Improving Deep Learning Methods for Robust Methane Plume Detection using Alternative Input Representations

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Abstract

Methane (CH4) is a prominent greenhouse gas responsible for about 20% of all atmospheric radiative forcing. As we notice trends in increasing global temperatures, understanding and detecting these emissions has become increasingly important. This requires the creation of robust greenhouse gas plume detectors. Previous work at the NASA Jet Propulsion Laboratory has shown Convolutional Neural Networks (CNN) to be an appropriate solution to map methane sources from future imaging spectrometer missions, such as Carbon Mapper. However, current models suffer from a high rate of false positives due to false enhancements in the detected images.

We have compiled datasets from two Airborne Visible/Infrared Imaging Spectrometer Next Generation (AVIRIS-NG) California campaigns. We then trained a GoogleNet CNN Classifier model on each campaign. The baseline current model uses a Unimodal column-wise matched filter (CMF). This results in a model known to be sensitive to false enhancements, such as water/water vapor, bright/dark surfaces, or confuser materials with similar absorption wavelengths to methane. We first note improvements between the Unimodal CMF model and a new Surface-Controlled CMF model, whose dataset matches that of the Unimodal CMF model, but removes enhancements not matching the absorption wavelength of methane. From this, we note minimal improvement (1% increase in F1 score). We then experiment with various auxiliary products measuring albedo (rgbmu, SWALB), vegetation (NDVI, ENDVI), and water (h2o, NDWI) indices designed to combat issues known to produce false enhancements. After training on these new input representations for both campaigns, we noticed a significant improvement in the multi-channel model's results. We observe an increase in the F1 score for classifying positive tiles from 0.78 to 0.86 when trained using auxiliary albedo indices, showing promise for future use of auxiliary products in improving methane plume detectors.

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Background

Methane Detection

- Methane (CH4) is a greenhouse gas largely responsible for increasing global temperatures
- We want to detect and monitor plumes from airborne and spaceborne missions
- Carbon Mapper is launching a hyperspectral satellite to perform such monitoring globally

CNN Model

- Using Convolutional Neural Networks, we have created deep learning models to automate methane detection
- The current unimodal CMF pipeline suffers from a high rate of false positives due to false enhancements
- We've improved this performance by **29.7%** by adding auxiliary products as input

Methods

- Introduce the Unimodal CMF model with auxiliary products from radiance
  - Water Indices: CIBR water vapor @ 940+1140nm, NDWI = NIDX(NIR, SWIR1)
  - Albedo: Mean RGB, SWALB = SWIR2/cos(sza)
  - Vegetation: NDVI = NIDX(NIR, R), ENDVI = NIDX(NIR + G, 2B) where NIDX(B1, B2) = $\frac{B1-B2}{B1+B2}$

H2O: CIBR water vapor @ 940+1140nm

Mean RGB

NDVI = NIDX(NIR, R)

NDWI = NiDX(NIR, $SWIR_1$)

SWALB = $SWIR_2$/cos(sza)

ENDVI = NIDX(NIR + G, 2B)
Where NIDX(B1, B2) = $\frac{B1-B2}{B1+B2}$

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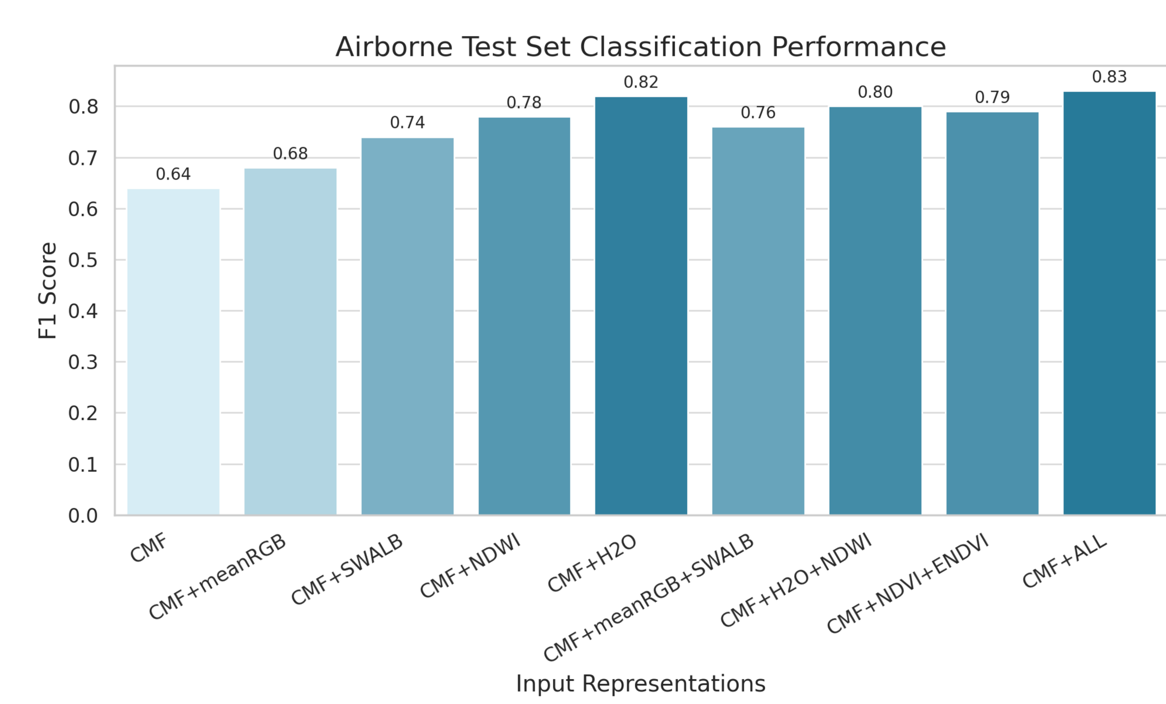
Data

