# MEQNet: Deep Learning for Methane Point Source Emission Quantification from Sentinel-2 Observations

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## Abstract

Mitigating methane emissions is critical for addressing global warming, and accurate point-source quantification is crucial for identifying super-emitters and targeted mitigation. Sentinel-2's fine spatial resolution, global coverage and open accessibility make it highly promising for large-scale monitoring. Current quantification methods, whether retrieval-based physical models or AI models trained on simulated data, are computationally costly, make restrictive assumptions, generalize poorly to real imagery, and are sensitive to surface reflectance, leading to unreliable emission estimates. We propose an end-to-end *Methane Emission Quantification Network (MEQNet)* that directly estimates methane column enhancements and emission rates from bi-temporal Sentinel-2 imagery and auxiliary wind data. MEQNet builds a direct mapping from Sentinel-2 reflectance to emissions and rates, further distinguishing dynamic plumes from background interference by exploiting methane-sensitive spectral bands and modeling spectral-temporal differences. Integrating 10-meter wind vectors further enables physically consistent rate estimation by accounting for plume transport dynamics. To enhance model generalizability, we construct a dataset using real Sentinel-2 observations with emissions from hyperspectral measurements and inventories, covering diverse surface and emission types. Experimental results demonstrate that MEQNet enables scalable, rapid, and accurate methane emission quantification across complex surfaces.

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## 1 Introduction

Methane, as a major anthropogenic greenhouse gas, has contributed approximately 20% to global warming [1]. A relatively small number of large, intermittent super-emitters, such as oil and gas facilities and coal mines, have been shown to contribute significantly to total anthropogenic methane emissions [2, 3, 4]. Accurately detecting these globally abnormally high point sources and quantifying both their methane enhancements and associated emission rates are vital for effective monitoring, regulation, and mitigation of their climate impacts.

To enable global, high-frequency, and publicly accessible monitoring of methane point-source emissions, multispectral satellite platforms such as Sentinel-2 provide significant advantages [5, 6, 7, 8] over hyperspectral satellites (e.g., PRISMA [9], EMIT [10], and EnMAP [11]) and airborne sensors such as AVIRIS-NG [12], which are constrained by limited spatial and temporal coverage. Sentinel-2, with its global coverage, high spatial resolution (10–20 m), and frequent revisit cycle [13], has shown strong potential for detecting and monitoring large methane plumes from super-emitters at regional to global scales [14, 15, 16]. Notably, its two shortwave infrared (SWIR) bands, Band11 and Band12, are sensitive to spectral features of methane absorption, enabling the identification and quantification of point-source methane emissions [17, 18, 19].

Most existing approaches quantify methane emissions by first retrieving methane column concentration enhancements from Sentinel-2 SWIR reflectance using simplified radiative transfer models (RTMs), and then estimating emission rates through the integrated mass enhancement (IME) method combined with external wind field data [18, 19]. Although widely applied, the retrieval process is computationally intensive and relies on fragile physical assumptions (e.g., spatially uniform and temporally stable surface albedo, manual methane-free background selection, and parameter tuning for plume detection thresholds) [15, 17], and is highly sensitive to surface reflectance interference, ultimately leading to inaccurate estimates of both plume location and emission rates. In addition, several recent works have studied AI models for automating methane emission rate estimation from remote sensing imagery [20, 21, 22, 23]. However, these models are typically trained and evaluated on synthetic or simulated datasets, with limited validation against real satellite observations. These factors limit their generalization, processing efficiency, and applicability across diverse surface and atmospheric conditions in real-world operational settings [14, 24].

To address these limitations, we propose MEQNet, a novel deep learning framework for methane emission quantification designed to suppress surface-induced false positives, accelerate processing, and improve generalization across various surface scenarios. MEQNet builds a direct mapping from Sentinel-2 reflectance to methane emissions and emissiono rates. Its core innovations are focused on incorporating spectral and temporal differences to capture dynamic plume behavior, a guided attention mechanism based on Normalized Difference Methane Index (NDMI) image to enhance spectral sensitivity to methane, and the integration of 10-meter wind vectors into deep learning model guided by physical principles of plume diffusion for emission rate estimation. We further construct a real-world methane quantification dataset by pairing Sentinel-2 imagery with Carbon Mapper measurements, enabling supervised training and evaluation on actual emission events. This approach does not rely on physical model assumptions or simulated data, allowing for an efficient and more generalizable methane emission quantification process from Sentinel-2 observations imagery.

