GeoFoundation Model-Driven Semantic Segmentation of Wildfires

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Problem and Motivation

- Wildfires affect millions of square kilometers each year, creating major environmental and economic impacts
- Accurate burned-area maps support emergency response and environmental monitoring
- Manual mapping is slow and labor-intensive
- Spectral approaches can struggle with atmospheric effects, terrain, vegetation, and spectral ambiguity

Why Foundation Models?

- Traditional segmentation models such as U-Net rely on task-specific supervised training and labeled data
- Foundation models pretrained on satellite imagery provide transferable representations for downstream tasks

Dataset and Task

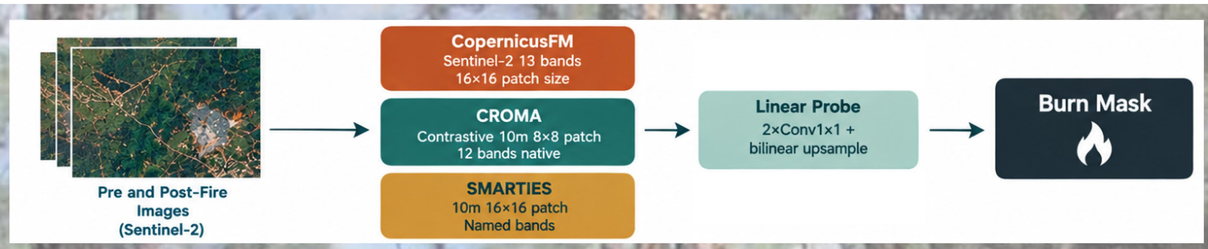
- We compare **CopernicusFM [2], CROMA [3], and SMARTIES [4]**, for burned-area segmentation on the **CaBuAr [1]** dataset, which contains 424 paired pre-/post-fire **Sentinel-2** scenes with 12 spectral bands at 20 m resolution. (Prithvi-EO 2.0 [7] was evaluated initially but excluded from fusion due to a resolution mismatch)
- **Task:** Binary semantic segmentation of burned area from paired pre- and post-fire Sentinel-2 imagery.

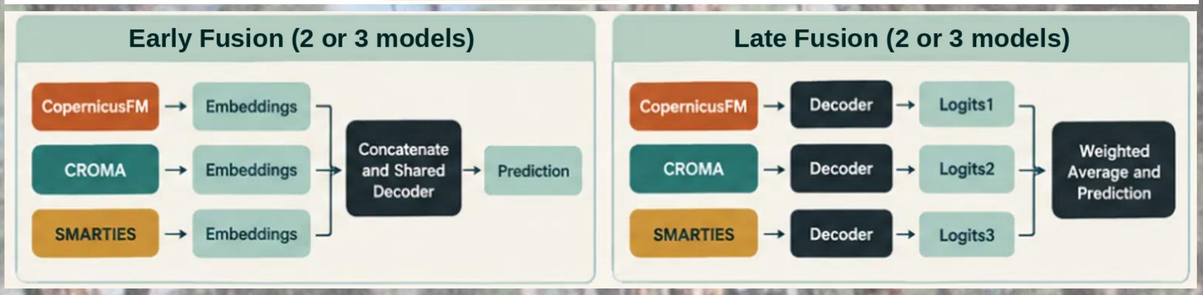
Individual Foundation Model Results (Linear Probe)

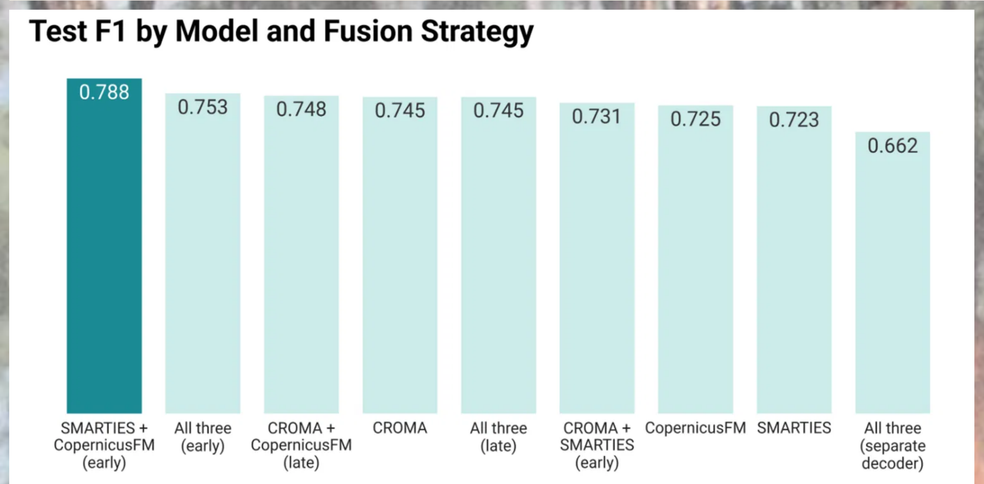
Foundation Model	Decoder	Test F1 ↑	Test mIoU ↑	Precision	Recall
Prithvi EO 2.0	Linear probe	0.7529	0.7418	0.9658	0.6169
CROMA	Linear probe	0.7447	0.5932	0.9481	0.6131
CopernicusFM	Linear probe	0.7246	0.5681	0.9344	0.5917
SMARTIES	Linear probe	0.7229	0.5660	0.9424	0.5863

