Satellite-derived Combustion Activity Estimation Using Machine Learning and NASA's Black Marble Product Suite for Evaluation of Greenhouse Gas Emission Inventories

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Introduction and Motivation

Nighttime observations from the Visible Infrared Imaging Radiometer Suite (VIIRS) are used to detect combustion from biomass burning [1, 2], gas flaring [3] using thermal band signals. These detections contribute toward estimation of greenhouse gas emissions from these occurrences. Assessment of error and uncertainty in VIIRS-detected combustion is a crucial but missing element which reduces the transparency of emission estimates.

We introduce a *machine learning-based methodology that detects the anomalous signal associated with combustion from NASA's Black Marble product suite [4]* and generates an independent detection set to *facilitate error and uncertainty assessment [5]*. We also jointly use the thermal and light emission signal of combustion and *observe VIIRS Day/Night Band (DNB)-based light emission signal to improve detection*.

Objective

- Machine learning based multispectral model to extract nighttime signatures of combustion using NASA's Black Marble Product Suite.
- Facilitate intercomparison of VIIRS-derived combustion activity for approximating detection uncertainty and increase the transparency of satellite-based emission reports.

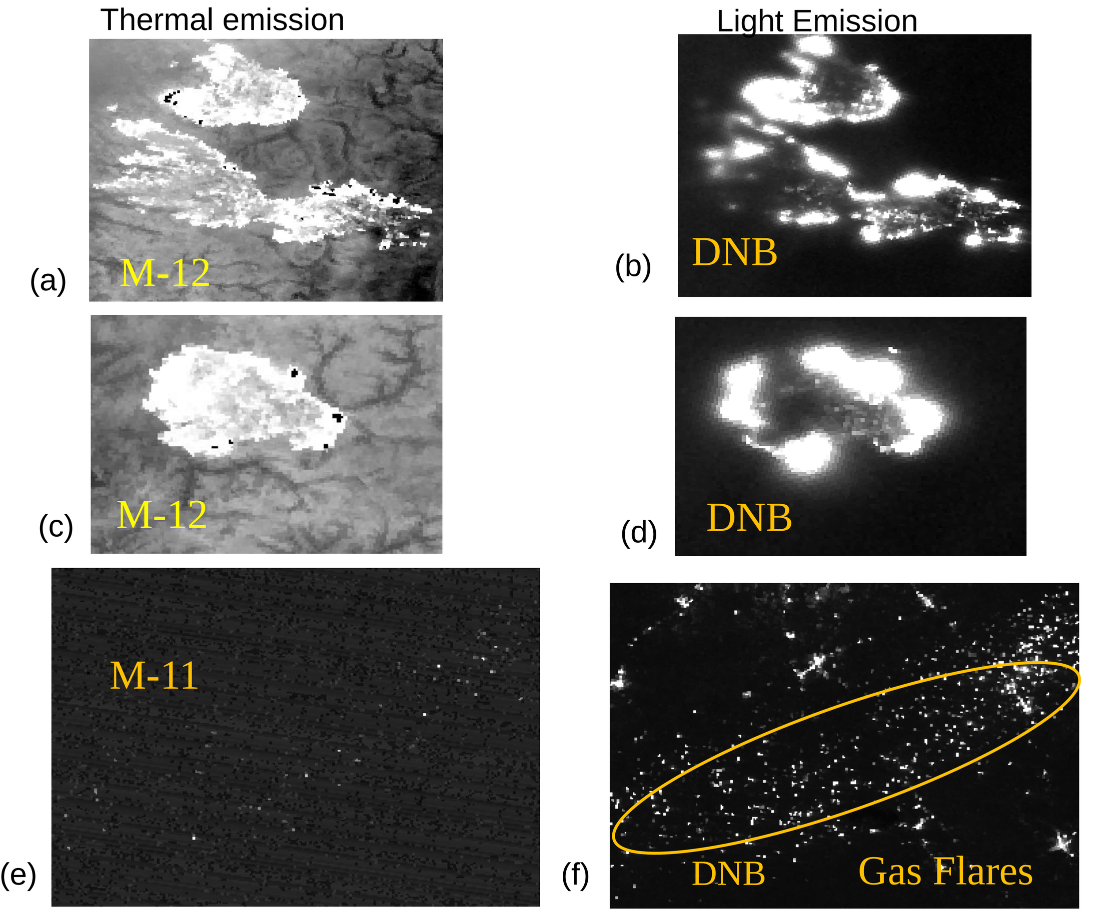

Fig. 1 Comparison of (a), (c) thermal and (b), (d) light emission of fires; (e) and (f) of gas flares shows combustion signature in different bands.

Proposed Approach

- Characterize the higher (anomalous) light and thermal emission from combustion compared to the background
- Monitor deviations from background to detect anomalies.
- Jointly use both thermal (VIIRS Moderate (M) Bands) and light emission (VIIRS DNB) anomaly score of a pixel using six M-bands and the DNB radiance.

Datasets:

- Daily top-of-atmosphere VNP46A1, six M-bands (M-10 to M-16), DNB
- Case study around the Eagle Ford Shale, Texas, United States a densely welled gas flaring site (January- February 2021, with 38 observations to encompass the lunar cycle).
- World Settlement Footprint layer for masking urban signals [6]

