

Real-Time Wildfire Localization on the NASA Autonomous Modular Sensor using Deep Learning

Yajvan Ravan*, Aref Malek*, Chester V. Dolph, Nikhil Behari***

NASA Langley Research Center

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* OSTEM Internship Program, Langley Research Center

** Langley Research Center

Problem: Wildfire Detection

THE CHALLENGE

Impact of Wildfires

- Wildfires are a worsening problem with climate change
- \$15.5 billion in damages and response costs (2021)
- Over 1 in 6 US homes at risk over the next 30 years

Current Detection Pipeline

- Fires detected by manual inspection of high-altitude aerial imagery
- Human firespotters label fire perimeters and heat sources
- Information often used 12+ hours after original flight



NASA, NASA Earth Observatory image by Wanmei Liang, using MODIS data from N
EOSDIS LANCE and GIBS/Worldview. - NASA Earth Observatory, [https://
earthobservatory.nasa.gov/images/151407/raging-fires-in-nova-scotia](https://earthobservatory.nasa.gov/images/151407/raging-fires-in-nova-scotia)

Current Detection Methods

AERIAL IMAGING SYSTEMS

NIROPS (National Infrared Operations)

- High-altitude line-scanner systems (Phoenix/AMS)
- Scan volumes reach 100k-400k acres/hour
- Geo-rectified TIFFs and shapefiles delivered before morning briefings

State Programs

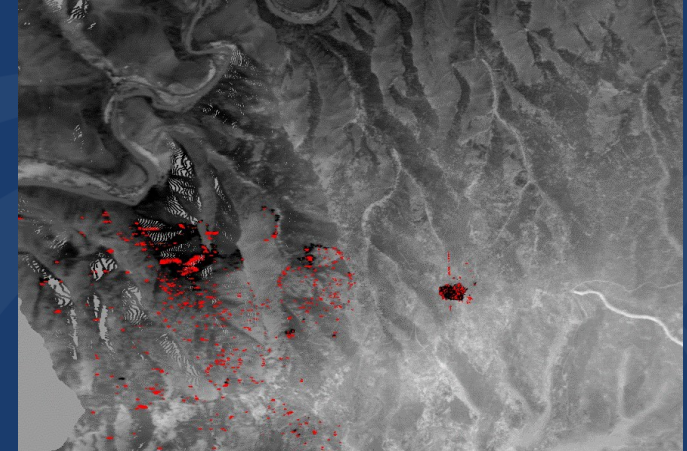
- California FIRIS: Near-real-time perimeter intelligence to CAL FIRE
- Colorado MMA: IR/EO mapping streamed to CO-WIMS

Images:

1. Gonalo Perrolas , Milad Niknejad *, Ricardo Ribeiro and Alexandre Bernardino (2022)
2. USFS (Special Thanks to KAZ for giving us this data)



LANDSAT 8



Phoenix Sensor



AMS

Existing Solutions

PRIOR APPROACHES

Color-Rule Algorithms

- Schroeder, Murphy, Kumar-Roy conditions using band ratios
- Pre-determined thresholds for spectral band intensities
- Strongly prone to false positives

Deep Learning Approaches

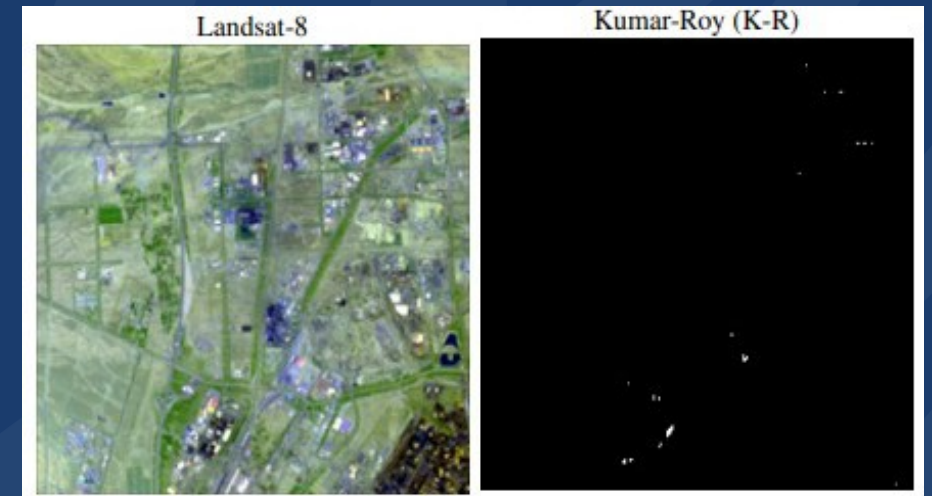
- Object detection: YOLO, Faster R-CNN
- Segmentation: U-Net, DeepLabV3+, TransUNet
- Limited to low-altitude, RGB, or satellite imagery

