

Fire Characterization and Fire-Related Land Cover Classification Using Hyperion Data over Selected Alaskan Boreal Forest Fires

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Motivation

- Boreal forest fires play an important role in influencing regional ecology, air quality, and climate.
- Imaging spectroscopy has great potential to investigate such fires and related landcover changes, but has been under-utilized so far
- Imaging spectroscopy data for Alaskan boreal forest fires (eg. from AVIRIS) is practically non-existent.
- A limited number of EO-1 Hyperion scenes are available for active boreal forest fires. Despite being noisy, they serve as a good basis to explore the applicability of current and future imaging spectroscopy data for boreal fire related studies.

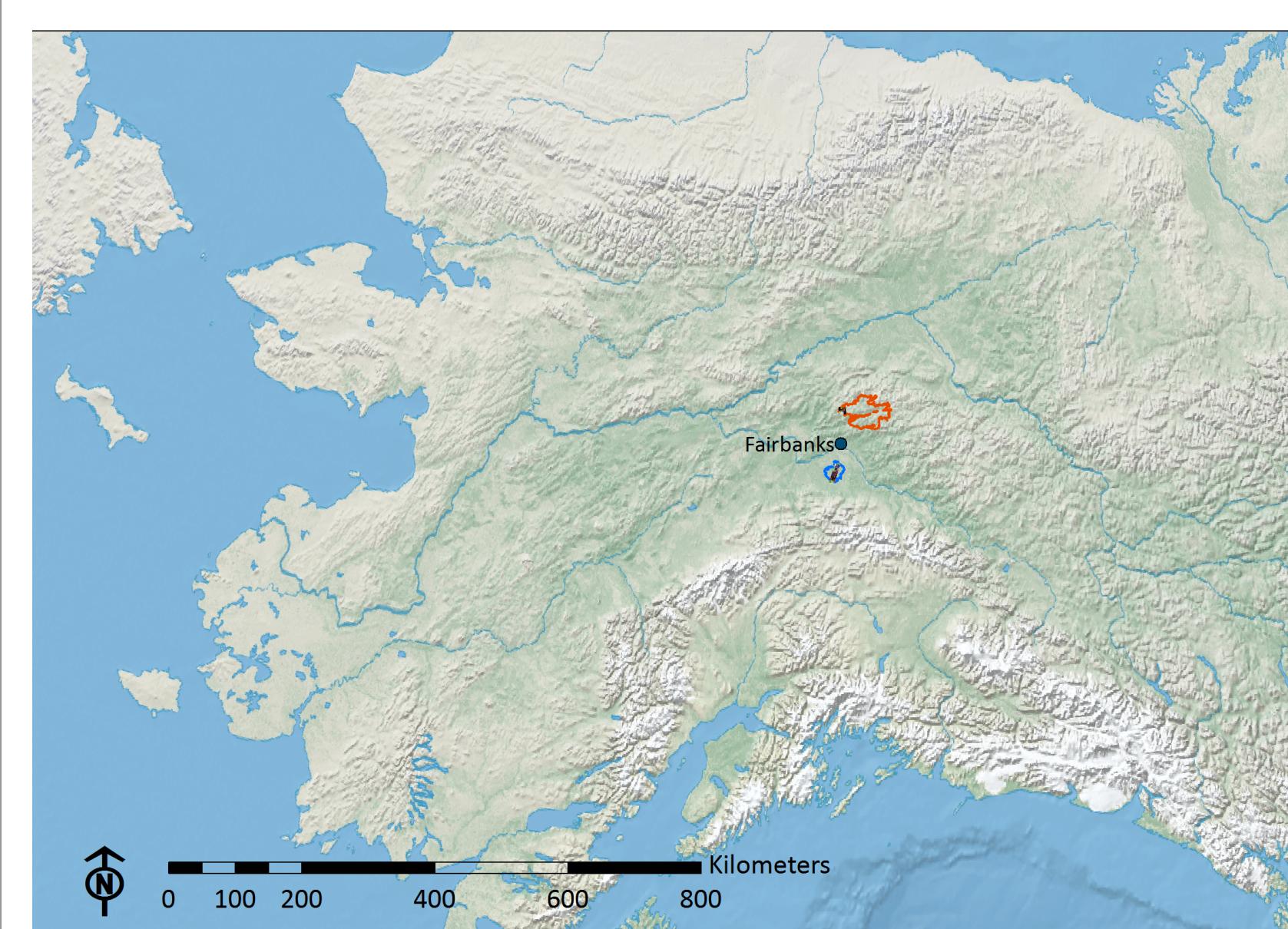
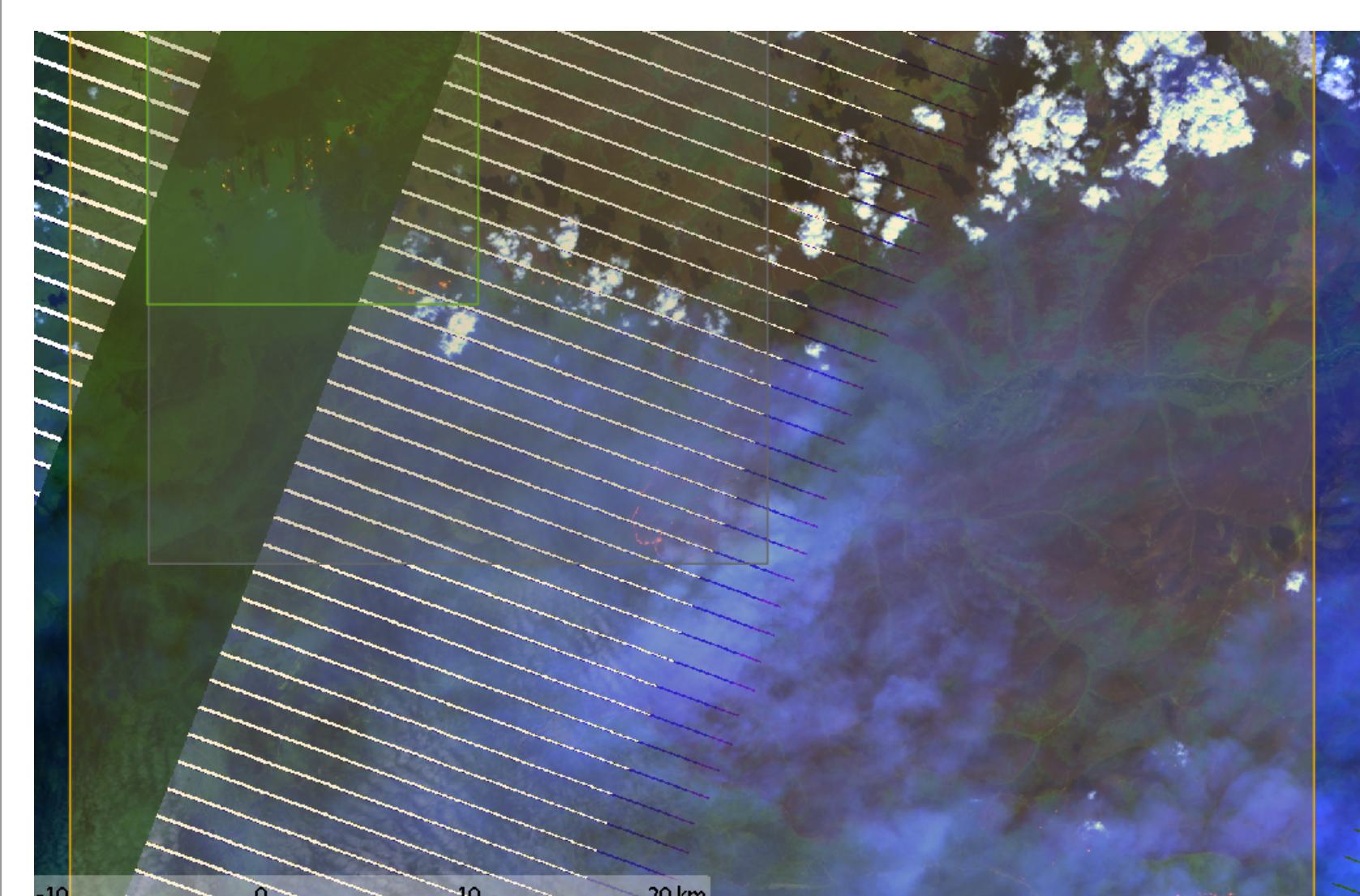
Science questions:

- Can the spectral information be used to distinguish fire-related landcover classes (high-intensity fire, low-intensity fire, etc.)?
- What is the best method to detect fire using imaging spectroscopy data?
- How can sub-pixel temperature and fractional area be extracted?