Multispectral Anomaly Detection

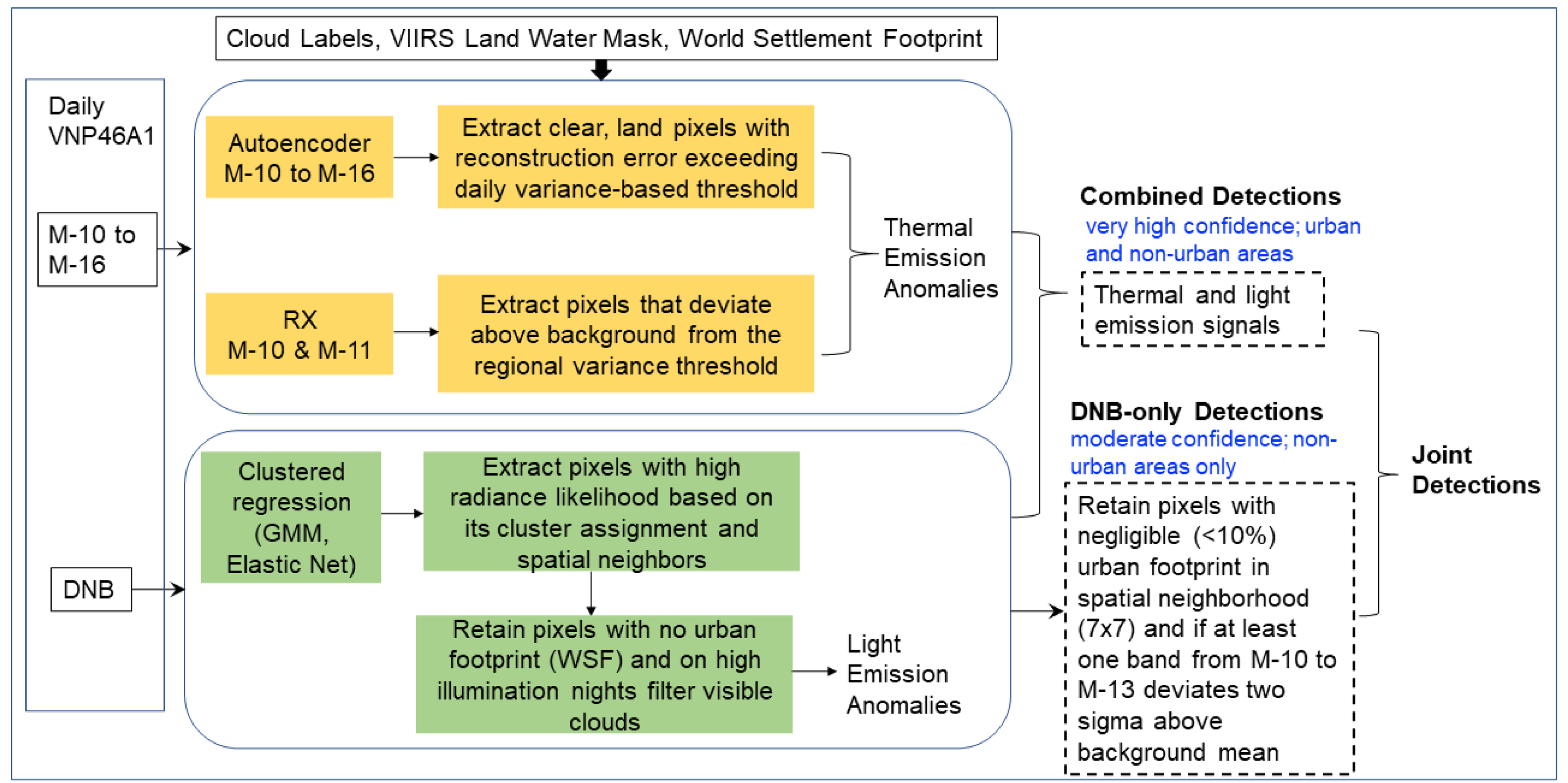

Fig. 2. Anomaly detection using Visible/Infrared (light) and thermal infrared emission properties of combustion pixels (RX: Reed Xiaoli detector, GMM: Gaussian mixture Model)

Results: Detected Sets

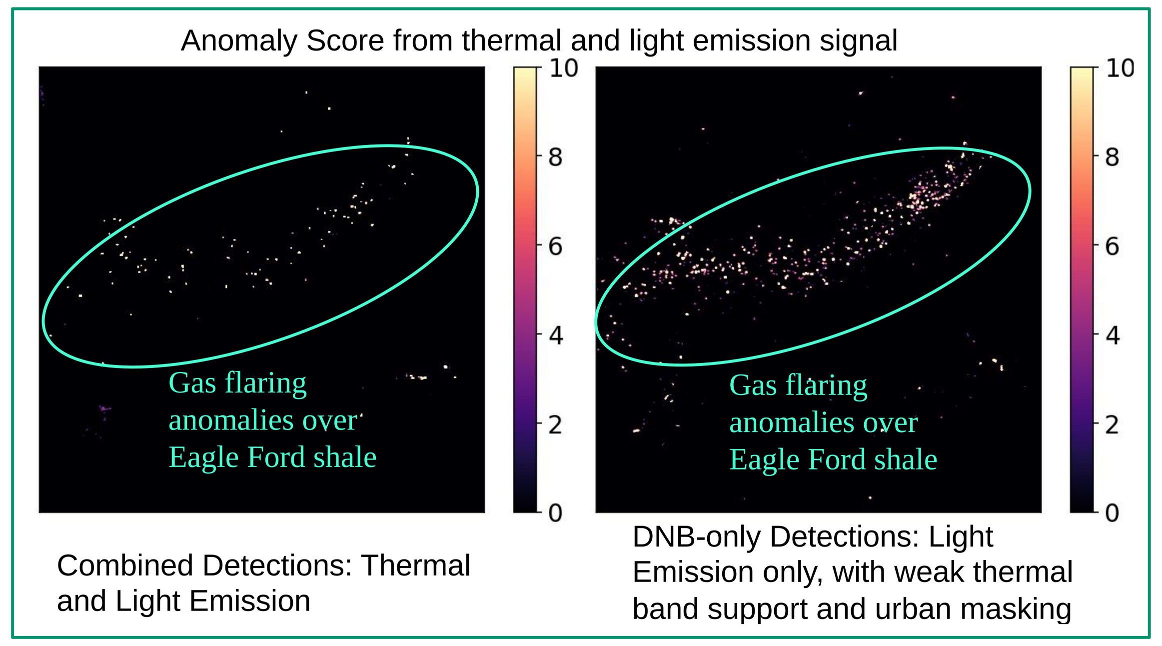

Fig 3: Anomaly score of thermal and light emission from gas flares on DOY 33, 2021. Combined detections are pixels showing anomalous thermal and light emission signals and have higher confidence. DNB-only detections are urban-masked light emission signals with weak thermal band support. Light emission signal captures weaker anomaly signals and can improve detection of emission causing activity from nighttime lights. Here 79.04% of the DNB-only detections are missed by the combined approach

