Methane Emission Quantification through Satellite Images

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Introduction

- **Problem:**
  - Man-made methane is a greenhouse gas over 25 times as potent as carbon dioxide and is a substantial contributor to climate change. Cutting methane emissions in half by 2030 can avoid 0.5°C of global warming by 2100. [1]
  - Precise and frequent measurements of methane emissions are a necessary step to keeping companies and nations accountable for their emissions and benchmarking their emission reduction efforts. Currently, the energy sector consistently under-predicts methane emissions by 50-70%. [3] We sought to improve the accuracy of global methane emission quantification by construction computer vision models that perform instance segmentation on methane satellite images.
- **Data and Task:** Satellite spectroscopy enables the detection of methane emissions by utilizing bandwidths of short-wave infrared light that are particularly sensitive to methane. **Creating masks for methane plumes is crucial to accurately quantifying methane emissions and identifying methane leaks.** Our work focuses on this task using both a statistical method and Convolution Neural Networks (CNNs). Due to the limited number of methane-detecting satellites currently in orbit, we used simulated satellite images of methane plumes, generated by a physics-based model from Orbio Earth that incorporates various wind speeds, land cover types, emission sources, and background noise.

Pre-processing

- **Data Scaling and Normalization**
  - One major hurdle with the data is the distribution of its values. The non-zero values for the input retrieval images are very clustered together, making it difficult to distinguish between values that should be masked and those that should not. In order to spread out this distribution, we took the natural log of each pixel, then normalized the flattened image.

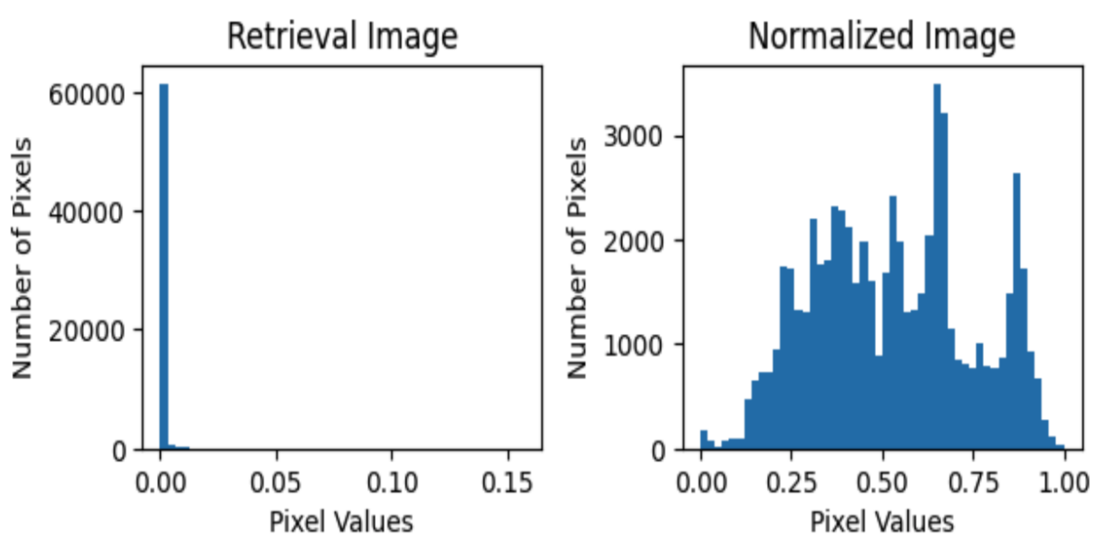

Figure: Histograms of Input Data Before and After Pre-processing

Methods

To perform the methane plume segmentation, we built two models, one based on the architecture of **U-Net**, and one utilizing a threshold-based masking model.

- **U-Net:** We first utilized U-Net because of its proven track record with segmentation problems. It features a U-shaped model architecture where the input image is gradually compressed into a lower-dimensional representation and then decompressed.[2] The purpose of compression is to allow to model to focus on both low-level details and high level abstractions. To utilize both pieces of information during predictions, the U-Net model additionally includes skip connections between the two sides of 'U'. Lastly, we applied an arbitrary threshold to filter out weak predictions.
- **Threshold Model:** We also constructed a simple statistical model using the following basic formula: Calculate median, $\tilde{x}$, and standard deviation, σ, of the methane values in each input image; Pick a standard deviation factor K; define a threshold (T) as

$$T = \tilde{x} + K * \sigma$$

Lastly, set all points above the threshold as 1s, and all values below as 0s. We initially built this model to use as a baseline, but to our surprise, it performed quite well on the data, in fact out-performing our neural net models.