Images:

1. Toulouse, T., Rossi, L., Campana, A., Celik, T., and Akhloufi, M. A. (2017)
2. de Almeida Pereira, G. H., Fusioka, A. M., Nassu, B. T., and Minetto, R., (2021)



RGB/Ground Imagery



False Positive in city

Existing Datasets

Limitations of Prior Datasets

- Corsican Fire Database: Terrestrial
- Pereira et al. : Automatically annotated satellite imagery
- Flame 2/Flame 3: UAV only (60 m)
- Visifire: Terrestrial
- AIDER: UAV only



Flame 2



Corsican`



Pereira



AMS

Images:

1. Shamsoshoara, A., Afghah, F., Razi, A., Zheng, L., Fulé, P. Z., and Blasch, E. (2021)
2. Toulouse, T., Rossi, L., Campana, A., Celik, T., and Akhloufi, M. A. (2017)
3. de Almeida Pereira, G. H., Fusioka, A. M., Nassu, B. T., and Minetto, R., (2021)

Our Approach: Multi-Spectral Deep Learning

GAPS IN EXISTING WORK

Limited Scope for High-Altitude Deployment

- Most work focuses on terrestrial, low-altitude UAV or satellite imagery
- 3-50km altitude range is underexplored

Incomplete Spectral Data

- Primarily RGB wavelengths only
- Missing IR, SWIR, thermal bands critical for detection

Real-Time & Reproducibility

- No demonstrated real-time deployment
- Limited open-source, manually-annotated datasets

KEY INNOVATIONS

12-Channel Multi-Spectral Input

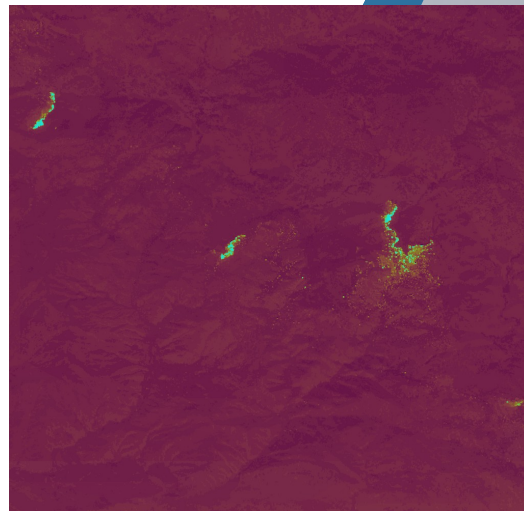
- RGB + SWIR + IR + Thermal bands
- Enables detection at nighttime and behind clouds/smoke
- SWIR, IR, and thermal bands most important for detection

Human-Annotated Dataset

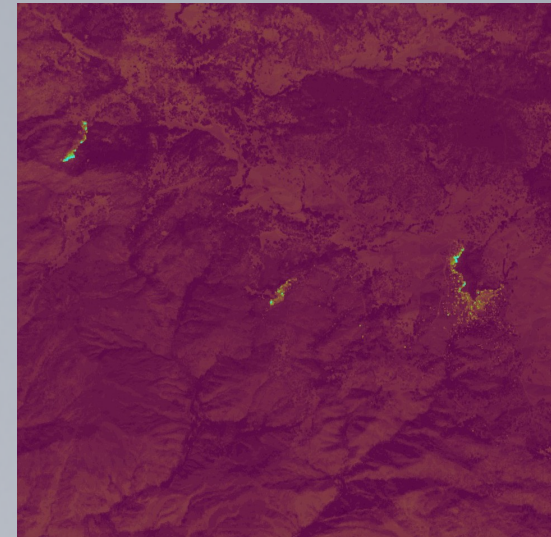
- 4,259 training patches from 18 NASA AMS flights
- 85 test patches from 2 MASTER flights
- Manually labeled fire perimeters (vs. auto-generated)

