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

Anagha Satish[1], Brian Bue[2], Jake Lee[2] , Andrew K Thorpe[2] , Daniel Cusworth[3] , Alana Ayasse[3,4] , Riley Duren[3,4]
[1] California Institute of Technology, [2] NASA Jet Propulsion Laboratory, California Institute of Technology; [3] Carbon Mapper; [4] University of Arizona

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) = $\frac{B1-B2}{B1+B2}$

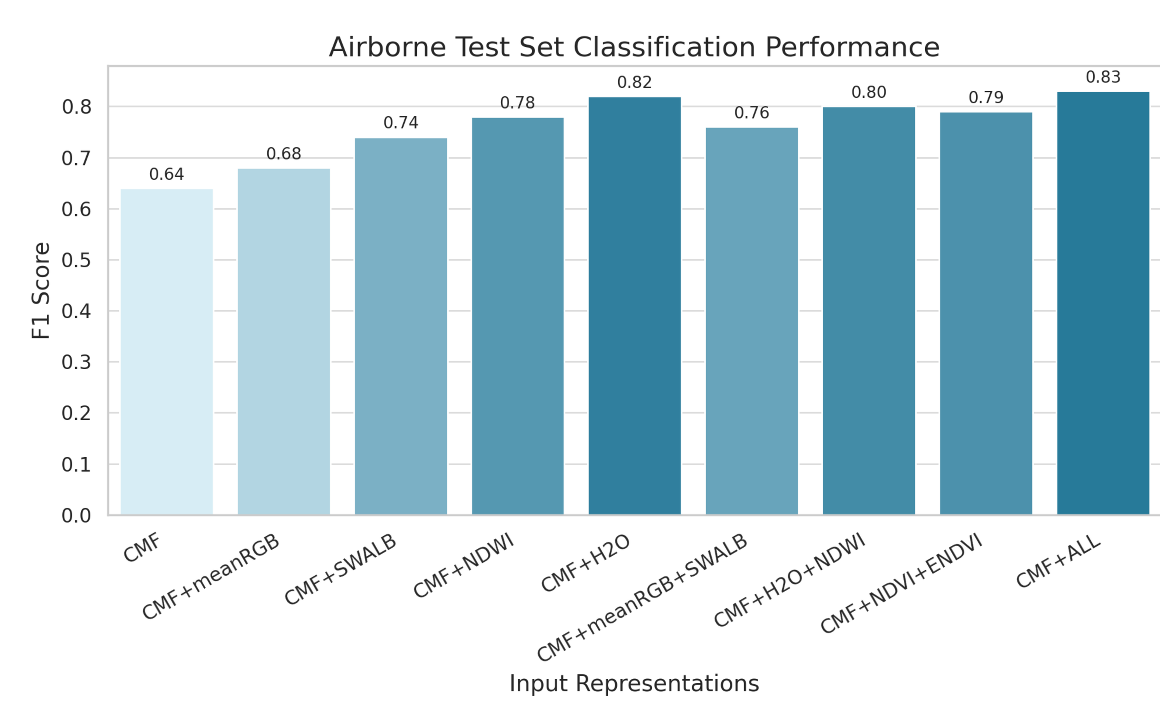
A43R-3021

Data

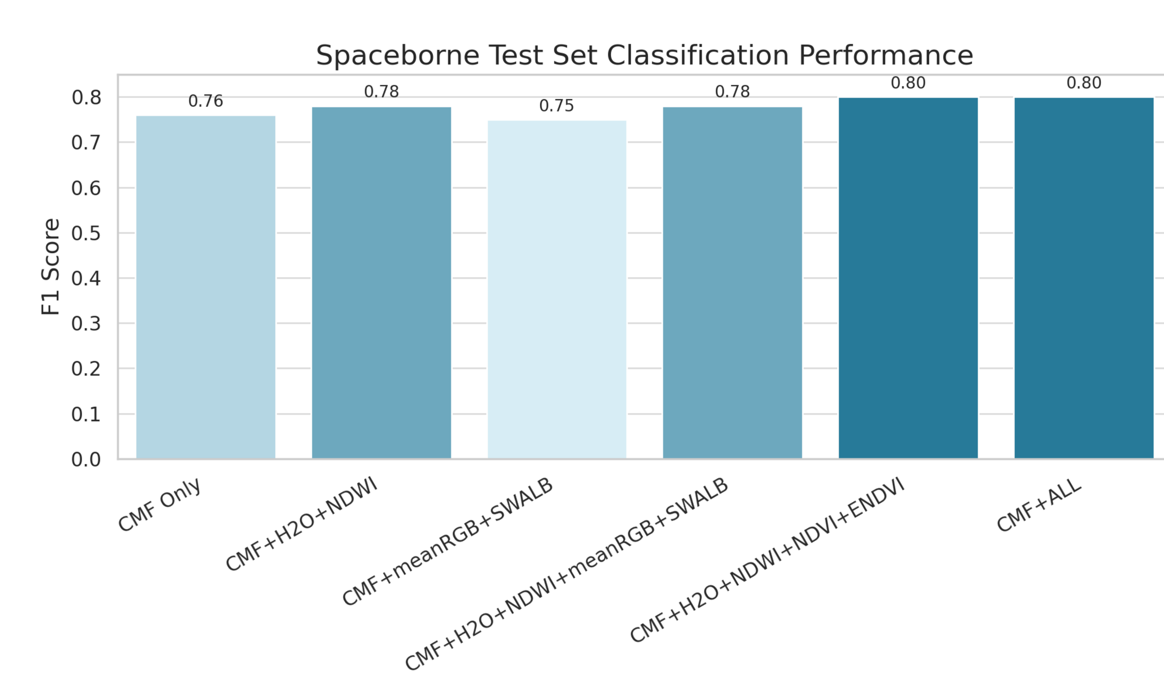
- Primarily using data from three airborne campaigns
- Using data from two AVIRIS-NG California campaigns from 2018 (CalCH4) and 2020 (COVID)
- Using data from GAO California campaign from 2020
- Additionally, experiment with spaceborne data from EMIT spectrometer aboard the ISS