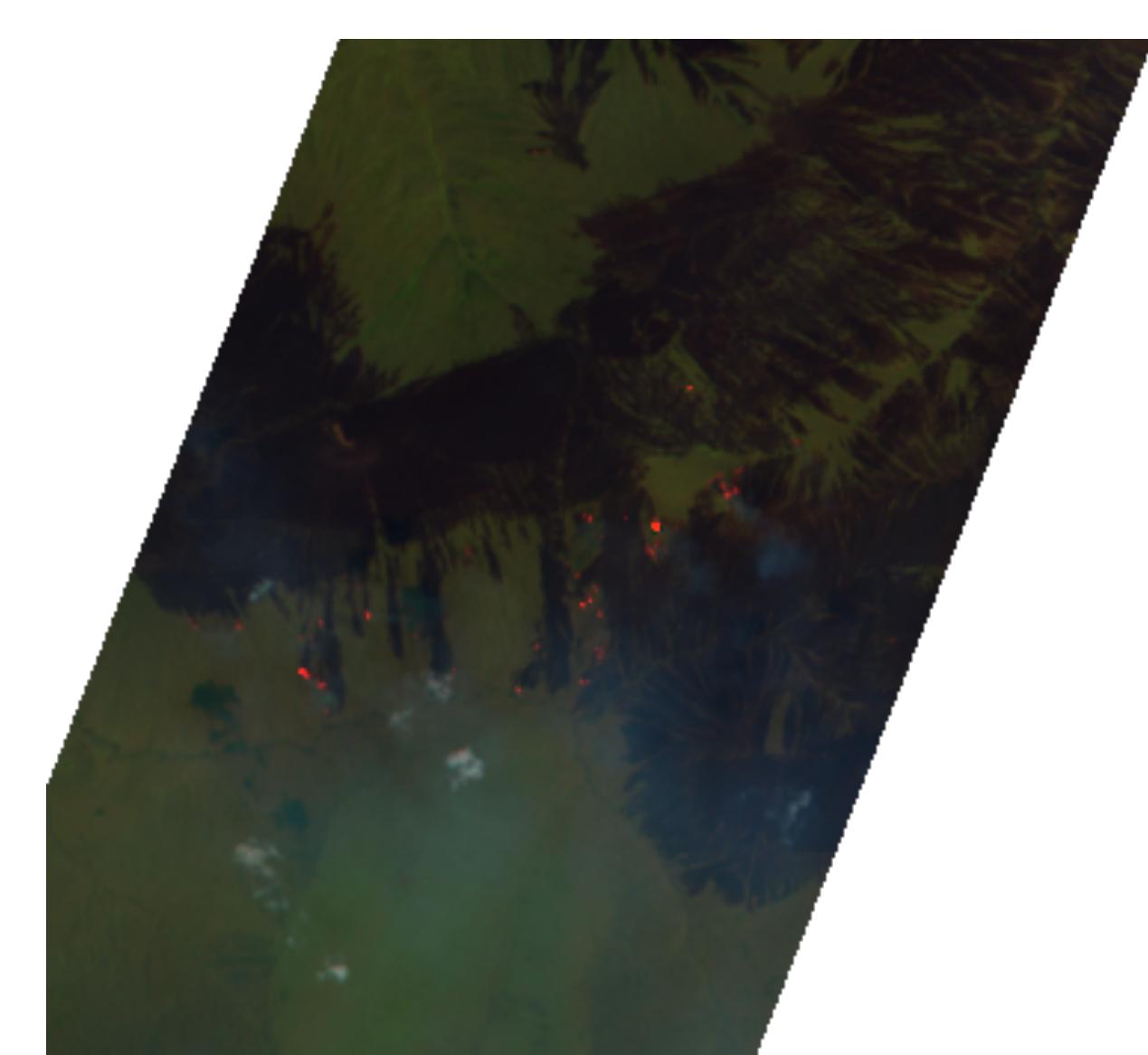
Study Areas

Two large fire events during dry high-fire years. Both strongly impacted Fairbanks air quality.

