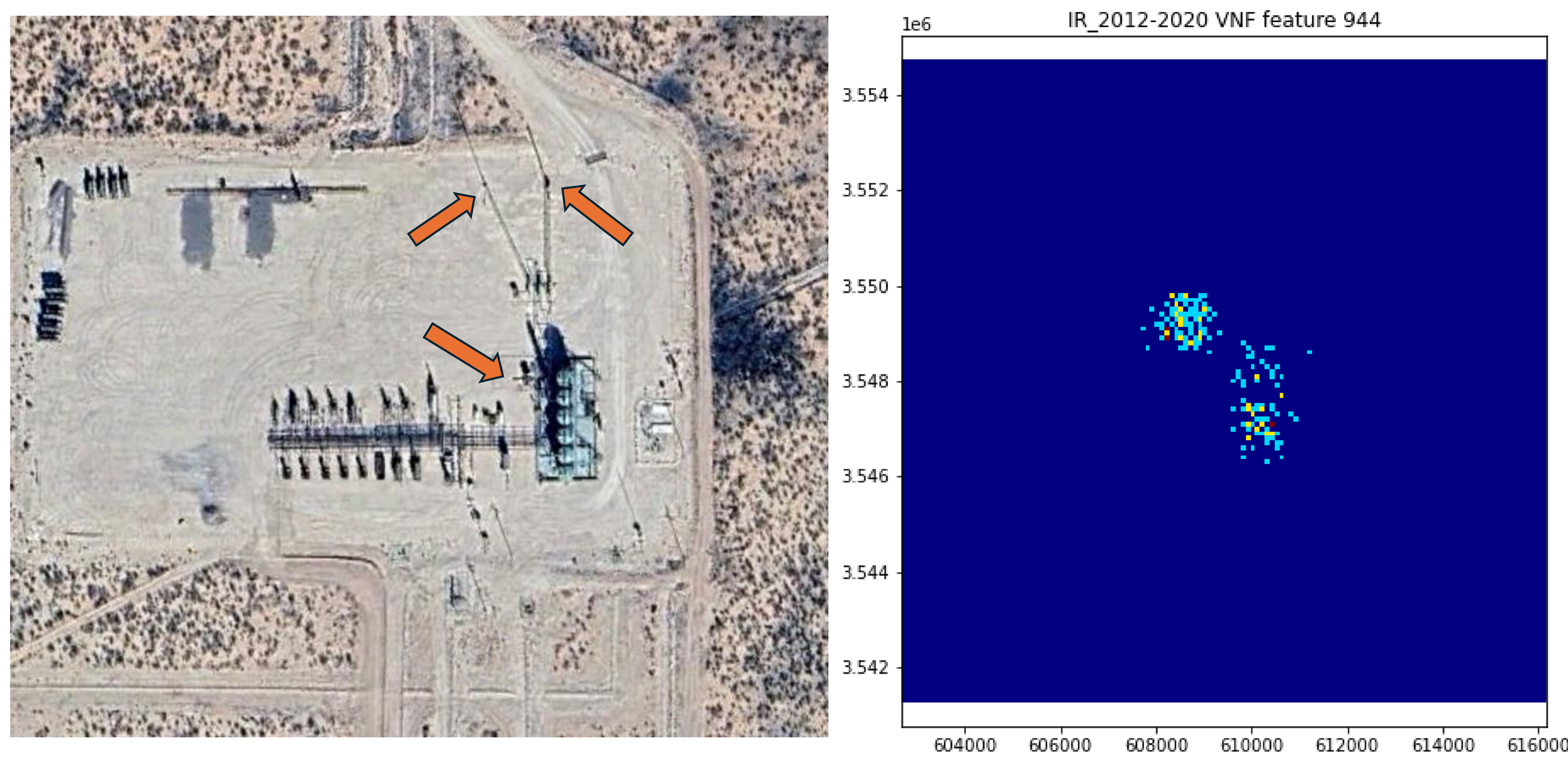
Bridging the Gap Between Daytime VHR Imagery and Nighttime Satellite Detected Hotspots in Flare Classification

An Application of Computer Vision to Improve Satellite Remote Sensing

Background:

- Flaring, the burning of excess natural gas, is often self-reported by site operators, leading to inaccurate emission data. Satellite data can identify high-temperature sources indicative of flaring.
- The Earth Observation Group at the Payne Institute for Public Policy at Colorado School of Mines develops a catalog of detections throughout the world.



Comparison of High-Resolution Satellite imagery (left) vs VIIRS Infrared Detection (right)

See more at: eogmap.mines.edu/giree

Problem:

Thousands of new high-temperature sources are detected by remote sensing satellites. Classifying these detections at near real time is difficult.

