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Dual-Stream Attention U-Net for High-Precision Methane Plume Segmentation from Sentinel-2 Imagery

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ABSTRACT

Methane (CH_4) is a potent greenhouse gas with a global warming potential approximately 84 times greater than CO_2 over a 20-year horizon, making accurate and continuous monitoring essential for climate change mitigation. However, current multispectral monitoring approaches often suffer from low sensitivity and high false-positive rates when detecting methane plumes from satellite imagery. To address this challenge, we propose a Dual-Stream Attention U-Net for automated methane plume segmentation. The proposed architecture integrates atmospherically corrected 12-band Sentinel-2 reflectance imagery with Multi-Band Multi-Pass (MBMP) maps through a dual-encoder design. Features from both streams are fused at the bottleneck stage, while attention gates suppress background noise and emphasize plume-related regions. The model is trained using a combined Dice and Binary Cross-Entropy (BCE) loss to address severe class imbalance, and test-time augmentation (TTA) is applied to improve prediction robustness. Trained on the training split and evaluated on the test split of the CH4Net dataset, the proposed method achieves an Intersection over Union (IoU) of 74.09% and a balanced accuracy of 96.56%, outperforming the original CH4Net baseline of 57% IoU. Qualitative results further demonstrate improved detection of faint methane plumes in complex backgrounds. These results indicate that the proposed framework provides an effective and scalable solution for automated methane monitoring using multispectral satellite imagery.

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1. Introduction

Methane (CH_4) is recognized as one of the most potent greenhouse gases, with a global warming potential approximately 84 times that of CO_2 over a 20-year horizon (Jahan et al., 2024; Maasakkers et al., 2022). It is the second-largest contributor to anthropogenic climate change since the pre-industrial era, accounting for roughly one-third of the observed warming (Jiang et al., 2024; Maasakkers et al., 2022). Owing to its relatively short atmospheric lifetime of about twelve years compared to carbon dioxide (Kirschke et al., 2013; Vaughan et al., 2024), rapid and substantial reductions in methane emissions can yield significant near-term climate benefits (Růžička et al., 2023). Consequently, strategies aimed at identifying and mitigating methane releases, particularly from concentrated, high-emission point sources referred to as “super-emitters”, have become a priority in global climate policy. (Mohammadimanesh et al., 2025; Daniel J. Varon et al., 2020)

The atmospheric burden of methane is increasing at an alarming rate, necessitating immediate and precise mitigation efforts(Jiang et al., 2024; Mohammadimanesh et al., 2025). While diffuse sources contribute significantly to the global methane budget, super-emitters present a unique mitigation opportunity. Because a small number of these sites account for a disproportionately large fraction of total emissions, they are crucial targets for effective climate action. (Mohammadimanesh et al., 2025; Daniel J. Varon et al., 2020)

High-emission sources occur predominantly in fossil fuel extraction, processing infrastructure, and waste management facilities (Thorpe et al., 2017). For example, landfill sites, which contribute ~18% of global anthropogenic methane emissions, are projected to more than double their output by 2050 unless mitigation strategies such as active covers, biogas recovery, and organic waste diversion are systematically implemented (Jahan et al., 2024; Mohammadimanesh et al., 2025). The potential reduction achievable by addressing these known sources is substantial. In the oil and gas sector, emissions often arise from fugitive releases, venting, and incomplete combustion processes associated with upstream and midstream operations. Similarly, oil and gas production basins exhibit leakage rates substantially above national averages, with certain regions showing more than 60% higher methane intensity than baseline estimates (Rouet-Leduc & Hulbert, 2024). Such disproportionate contributions underscore the importance of precise detection, quantification, and continuous monitoring of individual point-source emissions. Accurate quantification is essential not only for regulatory compliance but also for prioritizing infrastructure upgrades where abatement offers the highest climate return on investment. (Chan Miller et al., 2024; Mohammadimanesh et al., 2025)

Satellite remote sensing has emerged as a transformative technology for this purpose, enabling scalable monitoring from the local to the global scale (Hemati et al., 2024). The capability to survey remote, often inaccessible, industrial sites repeatedly and systematically bypasses the logistical constraints inherent in ground-based measurement campaigns. Spaceborne instruments operate across spectral ranges sensitive to methane absorption, particularly in the Shortwave Infrared (SWIR) region, where methane exhibits distinct absorption features. Broadly, spaceborne instruments can be categorized into "area flux mappers" and "point source imagers" (Mohammadimanesh et al., 2025; Vaughan et al., 2024).