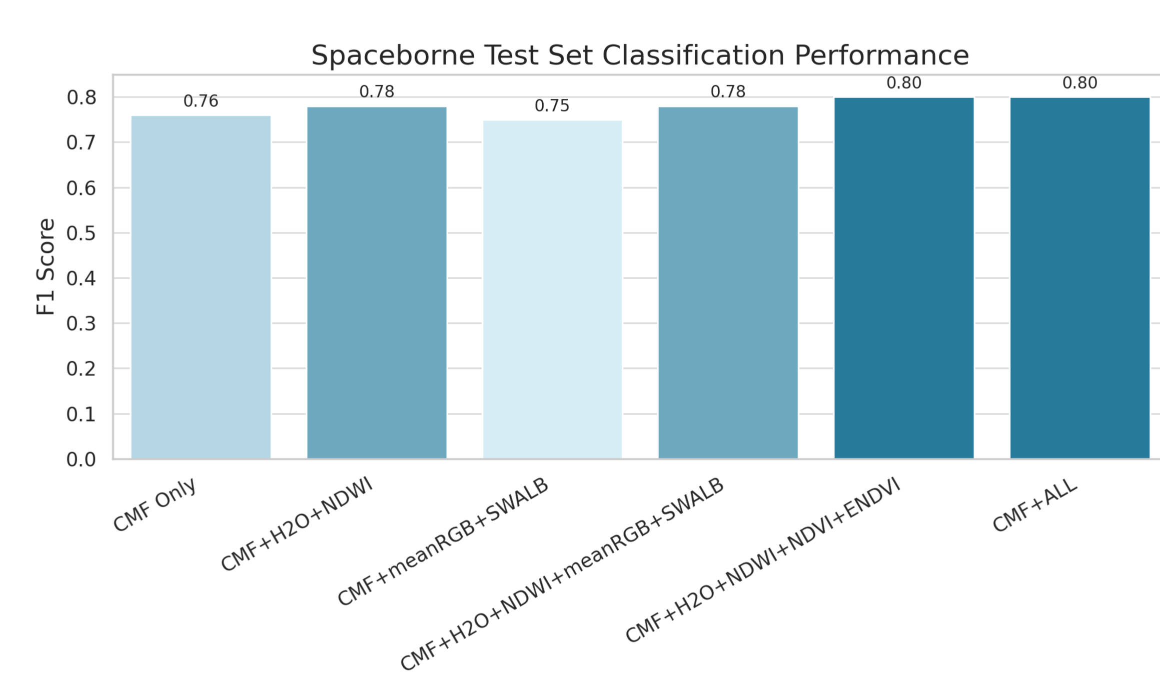
- Primarily using data from three airborne campaigns
- Using data from two AVIRIS-NG California campaigns from 2018 (CalCH4) and 2020 (COVID)
- Using data from GAO California campaign from 2020
- Additionally, experiment with spaceborne data from EMIT spectrometer aboard the ISS

Results

- Trained models with various combinations of auxiliary products on airborne dataset (CalCH4 (2018) + COVID (2020) + GAO (2020))
- F1 Score increases from 0.64 to 0.83 **(29.7%)** with the inclusion of all six auxiliary products
- Notably, even the inclusion of one aux product (if correctly chosen) can have a positive effect on model F1 Score