References

[1] Cambrin et al., CaBuAr, IEEE GRSM 2023.
[2] Wang et al., CopernicusFM, ICCV 2025.
[3] Fuller et al., CROMA, NeurIPS 2023.
[4] Sumbul et al., SMARTIES, ICCV 2025.
[5] Xiao et al., UPerNet, ECCV 2018.
[6] Ronneberger et al., U-Net, MICCAI 2015.
[7] Szwarcman et al., Prithvi-EO-2.0, arXiv 2024.



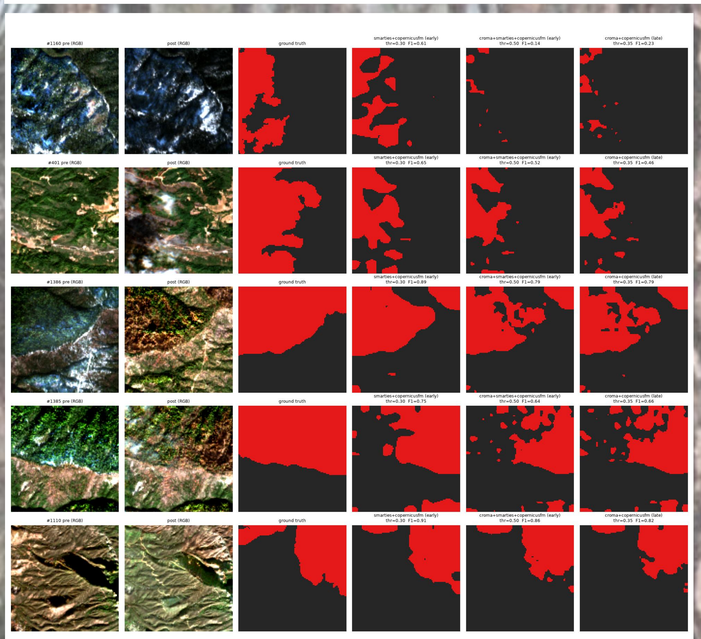




Best Test F1
0.7878
SMARTIES + CopernicusFM (Early Fusion)

Highest Precision
0.9744
CROMA + SMARTIES (Late Fusion)

Best Test mIoU
0.6499
SMARTIES + CopernicusFM (Early Fusion)



Key

1 Pre-fire (RGB)
2 Post-fire (RGB)
3 Ground truth
4 SMARTIES + CopernicusFM (early)
5 CROMA + SMARTIES + CopernicusFM (early)
6 CROMA + CopernicusFM (late)

Burned Unburned

Acknowledgements

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Methodology

- **Frozen encoders** — weights fixed during training; only decoder updates
- **224×224 crops** — tiled inference at test time covers full 512×512 scenes
- **Combined Dice+BCE loss** — handles severe class imbalance (<5% burned pixels)
- **Feature fusion** — compare separate-decoder, early, and late fusion of **two or three** foundation-model representations.

Key Findings

- **Fusion is selective** — **SMARTIES + CopernicusFM** (early) beats the best single encoder, CROMA, by +0.043 F1, but **CROMA + CopernicusFM** (early) falls below
- **SMARTIES + CopernicusFM** achieves the best test F1 (0.7878) and mIoU (0.6499)
- **CROMA + SMARTIES (late fusion)** achieves the highest test precision (0.9744)

Challenges

- **Class imbalance** — burned pixels constitute <5% of each scene; addressed with combined Dice+BCE loss
- **Spectral adaptation** — CopernicusFM was pretrained on different band configurations than CaBuAr's 12-band Sentinel-2 input

Conclusion and Future Work

- **Frozen encoders** with a trained linear probe reach F1 = 0.7878 and mIoU = 0.6499 (SMARTIES + CopernicusFM, early fusion)
- **Gains come from recall** — SMARTIES + CopernicusFM (early fusion) achieves recall of 0.6767 vs. 0.6131 for CROMA, while maintaining precision of 0.9426.
- **Future:** Add **SpectralGPT** and **SatMAE** to the fusion group; evaluate on additional wildfire datasets beyond California; explore active learning for rare fire event annotation; move from binary to multi-class severity for burned areas; calibrate thresholds or learn them on validation data

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