Area Flux Mappers are designed for broad spatial coverage and trend analysis. These sensors, such as the Tropospheric Monitoring Instrument (TROPOMI) aboard Sentinel-5P, deliver daily global coverage at moderate spatial resolutions ($\sim 5.5 \times 7$ km^2), supporting regional and urban-scale emission inventories (Hemati et al., 2024). While invaluable for understanding large-scale atmospheric concentration changes and validating national emission reports, these data's spatial resolution limits the ability to precisely attribute emissions to individual facilities or specific super-emitters (Chan Miller et al., 2024; He et al., 2025).

Point Source Imagers, conversely, are designed for the high spatial resolution required for plume localization. Multispectral sensors, exemplified by the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) or, more recently and relevantly, the multispectral bands of Sentinel-2, achieve spatial resolutions down to 20 m in methane-sensitive SWIR bands. This resolution is critical for resolving the structure of plumes emanating from individual facilities (He et al., 2025; Vaughan et al., 2024). The successful deployment of these high-resolution instruments relies on advanced processing techniques that can extract the faint spectral signature of a methane plume against a highly variable terrestrial background (Rouet-Leduc & Hulbert, 2024).

Despite the technological advancements in sensor hardware, The reliable automated detection of methane plumes in multispectral data remains a significant scientific and engineering challenge. The primary difficulties stem from the low contrast of methane plumes, which often occupy only a few pixels, and the overwhelming spectral interference from the background surface and atmosphere (Růžička et al., 2023)

Conventional retrieval and enhancement algorithms, such as the Multi-Band Multi-Pass (MBMP) method, have historically served as the backbone of plume detection efforts. These algorithms operate on the principle of exploiting the spectral differences between methane-absorbing bands (e.g., Band 11 or 12 in Sentinel-2) and reference bands that are minimally affected by methane absorption. The mathematical foundation often involves creating a residual image after atmospheric correction and scaling, aiming to highlight the spectral anomaly caused by the plume. However, these methods suffer severely from high false-positive rates caused by surface reflectance artifacts (e.g., bare soil, water bodies), atmospheric variability (e.g, aerosols, water vapor variations), and

heterogeneous backgrounds (Mohammadimanesh et al., 2025). Specifically, variations in surface albedo or atmospheric water vapor columns across the scene can mimic the spectral signature expected from methane, leading to spurious detections. As a result, these methods often require labor-intensive manual verification by expert analysts, significantly hindering operational scalability and real-time response capabilities (Daniel J. Varon et al., 2020).
To address the limitations of physics-based retrievals, recent advancements in remote sensing have significantly improved methane plume monitoring, with a shift toward advanced machine learning techniques. Initially, traditional methods such as the Multi-Band Multi-Pass (MBMP) approach (Daniel J Varon et al., 2020) leveraged Sentinel-2's SWIR bands 11 and 12 for high-frequency monitoring, achieving a detection limit of ~ 2.6 t/h. To address the limitations of traditional physical methods, deep learning approaches have gained traction, facilitated by the development of specialized datasets like S2MetNet (Radman et al., 2023). On this dataset, models such as EfficientNet-V2L have outperformed physical methods and other deep learning architectures in quantifying emission rates without relying on auxiliary data. Further expanding the modality, (Marjani et al., 2024) developed PRISMethaNet, which utilizes Deep Learning with Atrous Spatial Pyramid Pooling (ASPP) on PRISMA hyperspectral imagery to reduce quantification errors and demonstrate cross-sensor transferability. For multispectral data, (Vaughan et al., 2024) introduced CH4Net, a U-Net architecture specifically designed for Sentinel-2 imagery that successfully identified 84% plumes from single images while maintaining comparable false-positive rates to traditional methods. Despite these successes, existing single-stream deep learning models still face challenges in highly complex backgrounds, necessitating more robust architectures.
Building upon this foundation of high-resolution data availability and demonstrated deep learning efficacy, our work introduces a novel Dual-Stream Attention U-Net architecture explicitly designed to maximize detection robustness and sensitivity for operational monitoring.
The core innovation lies in the simultaneous processing of two complementary data streams within a unified deep learning framework:

1. Raw Sentinel-2 Spectral Bands**:** The primary stream processes the full stack of atmospherically corrected, atmospherically robust multispectral bands (including the critical SWIR bands sensitive to methane absorption). This stream enables the model to learn the target gas's inherent spectral characteristics, thereby enabling the extraction of characteristics directly from raw sensor measurements.
2. MBMP Enhancement Maps: The secondary stream ingests pre-calculated, spectrally enhanced products derived from conventional methods, such as the MBMP output. While these maps are noisy, they explicitly encode the spectral differences that researchers have historically relied on, providing the network with explicit spectral-difference features.

