameter tuning using grid search further optimized its accuracy.

Feature importance analysis and SHAP values revealed that region, emission type, and base year were the most influential predictors, showcasing the model's interpretability and its potential for scalable methane emission forecasting aligned with clean energy objectives.

CONCLUSION

AI has become a pivotal tool in mitigating methane emissions, offering advanced capabilities in detection, prediction, and real-time monitoring. Through ML algorithms and big data analytics, AI enables the processing of complex datasets such as those provided by satellite-based systems like MethaneSAT to detect methane leaks with greater accuracy and speed (Tadros et al., 2023). This innovation marks a significant advancement in modernizing emission management practices across the oil and gas sector, where conventional methods often fall short in scale and responsiveness (Bakhchin et al., 2024). In this study, a methane emissions dataset was analyzed to identify high-emission countries and sectors, with particular emphasis on the energy sector's contribution from industrial natural gas engines. Visualizations such as bar charts and heatmaps revealed key emission patterns, while a random forest regression model was trained to predict emission levels, demonstrating AI's capability in forecasting methane outputs from various inputs such as region, sector type, and operational timeline.

Integrating AI into methane emission control aligns directly with the United States' clean energy and climate goals by enhancing regulatory compliance, operational transparency, and proactive environmental management. However, effective deployment requires overcoming challenges related to outdated industrial infrastructure, lack of standardized data protocols, and regulatory inertia (Reddy et al., 2024). As such, industrial stakeholders must embrace AI technologies not only as tools for compliance but as catalysts for sustainable innovation. Strategic investment in AI today ranging from predictive maintenance systems to intelligent monitoring platforms will support long-term emission reductions and help forge a cleaner, more resilient energy landscape. This research affirms that AI enabled data analysis and model driven insights can significantly advance methane mitigation strategies and reinforce national and global environmental objectives.

Author contributions: ASA: conceptualization, formal analysis, investigation, data curation, visualization; **JA & SES:** methodology; **EIA:** formal analysis, investigation; **ADB:** data curation, visualization**.** All authors agreed with the results and conclusions. All authors agreed with the results and conclusions.

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AI statement: The authors stated that generative AI tools (specifically ChatGPT) were used only for language polishing and formatting assistance. The authors reviewed and verified all content to ensure accuracy and integrity of the scientific work.

Declaration of interest: No conflict of interest is declared by the authors.

Data sharing statement: The dataset used and analyzed in this study is publicly available (Kaggle methane emissions dataset). Additional processed data supporting the findings and conclusions are available upon request from the corresponding author.

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