## 2 Dataset

To enable the training and evaluation of models for accurate methane plume quantification from Sentinel-2 imagery, we constructed a dataset of real-world methane emission events. It integrates observations from the Carbon Mapper program's hyperspectral imaging spectrometers with co-located multispectral Sentinel-2 L1C imagery. Carbon Mapper [25] provides spatially explicit plume geometries, column enhancement estimates, and emission rates collected between 2016 and 2024 over multiple oil and gas production regions worldwide.

Positive samples containing methane plumes were generated by matching each Carbon Mapper detection to cloud-free (<10% cloud cover) Sentinel-2 imagery on the same date and covering the detected plume. Each match was paired with two Sentinel-2 tiles: a target image and a recent reference image within 1-10 days. Ground truth enhancement maps were created by rasterizing Carbon Mapper estimates to the Sentinel-2 spatial grid, and emission rates were directly extracted from Carbon Mapper data. To maintain class balance, negative samples were included in our dataset. They were obtained from cloud-free Sentinel-2 observations over the same sites and time period without reported plumes, with enhancement maps set to a background methane value and emission rates set to zero. Besides, we collect 10-meter wind data from the ECMWF-ERA5 hourly reanalysis product [26].

The final dataset includes 5,000 image pairs (2,500 positive and 2,500 negative) during 2016-2024. Each sample consists of: (1) a target Sentinel-2 image (*T*) with all 13 bands, (2) a reference Sentinel-2 image (*T-1*) with the same bands, (3) 10-mter wind vectors, (4) a ground truth methane column enhancement map ($mol\ m^{-2}$), and (5) an emission rate (kg/hr). This dataset provides precisely supervised data for deep learning-based methane emission quantification from Sentinel-2 imagery.

## 3 Methane Emission Quantification Network

The proposed quantification framework estimates both methane column enhancement and point-source emission rates from bi-temporal Sentinel-2 imagery and auxiliary wind field data. As illustrated in Figure 1, the overall architecture consists of two major components: (1) Enhancement Map Generator (EMG) and (2) Emission Rate Estimator (ERE). The EMG first extracts spectral and temporal features through two parallel encoders, one processing the raw 13 bands with a Cross Channel Module, and the other constructing the Normalized Difference Methane Index (NDMI) image and features to guide plume localization. The decoder integrates these features using a Change Guide Module and produces the predicted methane column enhancement map. This map, combined with 10m wind vector components, is then passed into the ERE, which applies a feature extractor followed by a multilayer perceptron (MLP) [27] to output the estimated methane emission rate.

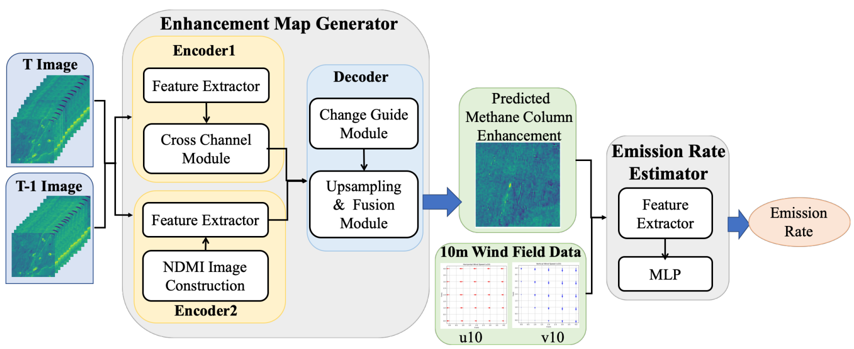


Figure 1: Overview of the Methane Emission Quantification Network. The proposed network takes bi-temporal Sentinel-2 13 bands imagery (at time *T* and *T-1*) as input and consists of two main components: (1) a Methane Enhancement Map Generator, which estimates the methane column enhancement via a dual-encoder-decoder architecture integrating spectral and NDMI features; and (2) an Emission Rate Estimator, which combines the predicted enhancement map with 10 m wind field data to estimate the methane emission rate.

### 3.1 Enhancement Map Generator (EMG)

The EMG is designed to directly learn the nonlinear mapping from Sentinel-2 reflectance to methane column enhancement, thereby replacing the traditional RTM-based inversion process. By leveraging the spectral and temporal variability in methane plumes relative to the stable surface background, EMG effectively enhances transient plume features while suppressing static surface interference. Three components are highlighted in its design:

**NDMI-Guided Branch** The Normalized Difference Methane Index (NDMI) is computed as:

$$NDMI = \frac{b_{11} - b_{12}}{b_{11} + b_{12}} \tag{1}$$

where $b_{11}$ and $b_{12}$ are spectral reflectance in Sentinel-2 Bands 11 and 12. This branch emphasizes the SWIR absorption features of methane and guides the network towards correct plume locations.