Crucially, the architecture is augmented with Attention Gates placed at various resolution levels within the U-Net's decoder path. These gates dynamically modulate the information flow from the encoder pathway, emphasizing plume-salient regions (where spectral anomalies are present) while suppressing irrelevancies arising from background variations, surface noise, or atmospheric artifacts in the input features. By fusing the deep feature learning capabilities of the spectral stream with the explicit feature engineering of the enhancement stream, mediated by context-aware attention mechanisms, we aim to create a synergistic model.

The main contributions of this study are:

- We propose a framework that simultaneously ingests raw multispectral Sentinel-2 data and pre-calculated MBMP enhancement maps, bridging the gap between deep feature learning and explicit domain-specific feature engineering.
- Attention-Guided Noise Suppression: We integrate Attention Gates into the U-Net decoder to dynamically emphasize plume-salient regions while suppressing false positives arising from surface albedo variations and atmospheric artifacts.
- Enhanced Operational Scalability: Through rigorous evaluation on the CH4Net benchmark, we demonstrate that the proposed model achieves superior detection robustness and sensitivity, reducing the need for manual verification in operational monitoring.

This Dual-Stream Attention U-Net architecture aims to deliver robust, highly scalable methane plume detection for operational environmental monitoring, paving the way for near-real-time identification and reporting of super-emitter events.

2. Methodology

This section details the dataset, the proposed deep learning architecture, and the training and evaluation strategies employed in this study. Our approach builds on the baseline established by CH4Net (Vaughan et al., 2024) while introducing several key innovations to improve methane plume segmentation performance.

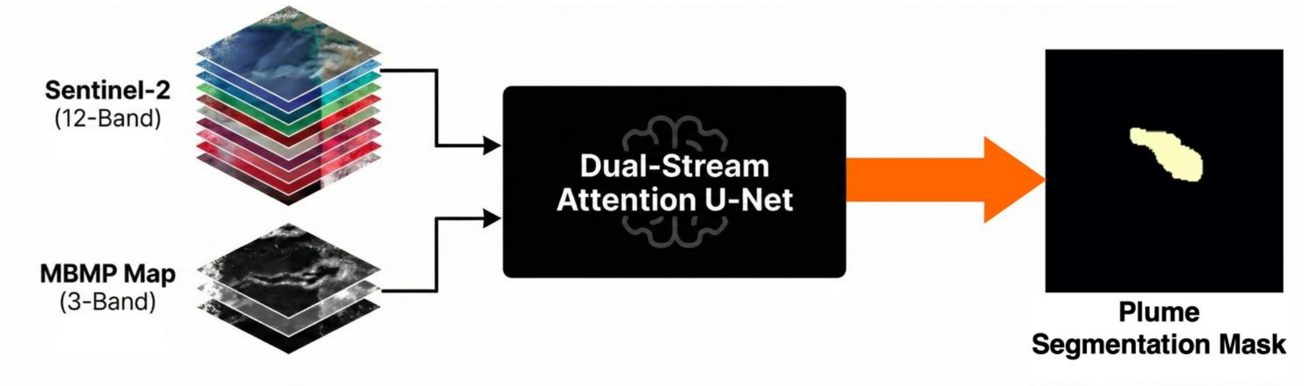

Figure 1. Overview of the proposed methodology. The Dual-Stream Attention U-Net simultaneously processes 12-band Sentinel-2 multispectral imagery and 3-band MBMP enhancement maps to generate a binary methane plume segmentation mask.

2.1 Dataset and Preprocessing

This study uses the publicly available CH4Net dataset from (Vaughan et al., 2024). This dataset comprises Sentinel-2 satellite imagery over known locations of methane super-emitters. For each sample, the dataset provides: (i) a 12-band Sentinel-2 image tile, (ii) a corresponding Multi-Band Multi-Pass (MBMP) product, and (iii) a manually annotated binary ground truth mask indicating the presence of a methane plume, as illustrated in Figure 2.

In our data loading pipeline, all input images (Sentinel-2, MBMP, and mask) are cropped to a uniform size of 100 × 100 pixels. For training, this cropping is performed at a random location within the larger tile to increase data variability. For validation and testing, a center crop is used. The 12-channel Sentinel-2 images are normalized to a range of [0, 1].