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

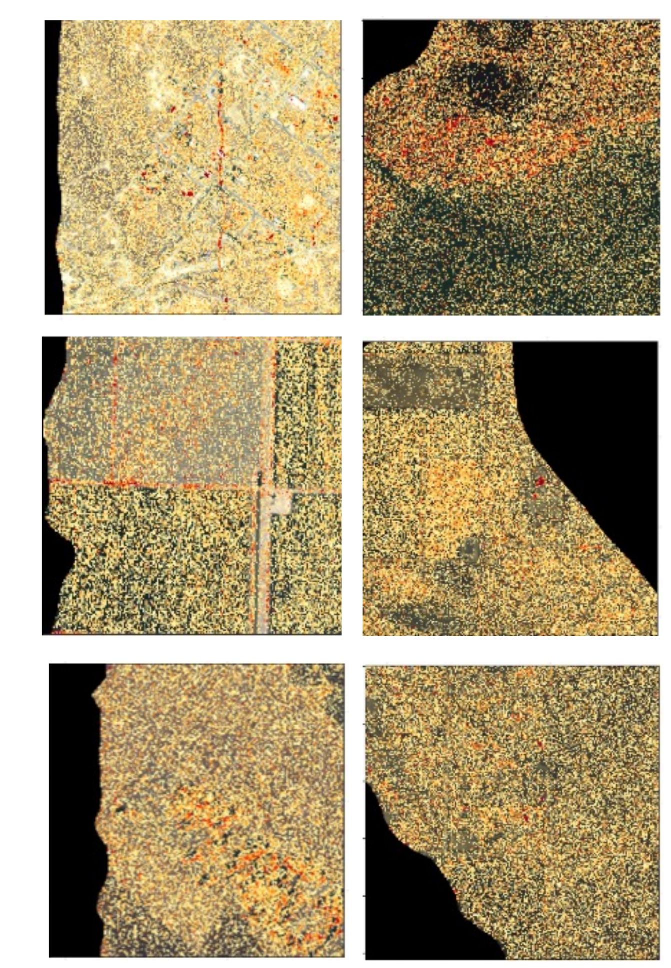


- Tested the impact of alternative input representation on models trained on EMIT Spectrometer data
- Observed smaller, but still significant increase in F1 from 0.76 to 0.80 **(5.3%)** with the inclusion of all six aux products

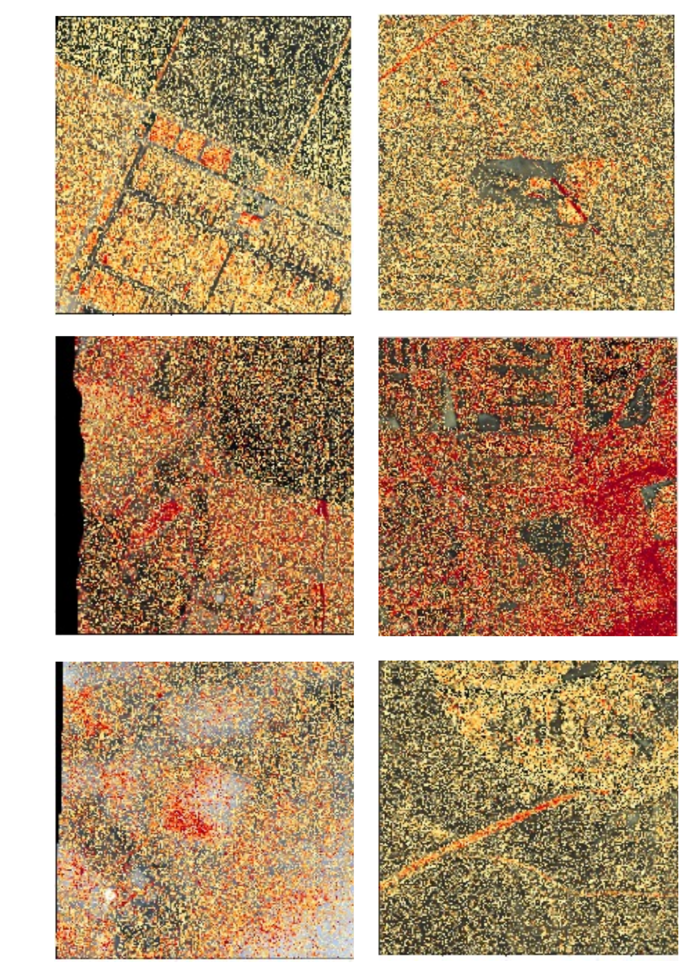


Airborne Analysis

- 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

Acknowedgements

- The Carbon Mapper team acknowledges the support of their sponsors including the High Tide Foundation and other philanthropic donors. A portion of this work was performed at the Jet Propulsion Laboratory, California Institute of Technology. Copyright 2023 California Institute of Technology. Government sponsorship acknowledged.
- Further funding was provided by the Michael and Edweena Werner SURF Fellowship