Detected downstream flare near Corpus Christi, TX — Detected upstream flare in the Permian Basin (TX)

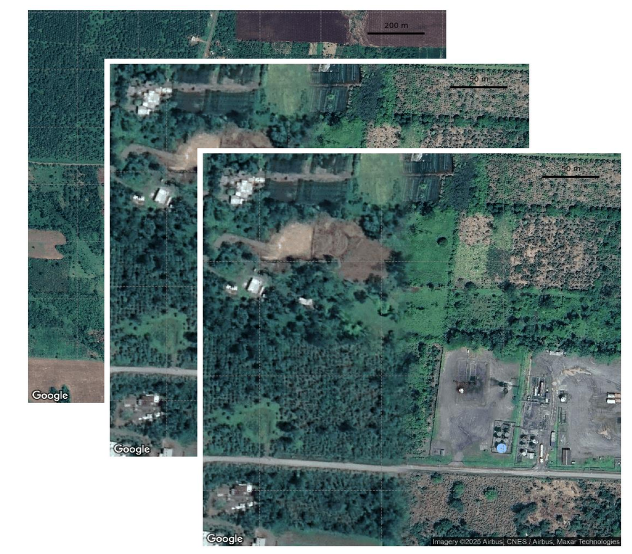
Detected landfill near Houston, TX — Detected midstream flare in the Permian Basin (TX)

How can very high-resolution (VHR) satellite imagery help classify flares?

Methods

Subtractive date pipeline to classify flares

Step 1: Fetch inputs for ML Model



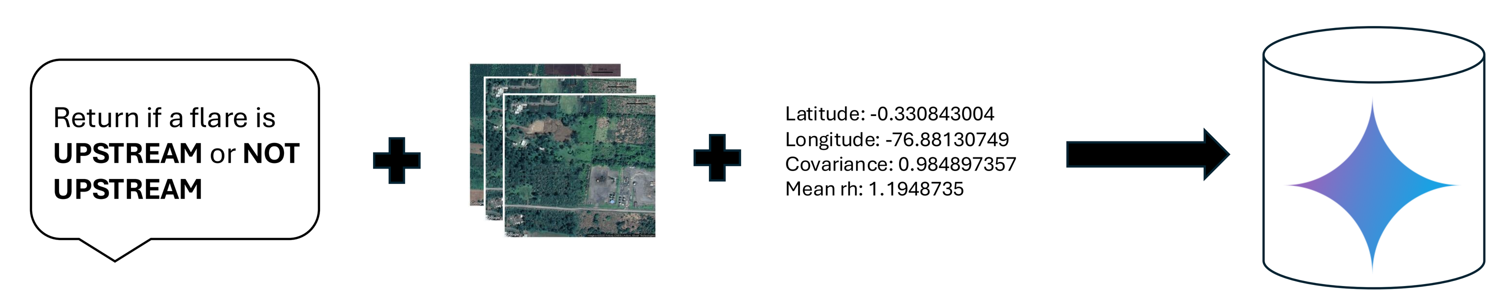
Imagery generated from Google Maps Static API

Latitude: -0.330843004
Longitude: -76.88130749
Covariance: 0.984897357
Mean rh: 1.1948735