For experimental consistency and reproducibility, the CH4Net dataset was divided into distinct training, validation, and test subsets. Specifically, 8,255 samples were used for training, 255 samples for validation, and 2,473 samples for testing, totaling 10,983 samples overall. This corresponds to approximate split ratios of 75.2% / 2.3% / 22.5% for training, validation, and test sets, respectively. The distribution of positive and negative samples was intentionally preserved according to the original CH4Net labeling scheme (599 plume-positive and 7,656 plume-negative samples in the training set). This explicit delineation ensures that both model robustness and evaluation reproducibility are maintained across all experiments reported in this study.(Vaughan et al., 2024)

2.2 Proposed Model: Dual-Stream Attention U-Net

To effectively leverage the distinct information present in both the raw spectral data and the feature-engineered MBMP product, we propose a novel Dual-Stream Attention U-Net. An overview of this proposed methodology and the parallel processing streams is illustrated in Figure 1. The architecture is based on the proven U-Net framework(Ronneberger et al., 2015) but is specifically adapted for multi-modal inputs through the following key components:

Dual-Stream Encoder: The model features two parallel encoder paths of identical structure. The first stream processes the 12-channel Sentinel-2 imagery, while the second stream processes the 3-channel MBMP image. To create this 3-channel input, the traditional single-channel MBMP output was mapped to an RGB color space, thereby providing a richer visual feature representation and improving the model's overall segmentation performance. Each encoder consists of four blocks, with each block containing two convolutional layers, batch normalization, a ReLU activation, and a max-pooling layer for downsampling. This dual-path design allows the model to learn separate, optimized feature representations from each input modality.

Bottleneck Fusion: The feature maps from the final stages of both the Sentinel-2 and MBMP encoders are fused at the architecture's bottleneck. This fusion is achieved by concatenating the two feature maps along the channel dimension, which are then passed through a final bridge block (a downsampling block) to create a unified, context-rich feature representation.

Attention-Gated Decoder: The decoder follows the standard U-Net architecture, progressively upsampling the feature maps from the bottleneck while incorporating high-resolution features from the encoder via skip connections.To enhance performance, we integrate Attention Gates (Oktay et al., 2018) into these skip connections.

A detailed schematic of these internal pathways, illustrating the fusion block, the attention-gated decoder, and the final probabilistic output calculation, is provided in Figure 3.

Crucially, the skip connections are sourced exclusively from the Sentinel-2 encoder stream. The Attention Gates take the upsampled feature map from the decoder and the corresponding feature map from the Sentinel-2 encoder as inputs. They learn to generate a spatial attention mask that re-weights the encoder's features, forcing the model to focus on salient regions relevant to methane plumes while suppressing irrelevant background noise before the features are passed to the decoder's convolutional blocks.

2.3 Training Details

The model was trained end-to-end using the following strategy:

Loss Function: A composite loss function was employed to effectively handle the significant class imbalance between the small number of plume pixels and the large background area. The total loss is a weighted sum of Binary Cross-Entropy with Logits (BCE) loss and Dice Loss, with equal weighting (α=0.5). This combination, often referred to as Combo Loss, benefits from BCE's stability while leveraging Dice's strength in segmenting foreground objects.

Data Augmentation: To improve model generalization and prevent overfitting, on-the-fly data augmentation was applied to the training data. The augmentation techniques included random horizontal flips, vertical flips, and random rotations of 90, 180, or 270 degrees.

Implementation and Hyperparameters: The model was implemented using PyTorch. Training was performed using the AdamW optimizer with a learning rate of 5e-4 and a weight decay of 1e-4. A batch size of 16 was used, and the model was trained for 250 epochs. Throughout training, the model weights that achieved the lowest loss on the validation set were saved for the final evaluation.

2.4 Evaluation Strategy

Test-Time Augmentation (TTA): During inference on the test set, we employed TTA to improve prediction accuracy. For each input image, six augmented versions were created (identity, horizontal flip, vertical flip, and rotations of 90, 180, and 270 degrees). The model predicted each augmented view. These predictions were then transformed back to their original orientation and averaged to produce a final, aggregated segmentation map.