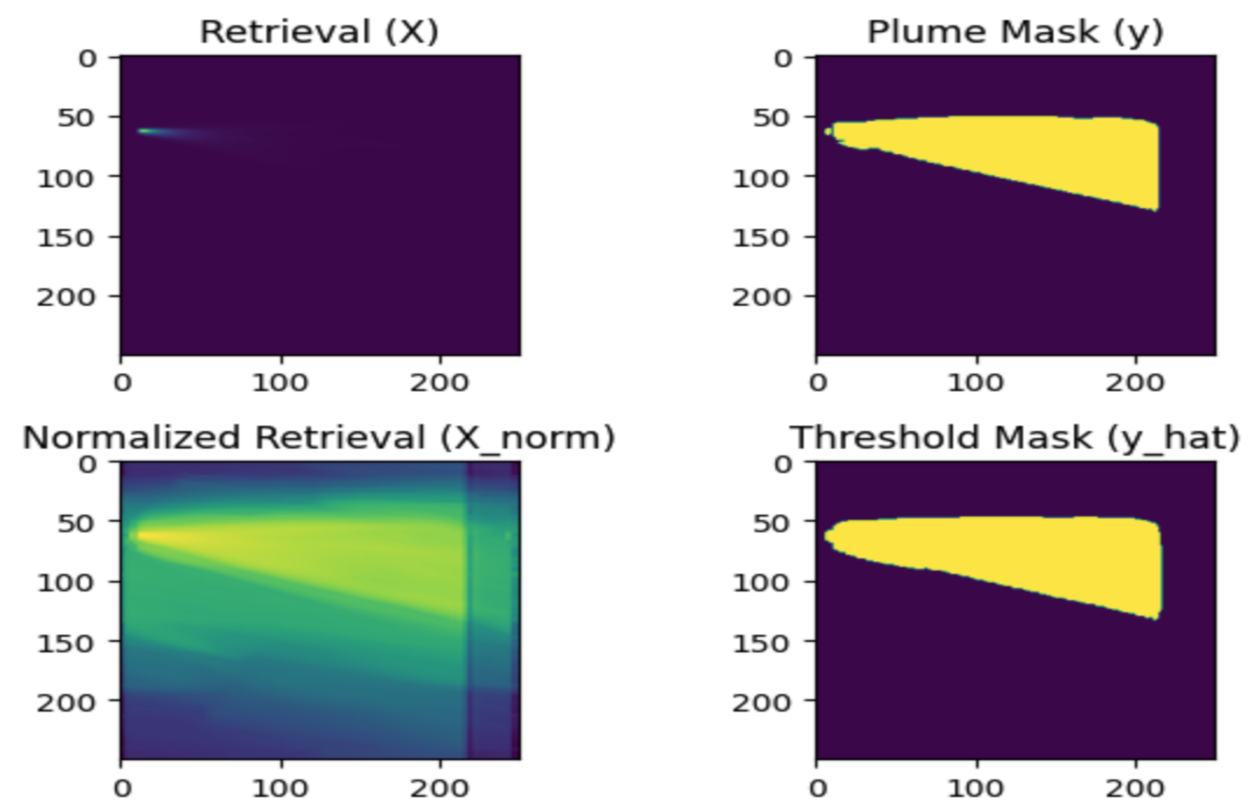

Figure: Example of Input Image (Retrieval), Normalized Image, Plume Mask, and Predicted Threshold Mask

- **Hyper-parameter Tuning** We hyper-tuned the U-Net using its Learning Rate (LR) and the filter threshold. We hyper-tuned the Threshold Model using the standard deviation factor, K.