Spectral Band Importance

Fire obscured in RGB but clearly visible in IR/SWIR/Thermal bands. Visual spectrum alone misses fires behind clouds, smoke, and at night. Multi-spectral approach enables robust detection in all conditions.



IR (3.6-3.8 μm)



SWIR (2.08-2.35 μm)

Dataset: NASA AMS Imagery

AMS SENSOR SPECIFICATIONS

Flight Parameters

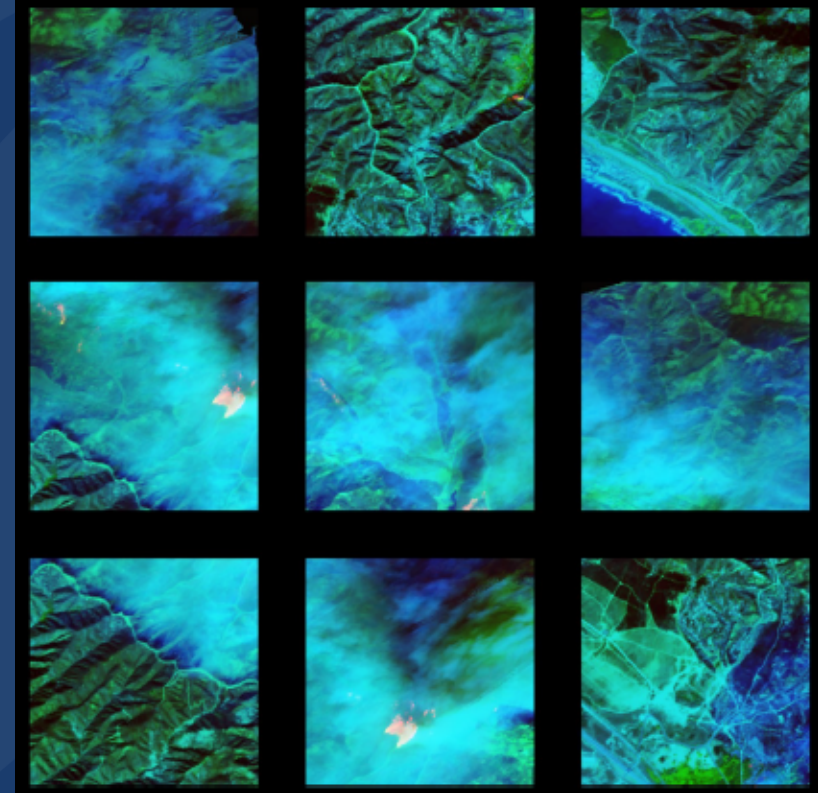
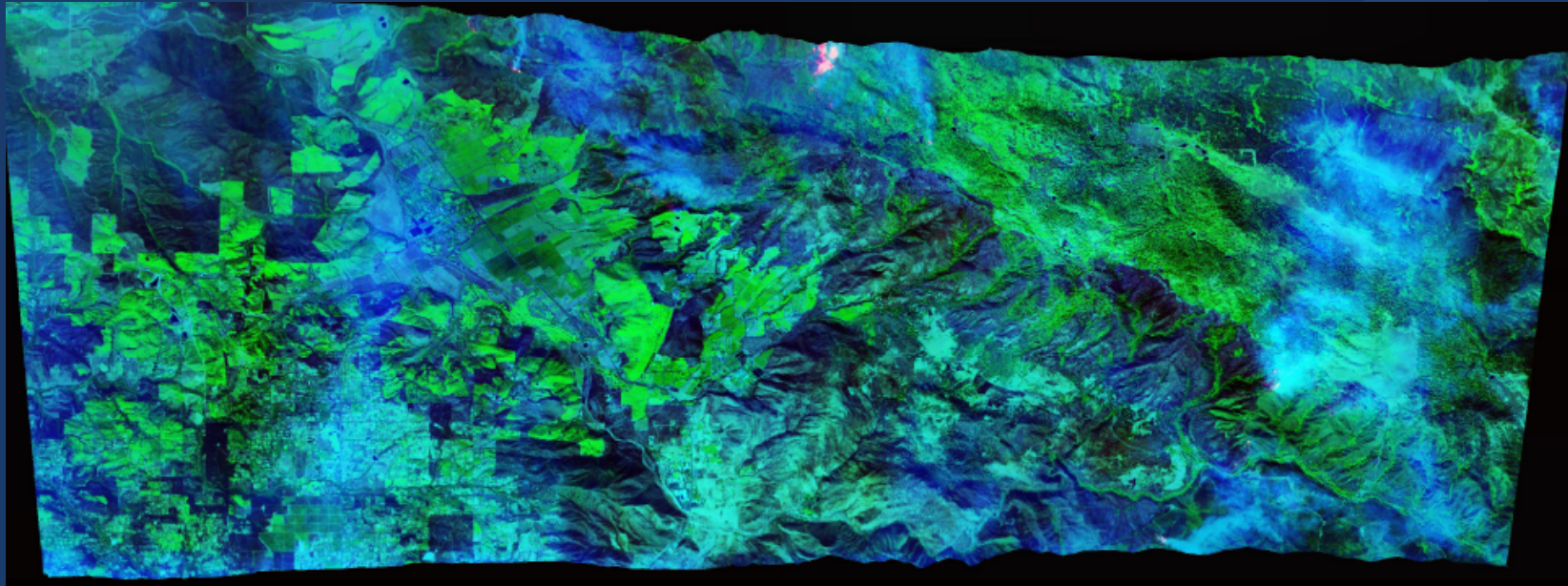
- 18 wildfire missions (2006-2019)
- Altitude: 13.5 km, GSD: 3-50 m/pixel
- Target radius: 15 nm (~1000 sq mi)