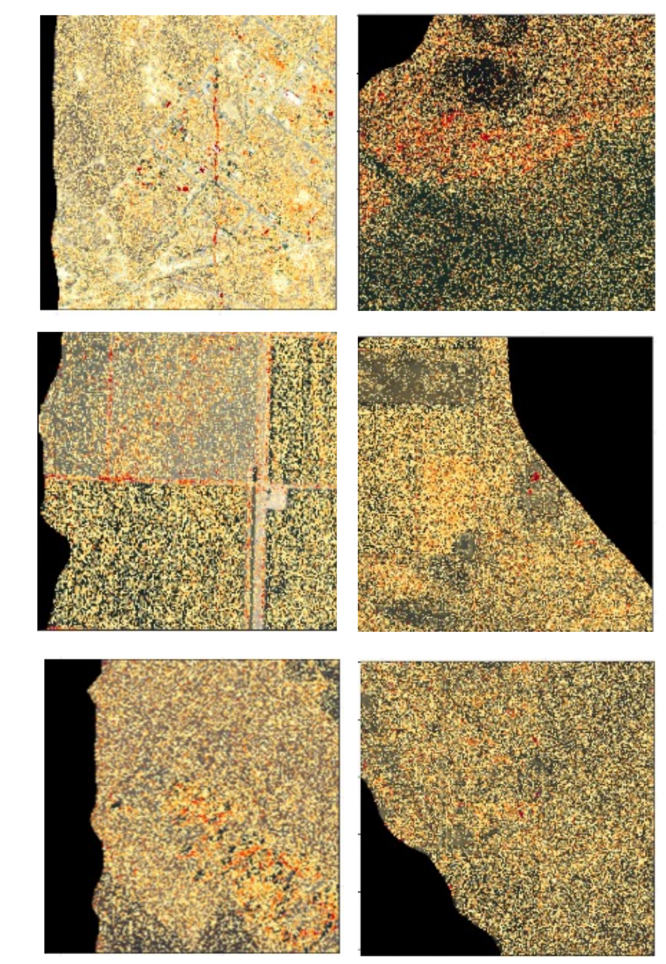


- Tested the impact of alternative input representation on models trained on EMIT Spectrometer data
- Observed smaller, but still significant increase in F1 from 0.76 to 0.80 **(5.3%)** with the inclusion of all six aux products

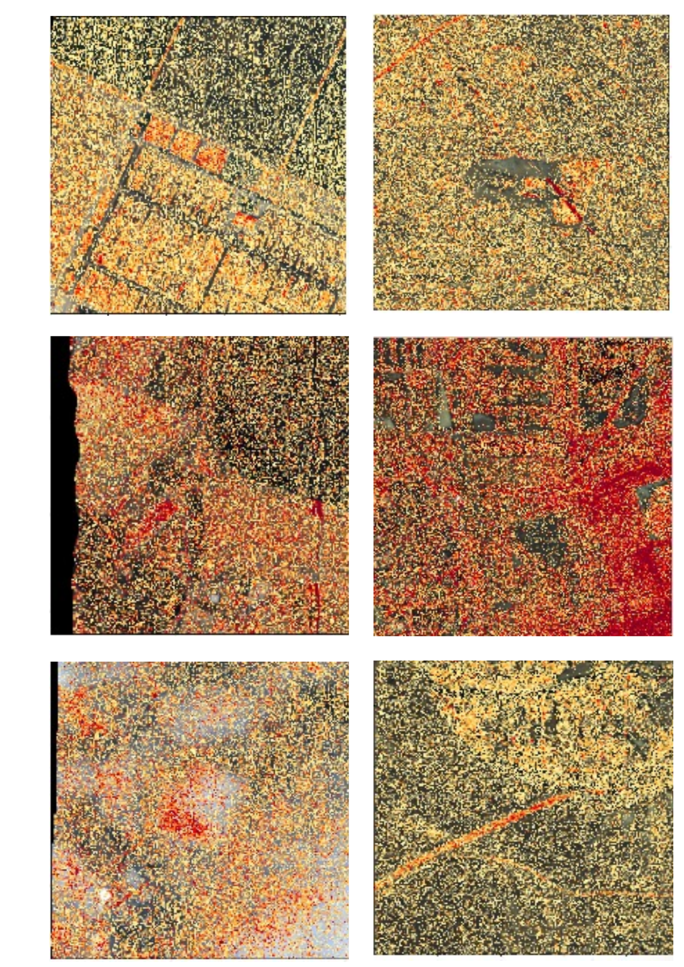


Airborne Analysis

- The CMF+All Aux model is able to reject many of the visibly obvious false positives produced by the CMF-only model



CMF-Only False Positives



All-Aux False Positives

Conclusions

- Observed improvements with CMF + All 6 Aux Products model. F1 score increased from **0.64 to 0.84**.
- Extended model to EMIT dataset. Observed greatest performance impact in CMF + All 6 Aux Products model. F1 score increased from **0.76 to 0.80**.
- Water aux products appeared to have largest impact on model F1 score (**0.82** airborne, **0.78** spaceborne)

Future Work

- Experiment further with alternate datasets and auxiliary products
- Further work is required with spaceborne data to determine the efficacy of auxiliary products

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