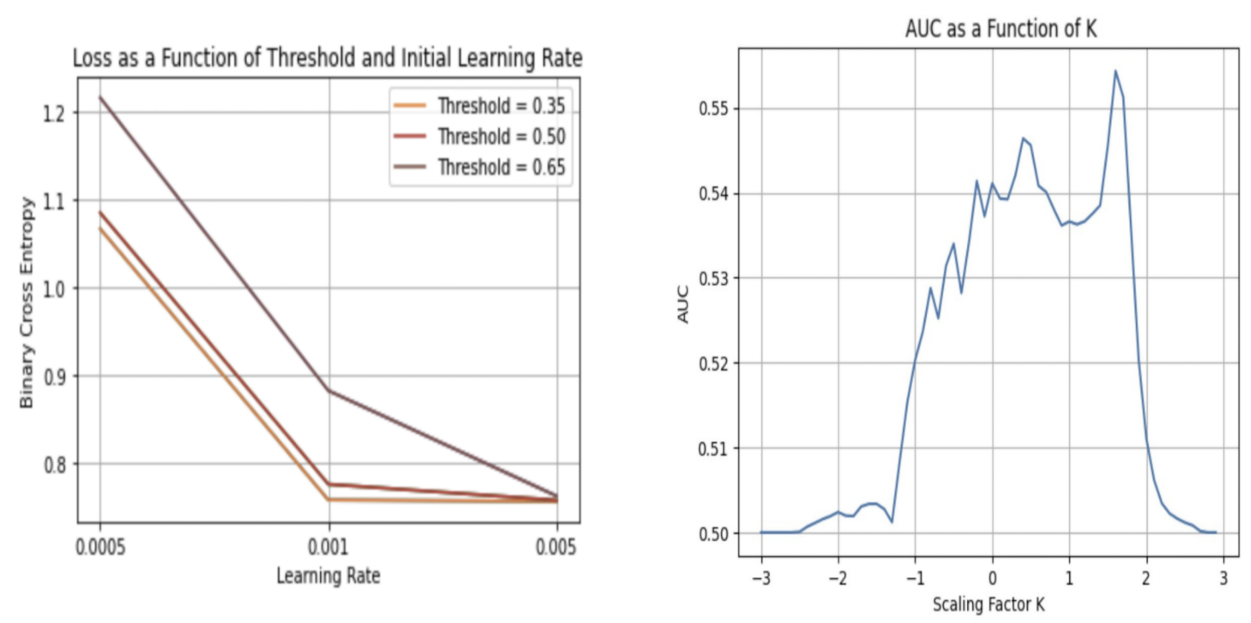

Figure: Hyper-parameter Tuning of U-net (left) and Threshold Model (right).

Results

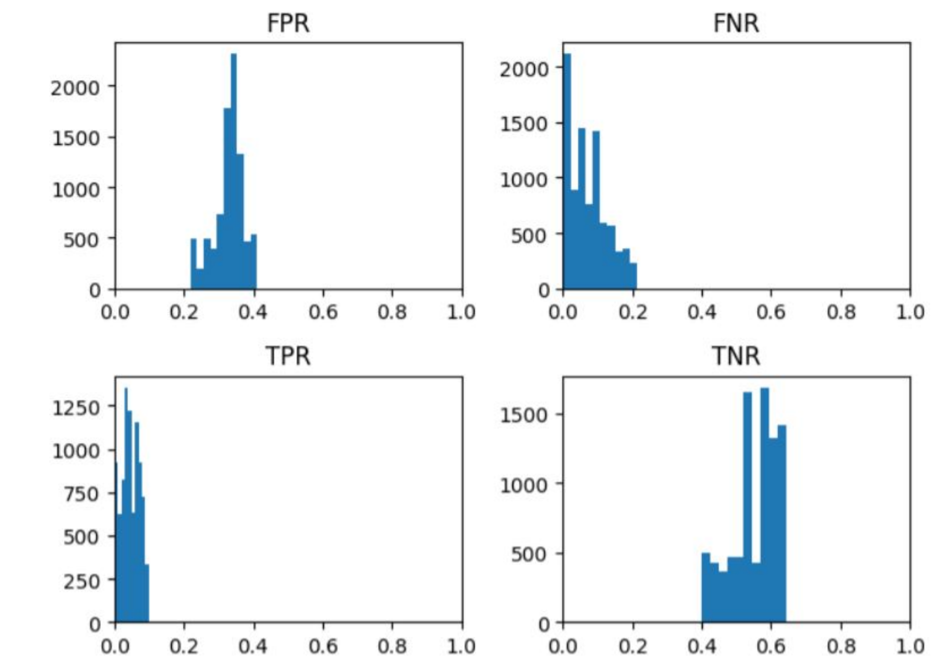

Figure: Histograms of Confusion Matrix Values for the Threshold Model

- We learned that as we increase K in the Threshold Model, we improve/decrease False Positive Rate (FPR), but worsen/decrease the True Positive Rate (TPR) at the same time. Generally, energy companies are most interested in minimizing false positives, but this comes at the cost of decreasing the model's ability to correctly predict positive values. Given this inherent trade-off, we decided to optimize for area under the ROC curve (AUC). Our maximum AUC was just above 0.55 for our optimal scaling factor value K=1.6. Although this value is far from ideal, we recognize the inherent challenges associated with this task, such as the distribution of satellite pixels, and the difficulties in choosing a relatively arbitrary threshold cutoff. We also used pre-trained models specifically designed for image segmentation such as Mask DINO and CBNet, which didn't perform better than our threshold model.

Conclusion and Future Work

- **Content Summarization:** In this capstone project, we applied a U-Net model and a statistical threshold model to methane plume instance segmentation. We found that the threshold model is the most fitting for the task, as it was better at correctly isolating methane plumes and had a significantly lower false positive rate which was the key performance indicator for our project.
- **Future Work:** In the immediate future, the next steps would include comparing other Neural-Network based approaches by bench-marking our threshold model. Our model can also play a major role in Orbio's future product offerings revolving around global methane modeling.

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References

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