Spectral Bands

- 12 channels: Blue through Thermal (0.45-11.26 μm)
- Key bands: SWIR (2.08-2.35 μm), IR (3.60-3.79 μm), Thermal (10.26-11.26 μm)

Band	Wavelength, μm
1	0.42–0.45
2	0.45–0.52 (TM1)
3	0.52–0.60 (TM2)
4	0.60–0.62
5	0.63–0.69 (TM3)
6	0.69–0.75
7	0.75–0.90 (TM4)
8	0.91–1.05
9	1.55–1.75 (TM5) (high gain)
10	2.08–2.35 (TM7) (high gain)
11	3.60–3.79 (VIIRS M12) (high gain)
12	10.26–11.26 (VIIRS M15) (high gain)
13	1.55–1.75 (TM5) (low gain)
14	2.08–2.35 (TM7) (low gain)
15	3.60–3.79 (VIIRS M12) (low gain)
16	10.26–11.26 (VIIRS M15) (low gain)

Dataset: NASA AMS Imagery



Dataset Preprocessing

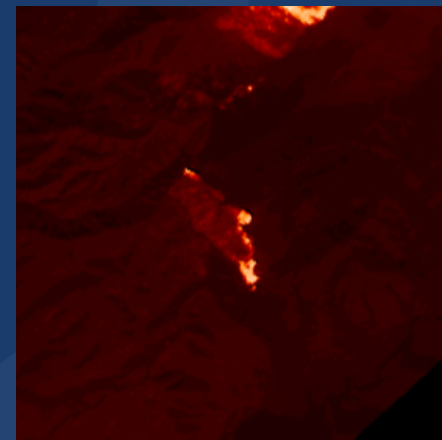
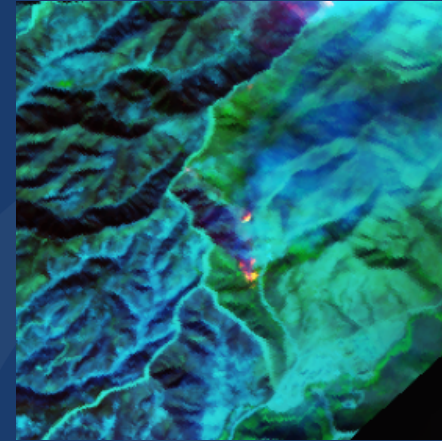
DATA PREPARATION