Multispectral Analysis of Detected Anomalies

Table 1: Clear night multispectral properties of anomalies and background

Bands, Detection Set	Active DNB-only (L'_k)	Active Combined (Ω_k)	Background DNB-only	Background Combined
DNB (nWcm-2 sr-1)	46.55 ±4.11	186.1191±17.65	3.5702 ± 0.5607	3.8662± 0.5465
M-10 (Wm-2m-1 sr-1)	0.044 ± 0.0161	0.0952 ± 0.01	-0.0002 ± 0.001	0.00009 ± 0.001
M-11 (Wm-2m-1 sr-1)	0.0238±0.0074	0.0682±0.0074	0.0002±0.0004	0.0004 ±0.0005
M-12 (K)	279.91 ±0.78	282.03 ±0.71	279.02 ±0.86	279.03 ±0.86
M-13 (K)	277.36 ±0.62	278.07 ±0.59	276.77 ±0.71	276.77 ± 0.71

- Light emission-only signals show a distinct signal compared to background in M-10 and M-11 bands, indicating that these are weaker anomalies that are missed in moderate band detection.
- Including DNB anomaly signal helps in lowering detection threshold without increasing false positives errors and improves combustion monitoring.

Towards Improved Spatio-temporal Monitoring and Uncertainty Estimates

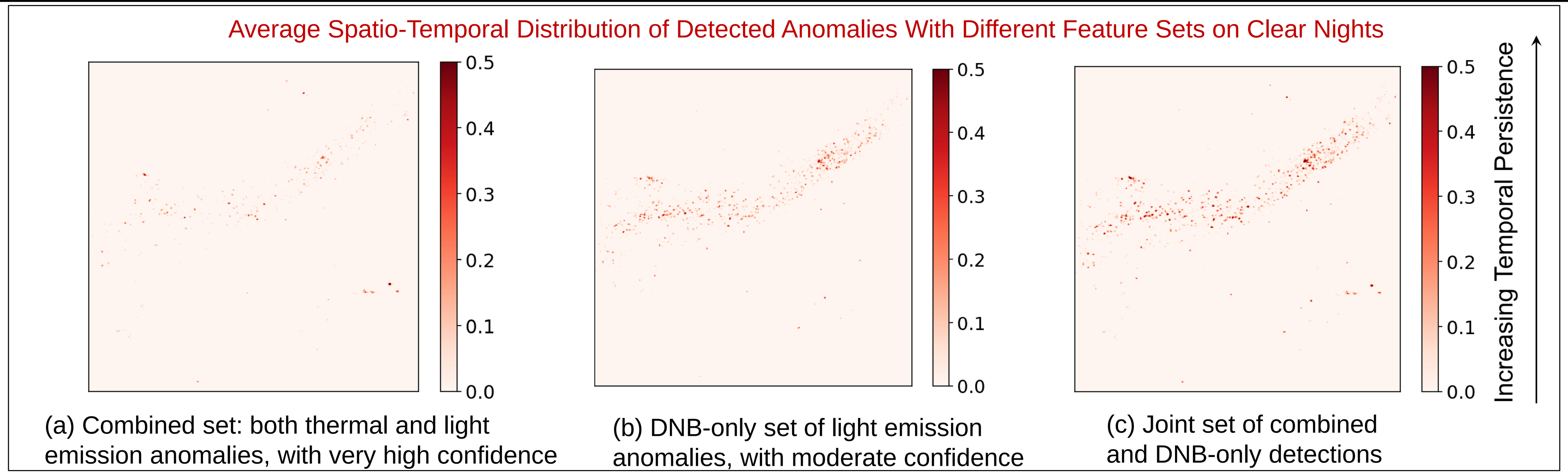

Fig. 4: Comparison of average clear night spatio-temporal distribution of anomalies at 30 arc second. Daily detections are binarized before determining temporal persistence. Temporal persistence of flaring at a location is determined from the intensity, with 1 indicative continued flaring throughout the study duration.