Post-processing and Metrics: The final probabilistic prediction map was converted into a binary mask using a post-processing pipeline consistent with the baseline CH4Net paper (Vaughan et al., 2024) as visualized in Figure 4. This involved applying a threshold at the 95th percentile of the prediction values to identify potential plume pixels, followed by a connected-component analysis to remove any detected regions smaller than a minimum area of 115 pixels. The performance was then evaluated using a suite of standard segmentation and classification metrics: Intersection over Union (IoU), Accuracy, Recall (True Positive Rate), and Balanced Accuracy.

Balanced Accuracy is defined as the average recall across classes, making it more informative than standard accuracy when classes are imbalanced. Mathematically, it is given by:

$$BA = \frac{1}{2}(TPR + TNR) \quad (1)$$

where TPR (True Positive Rate) measures the proportion of correctly detected plume pixels, and TNR (True Negative Rate) measures the proportion of correctly detected background pixels. Unlike standard accuracy, which can be misleadingly high when the background dominates the dataset, Balanced Accuracy provides a more equitable assessment by weighting both plume and non-plume detections equally. This property makes it particularly suitable for methane plume segmentation tasks, where plume regions occupy only a small fraction of each image.

3. Results

This section presents a comprehensive evaluation of our proposed Dual-Stream Attention U-Net. We first report the model’s overall performance across a full suite of metrics. Subsequently, we provide a direct comparative analysis against the CH4Net baseline model and illustrate the model's qualitative advantages through a visual case study.

3.1 Performance Details

The performance of our proposed model was rigorously evaluated on the CH4Net test set. The results, summarized in Table 1, demonstrate strong overall performance on the methane plume segmentation task. The model achieves high scores in both segmentation-focused metrics, such as IoU, and classification-focused metrics, including Balanced Accuracy, while maintaining a low False Positive Rate.

To contextualize these results and quantify the impact of our architectural and methodological innovations, we conducted a direct comparison with the original CH4Net baseline across the primary metrics reported in their study. As shown in Table 2, our proposed model significantly outperforms the baseline across all compared metrics. A key achievement is the substantial reduction in the False Positive Rate (FPR), indicating that our model is more robust to background artifacts. This is accomplished while simultaneously increasing the F1-Score and Balanced Accuracy, demonstrating an overall improvement in both precision and sensitivity.