Normalization

- Non-thermal bands: normalized by solar irradiance
- Thermal bands: brightness temperature (250-500 K)
- Resampled to consistent 10 m/pixel resolution

Dataset Balancing

- Only ~18% of patches contain >0.5% fire pixels
- Classification: duplicate fire samples
- Segmentation: weighted loss (50x for positive pixels)



Two-Tier Real-Time Architecture

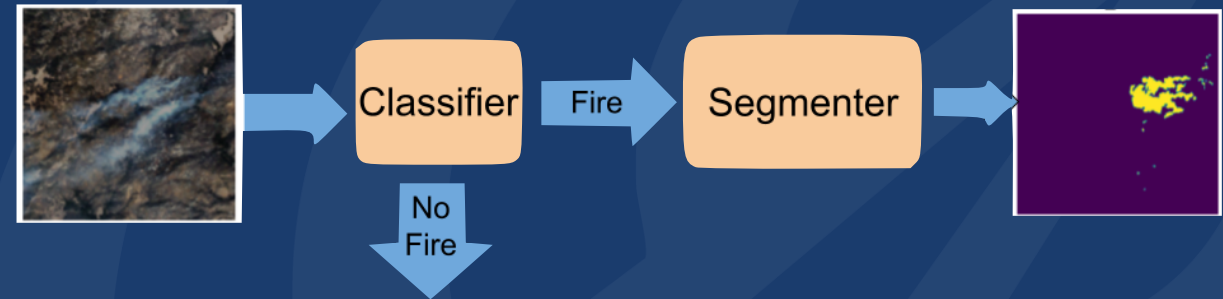
DUAL NETWORK DESIGN

Classification Network

- Quickly determines if fire exists in patch
- Fast inference: 1.19 ms/image
- Skips segmentation for 82% of patches (no fire)

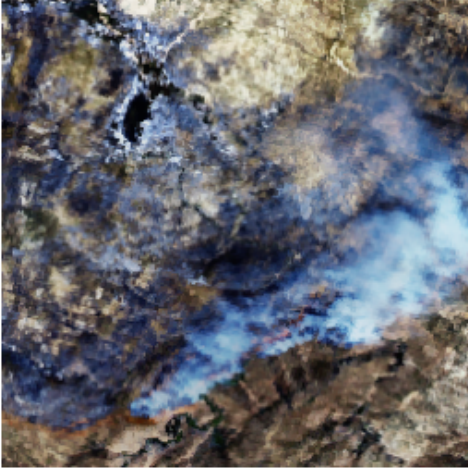
Segmentation Network

- U-Net architecture with skip connections
- Pixel-level fire localization
- Only runs when classifier detects fire