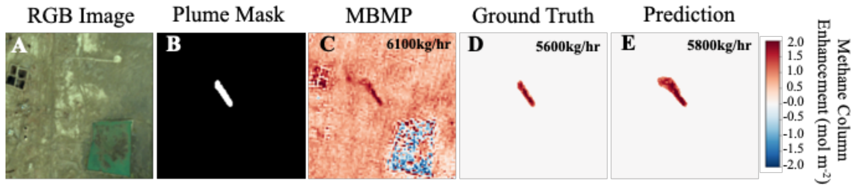


Figure 2: Example visualization of quantification results (location:37.92913°N, 53.92431°E) in Turkmenistan. A and B: Sentinel-2 RGB image of the source region and methane plume mask. C: retrieved methane column enhancement map from MBMP [17]. D and E: truth and predicted enhancement by the proposed model.

**Cross Channel Module** Embedded within the spectral encoder, this module captures inter-band correlations across multiple bands, effectively encoding spectral absorption features into the latent feature space. By integrating multi-temporal and multi-spectral reflectance data, it generates feature representations in spectral and temporal variations, providing the foundation for directly inferring methane enhancement without relying on RTM inversion.

**Change Guide Module** Placed in the decoder, this module integrates the two encoded features and guides spectral and spatial features to focus feature fusion more on plume regions using temporal difference features. Therefore, it can be combined with the fusion process to reconstruct the predicted methane column enhancement map, where each pixel value corresponds to an estimated concentration enhancement. By directing feature-space attention to temporal variations while suppressing static background interference, the module distinguishes methane-induced reflectance changes from unrelated spectral fluctuations, thereby enhancing the decoder's ability to accurately decode column concentration enhancements from raw reflectance features.

### 3.2 Emission Rate Estimator (ERE)

To convert the estimated enhancement map into a methane emission rate, the ERE takes as input the predicted methane enhancement map concatenated with the 10 m wind filed components ($u_{10}$, $v_{10}$). This module encoders spatial features of both plumes and wind vectors using a feature extractor, followed by a MLP to regress the methane emission rate $\hat{R}$. For the loss function, our network is trained end-to-end with a joint loss based on Mean Squared Error (MSE) [28]:

$$\mathcal{L}_{\text{total}} = \lambda_{\text{EMG}} \cdot \frac{1}{HW} \sum_{x=1}^{H} \sum_{y=1}^{W} (E_{x,y} - \hat{E}_{x,y})^2 + \lambda_{\text{ERE}} \cdot \frac{1}{N} \sum_{i=1}^{N} (R_i - \hat{R}_i)^2 \tag{2}$$

where $E$ and $R$ are ground truth enhancement maps and emission rates, $\hat{E}$ and $\hat{R}$ are predictions, $H$ and $W$ are the height and weight of the enhancement map, and $N$ is the number of samples. $\lambda_{\text{EMG}}$ and $\lambda_{\text{ERE}}$ are weighting parameters to balance enhancement map and emission rate prediction.

## 4 Results

We evaluate the proposed MEQNet against the MBMP-based method [17]. As shown in Figure 2, a representative example from an oil and gas production site in Turkmenistan, the enhancement map predicted by MEQNet exhibits a clearer plume with reduced surface interference, particularly in the top-left region, and the estimated rate is closer to the ground truth. Quantitatively, across the test set, MEQNet achieves a pixel-level enhancement $R^2$ of 0.91 and an emission rate $R^2$ of 0.94, while reducing processing time to under 2s per scene. These results demonstrate that MEQNet can provide fast, accurate, and generalizable methane emission estimates from Sentinel-2 imagery.

## 5 Conclusion

In this study, we propose a deep learning framework, MEQNet, for simultaneously estimating methane column enhancement and emission rates from Sentinel-2 imagery. MEQNet leverages differences in spectral and temporal features, an NDMI-guided attention module, and wind data to directly map reflectances to methane enhancement and emission rates, effectively distinguishing plumes from background interference. The model has been validated on a real-data dataset we constructed, achieving highly consistent results and outperforming traditional methods in accuracy and efficiency. Future work will focus on further validating and enhancing the model's robustness and generalization capabilities.

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