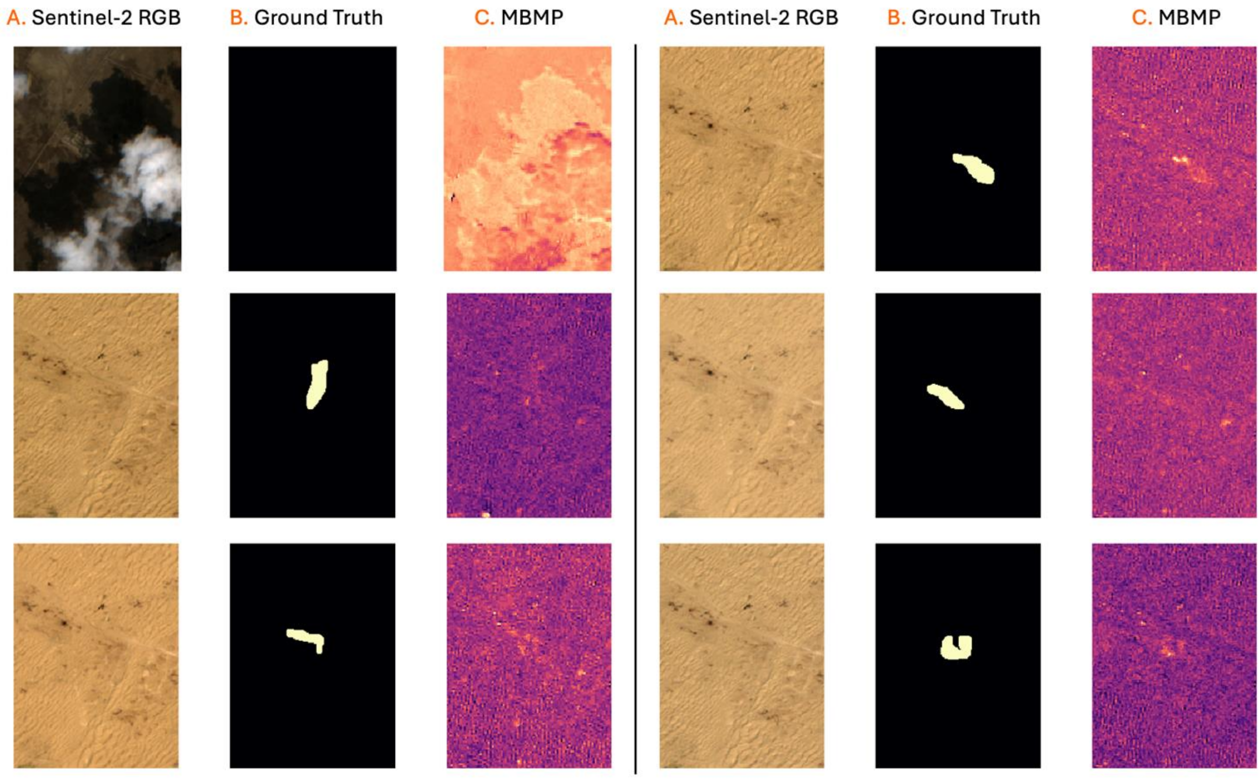

Figure 2. Representative examples of training data from the CH4Net dataset. The figure displays six distinct examples of methane plume scenarios arranged in a dual-column layout. For each example, the following are shown: (A) The true-color composite (RGB) image from Sentinel-2, providing visual context of the background surface; (B) The manually annotated ground truth mask, where yellow pixels designate the methane plume; and (C) The corresponding Multi-Band Multi-Pass (MBMP) enhancement product, utilized as a feature-engineered input to the model. These samples illustrate the diversity of plume morphologies, emission intensities, and complex background surface conditions (including cloud cover and desert textures) present across the dataset.

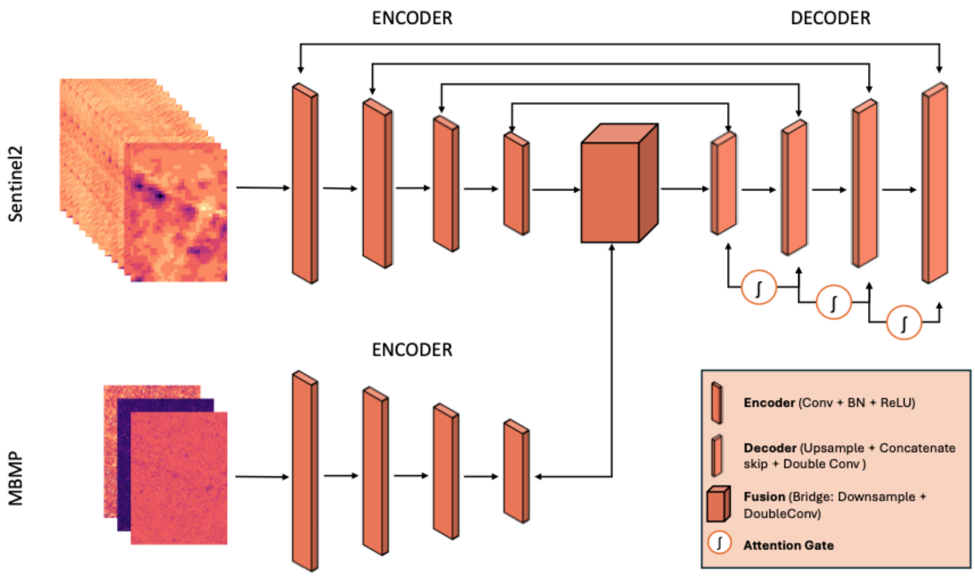

Figure 3. Schematic of the Dual-Stream Attention U-Net showing Sentinel-2 and MBMP inputs, fusion, attention-gated decoder, and probabilistic plume mask output versus ground truth