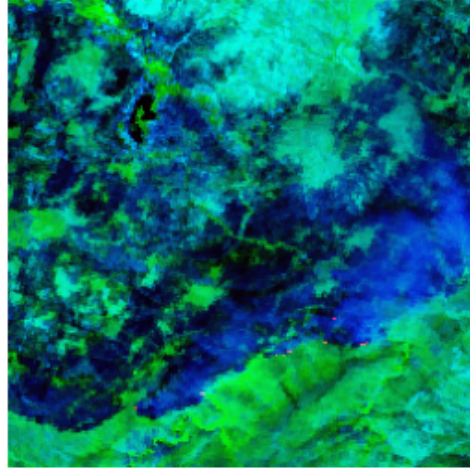


Results

Original Image



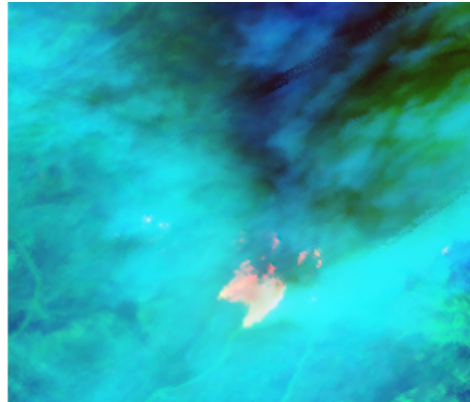
IR Emphasis



Ground Truth Mask

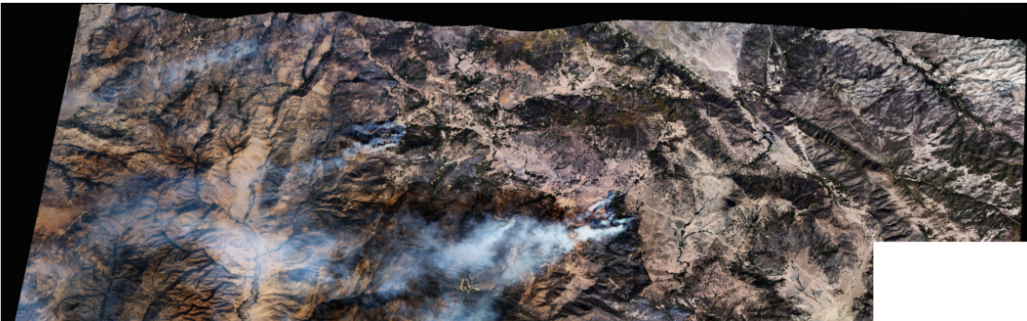


Our Result: FIRE!!



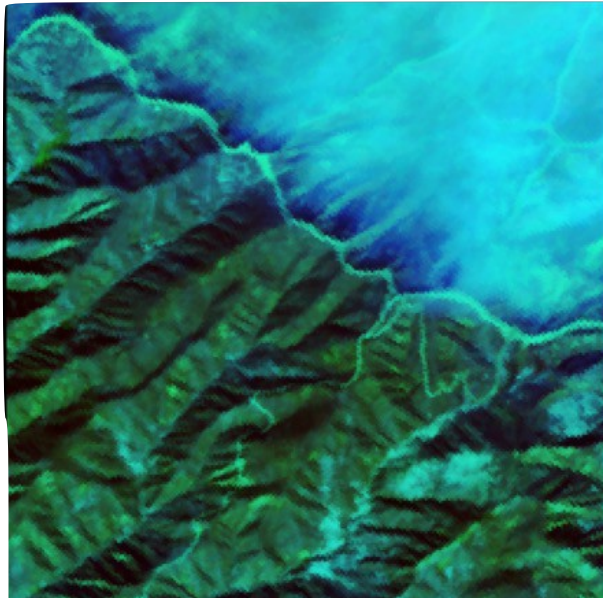
Results

Network	Acc. %	Prec. %	Recall %	IoU %	Inf. Time
Our Classifier	96.8	82.1	77.8		1.19 ms
Our Segmenter	96.0	58.6	84.0	74.0	7.75 ms
Pereira <i>et al.</i> 's segmenter	95.5	53.2	74.8	47.5	