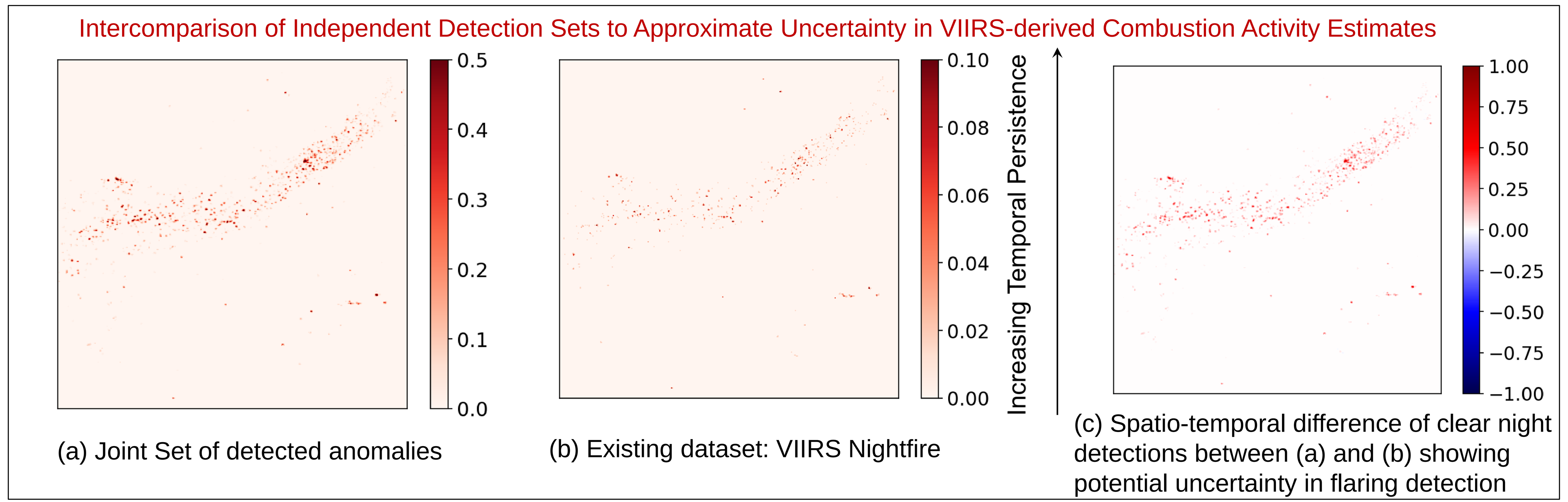

Fig. 5: Intercomparison of average clear night spatio-temporal distribution of anomalies (at 30 arc second) can potentially indicate detection uncertainty for more robust and transparent analysis of combustion activity estimates.

- Including light emission signal *improves improves localization (spatial) and tracking of the daily variation (temporal) of combustion*.
- Independent detections of anomalies (combustion) is expected to *contribute towards error and uncertainty assessment of these occurrences and for informing derived combustion activity estimates for increased transparency in emission reports*.

Conclusions and Future Work

- Jointly characterizing thermal and light emission signals from NASA's Black Product Suite VNP46A1 dataset improves combustion detection.
- Being a data-driven methodology can be used to approximate uncertainties in satellite-derived combustion activity estimates through intercomparison.
- Light emission only signals are possible weak anomalies missed by thermal bands.
- Improved localization and timely tracking of anomalies using data-driven approaches.

Future work:

- Extending the approach to different combustion classes
- Generalized detector that is robust to spatio-temporal variation.
- Improved masking and interpretation of DNB-only (light emission-only) signals from active gas flaring sites

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