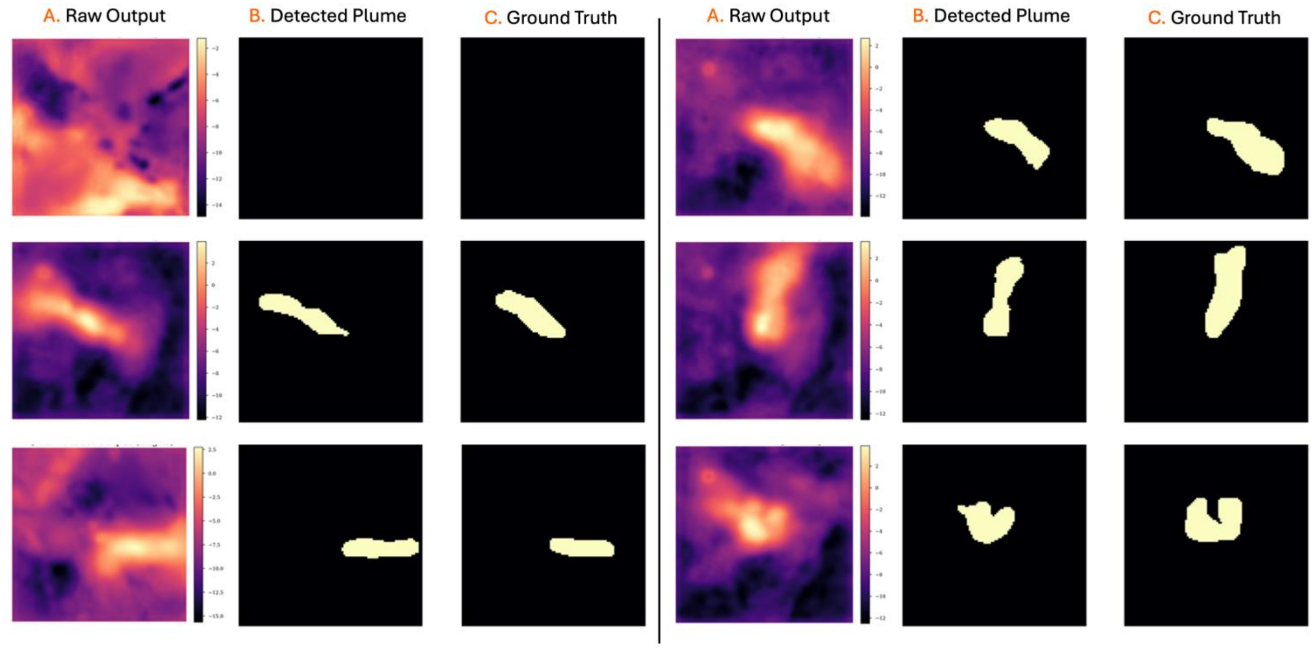

Figure 4. visualization of the model's post-processing pipeline. The figure shows the steps for generating a final binary mask from the raw model outputs for selected samples. (A) The raw probabilistic output (heatmap of logits) from the model. (B) The final binary mask was obtained by applying a 95th-percentile threshold and removing components smaller than 115 pixels. (C) The corresponding ground truth mask for comparison.

Table 1. Overall performance of the proposed Dual-Stream Attention U-Net on the test set.

Metric	Score
Intersection over Union (IoU)	74.09%
Accuracy	99.20%
Balanced Accuracy	96.56%
Recall (TPR)	93.17%

Table 2. Comparative analysis of key metrics against the CH4Net baseline on the test set.

Metric	CH4Net (Vaughan et al., 2024) (Baseline)	Our Proposed Model	Improvement
Balanced Accuracy	66%	96.56%	+29.56%
Intersection over Union (IoU)	57%	74.09%	+17.09%

4. Discussion

The results presented in Section 3 indicate that the Dual-Stream Attention U-Net noticeably improves methane plume detection performance compared to the CH4Net baseline. Significant gains in IoU and Balanced Accuracy demonstrate that combining two parallel processing streams, one utilizing raw Sentinel-2 spectral bands and the other leveraging pre-computed MBMP feature maps alongside Attention Gates, have led to more effective extraction of spatial and spectral features.

A direct comparison with the baseline highlights the proposed approach’s ability to achieve a better balance between accuracy and sensitivity, which is particularly important for satellite-based monitoring operating under diverse environmental conditions. This level of performance enables potential deployment in fully automated monitoring systems, reducing the need for frequent human validation while maintaining broad coverage.

From a research standpoint, the dual-stream design, coupled with attention mechanisms, represents a promising framework for other remote sensing applications that require detecting small or subtle targets in complex backgrounds. Extending this approach to other sensors, including hyperspectral or Landsat data, could broaden its applicability and enable the identification of additional atmospheric compounds or phenomena.

Nevertheless, a key challenge lies in the dependency on MBMP data, which requires a plume-free reference image for generation and may not always be obtainable in certain regions or under specific weather conditions. Future research should focus on reducing this dependency, for example, through weakly-supervised learning or synthetic data augmentation. Furthermore, incorporating direct emission rate estimation from segmented plumes could strengthen the link between the model's outputs and field-based assessments, thereby enhancing its practical relevance for decision-making and environmental policy.

5. Conclusion

This paper addressed the critical challenge of accurately and automatically detecting methane point source plumes from Sentinel-2 multispectral imagery. While Sentinel-2 provides valuable global coverage, conventional detection methods are often hampered by low sensitivity and high false positive rates, necessitating manual verification. To overcome these limitations, we introduced a novel deep learning framework based on a Dual-Stream Attention U-Net. Our architecture is uniquely designed to process both raw Sentinel-2 spectral bands and precomputed MBMP feature maps in parallel, leveraging attention gates to focus on salient plume features and suppress background noise.