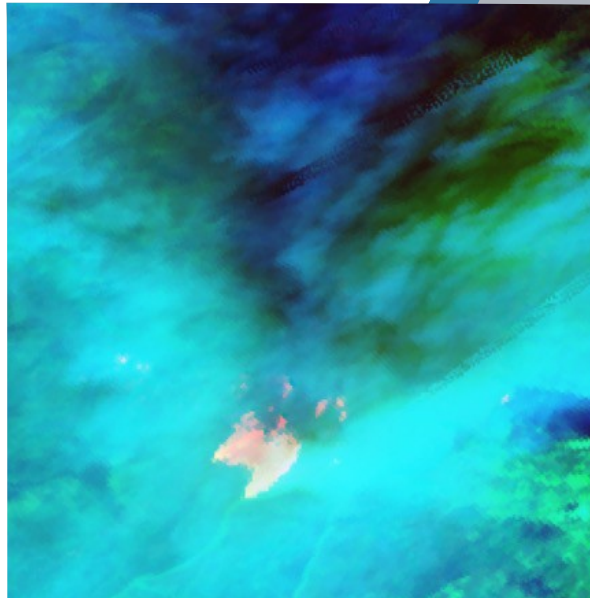


Example Results

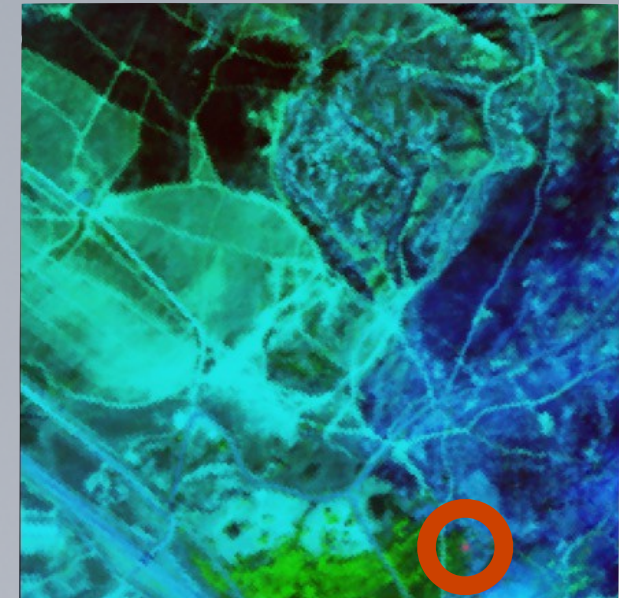
Fire occluded by clouds in visual spectrum but readily observable in IR band. Model correctly localizes fire including small spots on borders. Demonstrates effectiveness of multi-spectral approach.



Cloud cover could be confused for smoke



In RGB, fire would be obscured by cloud



Very small fire amidst noisy backdrop, easily missed by previous algorithms

Spectral Ablation

Key Findings

- RGB/non-thermal bands fail catastrophically (precision $\leq 30\%$, recall $< 10\%$)
- Fire detection signal concentrated in bands 9-12 (SWIR, IR, Thermal)
- Bands 9 or 10 alone match full model performance
- Bands 11 or 12 achieve close but notably worse results

Practical Implications

- Sensors should prioritize bands 9-12
- Memory-constrained? Use bands 10, 9, 2 subset
- Visual spectrum alone is insufficient for high-altitude detection

Channels	Accuracy %	Precision %	Recall %
11, 9, 2	96.4	78.6	80.0
10, 9, 2	97.4	83.3	84.4
9	97.1	88.9	74.4
10	95.4	85.3	71.1
11	94.4	66.9	62.2
12	95.8	97.5	63.3
1-8	89.8	30.0	4.4
5, 3, 2	89.5	12.2	7.8

Channels	Accuracy %	Precision %	Recall %	IoU %
11, 9, 2	95.6	54.9	79.8	71.6
10, 9, 2	96.6	64.0	76.8	75.0
9	96.6	67.8	60.4	71.7
10	97.0	67.8	76.6	76.4
11	96.4	57.7	66.2	71.5
12	95.8	58.4	63.4	69.5
1-8	94.7	21.5	1.1	47.8
5, 3, 2	94.6	18.4	1.8	48.1

Conclusions & Future Work

CONTRIBUTIONS & NEXT STEPS

Key Contributions

- First manually-annotated high-altitude multi-spectral dataset
- Two-tier real-time segmentation achieving 74% IoU, 84% recall
- Demonstrated importance of IR/SWIR/thermal bands

Future Directions

- Integration into operational wildfire pipelines
- Human-in-the-loop automation for field deployment
- Dataset and code to be made publicly available
 - <https://github.com/nasa/Autonomous-Modular-Sensor-Wildfire-Segmentation.git>

Thank You