Step 2: Create unique prompt to extract desired flares

Return if a flare is **UPSTREAM** or **NOT UPSTREAM**

Step 3: Feed inputs and prompt into LLM



Step 4: Remove identified flares, repeat process

Upstream Flares

ID	Additional Metadata
XX	YYY
XX	YYY
XX	YYY

Not Upstream Flares

ID	Additional Metadata
XX	YYY
XX	YYY
XX	YYY

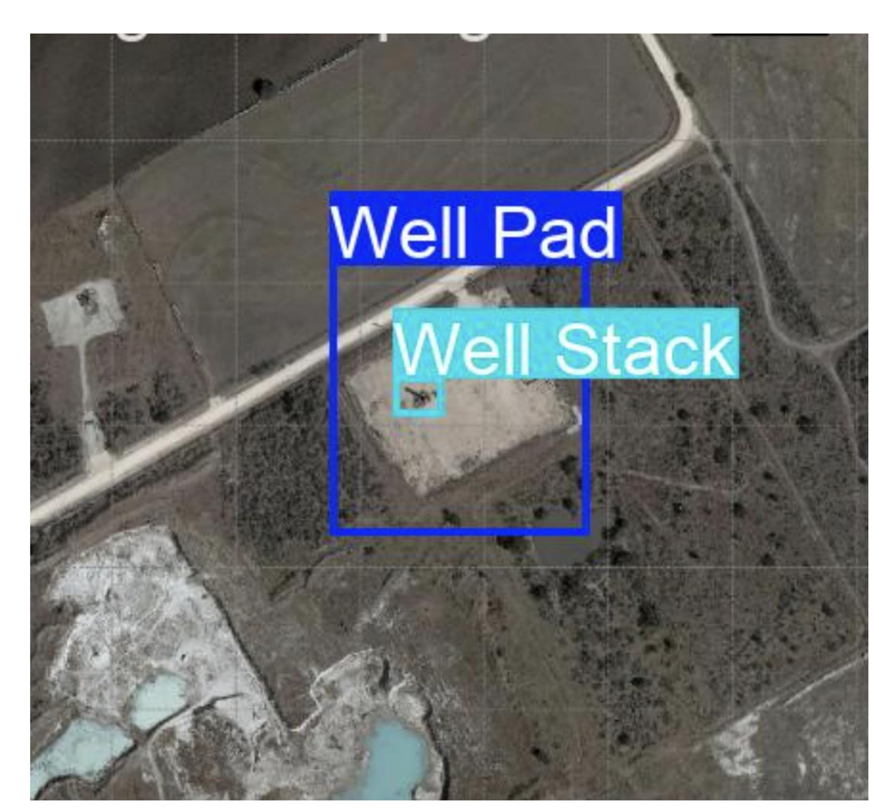
Other Methods

YOLO (You Only Look Once) image detection ML model to identify key infrastructure

- Does not perform well across regions
- Unbalanced training set

Matching detections with public databases

- Cannot identify flares in areas with insufficient data

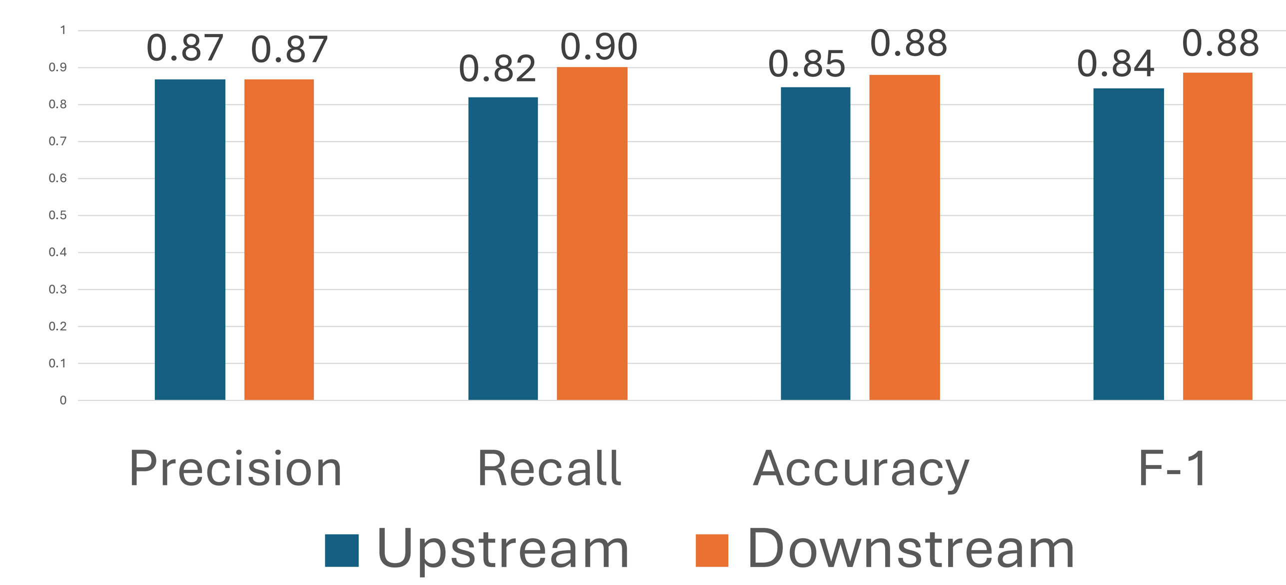


Sample YOLO detection of flare stack and pad in the Permian Basin (TX)

Project Challenges:

- Model performance across regions
- Prompt engineering and data selection
- Detection location precision
- Image recency
- Unbalanced training sets

Results:



- Model performs well at upstream and downstream classification tasks
  - Solves regional difference problem
- Certain less-important detections were confused
  - Steel Mill and Cement Plant
- Model performed exceedingly well on unique sites
  - Volcanoes

Acknowledgements:

- Elvidge, C.D.; Zhizhin, M.; Baugh, K.; Hsu, F.-C.; Ghosh, T. Methods for Global Survey of Natural Gas Flaring from Visible Infrared Imaging Radiometer Suite Data. Energies 2016, 9, 14. https://doi.org/10.3390/en9010014
- Elvidge, C.D.; Zhizhin, M.; Hsu, F.-C.; Baugh, K.E. VIIRS Nightfire: Satellite Pyrometry at Night. *Remote Sens.* **2013**, *5*, 4423-4449. https://doi.org/10.3390/rs5094423
- Ramachandran, N., Irvin, J., Omara, M. et al. Deep learning for detecting and characterizing oil and gas well pads in satellite imagery. Nat Commun 15, 7036 (2024). https://doi.org/10.1038/s41467-024-50334-9