The proposed model was trained and evaluated on the public CH4Net dataset. Experimental results demonstrate that our approach significantly outperforms the state-of-the-art CH4Net baseline model. Quantitatively, our model achieves substantial improvements in key segmentation metrics, including F1-Score and Intersection over Union (IoU), while critically reducing the False Positive Rate. Qualitative analysis further confirmed our model's enhanced sensitivity, successfully identifying plumes in challenging scenarios where the baseline model failed.

The enhanced accuracy and automation provided by our model represent a meaningful step towards building more robust and reliable satellite-based monitoring systems. By reducing the need for manual inspection and improving detection accuracy, this work contributes to the global effort to track and ultimately mitigate harmful methane emissions. However, a current limitation of this dual-stream approach is its reliance on the MBMP product, which requires both a target image and a clear, plume-free reference image for its generation (Daniel J Varon et al., 2020). This dependency could pose a challenge in operational scenarios where such a reference image is not readily available. Future work will focus on extending this framework to quantify emission rates directly from segmented plumes and on exploring architectures that achieve similar performance without this multi-pass requirement, thereby improving its generalizability across diverse geographic regions and environmental conditions.

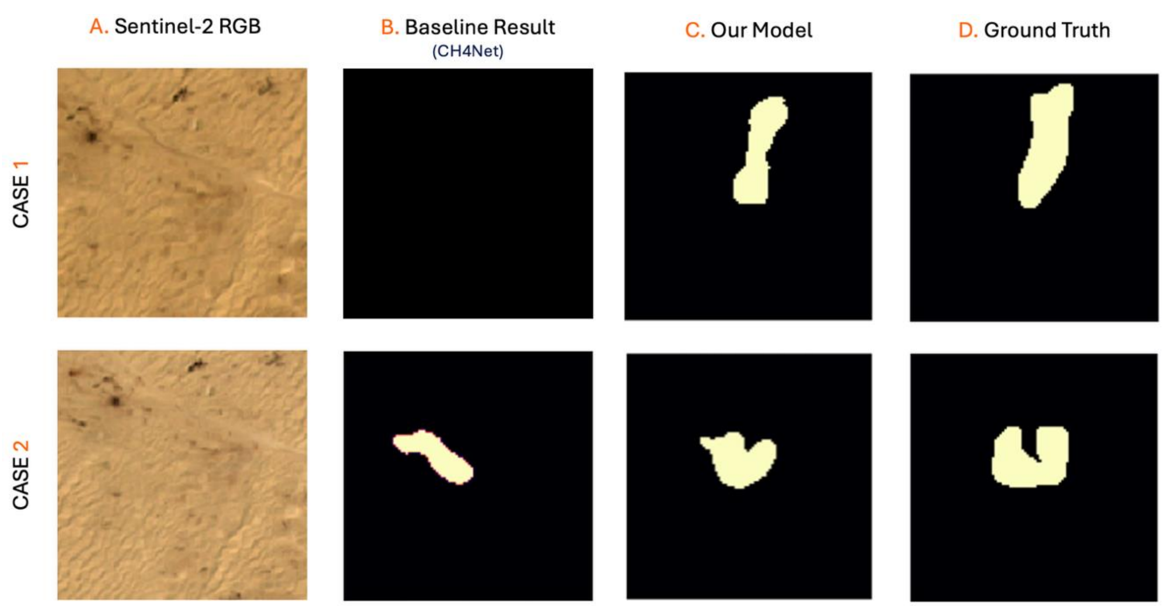

Figure 5. Qualitative comparison of methane plume segmentation performance across two challenging scenarios. Columns present (A) the Sentinel-2 RGB input imagery, (B) predictions from the CH4Net baseline, (C) predictions from our proposed Dual-Stream Attention U-Net, and (D) the corresponding ground truth masks. In Case 1 (top row), the baseline model completely fails to detect the methane plume against the textured background. In contrast, our proposed model successfully segments a distinct plume that closely aligns with the ground truth. In Case 2 (bottom row), the baseline model drastically underestimates the plume extent and predicts an incorrect shape. In contrast, our model accurately captures the more complex, U-shaped morphology of the actual emission. Detected plumes are visualized in yellow for high contrast.

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