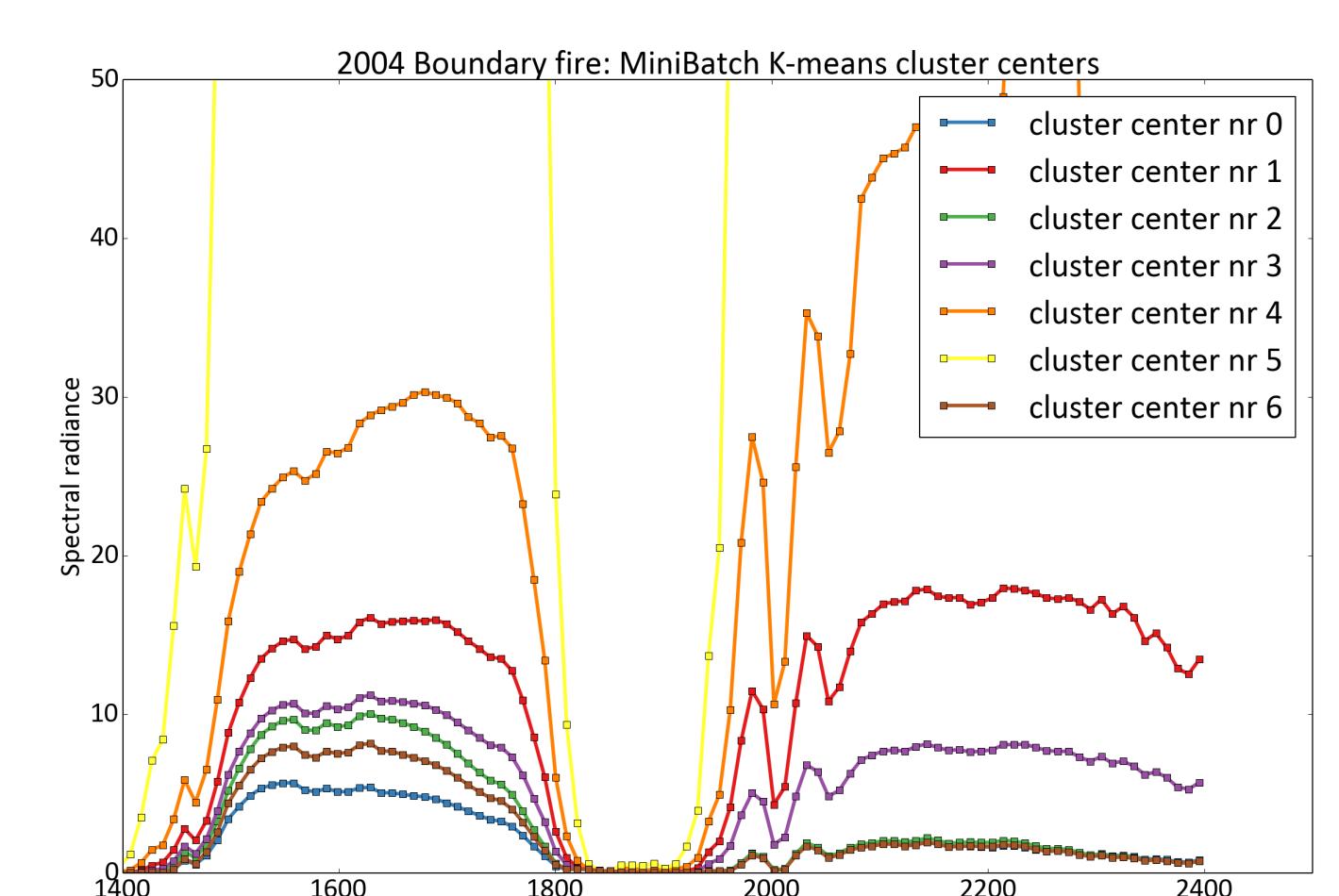
- North: 2004 Boundary Fire
- South: 2009 Wood River 1 Fire



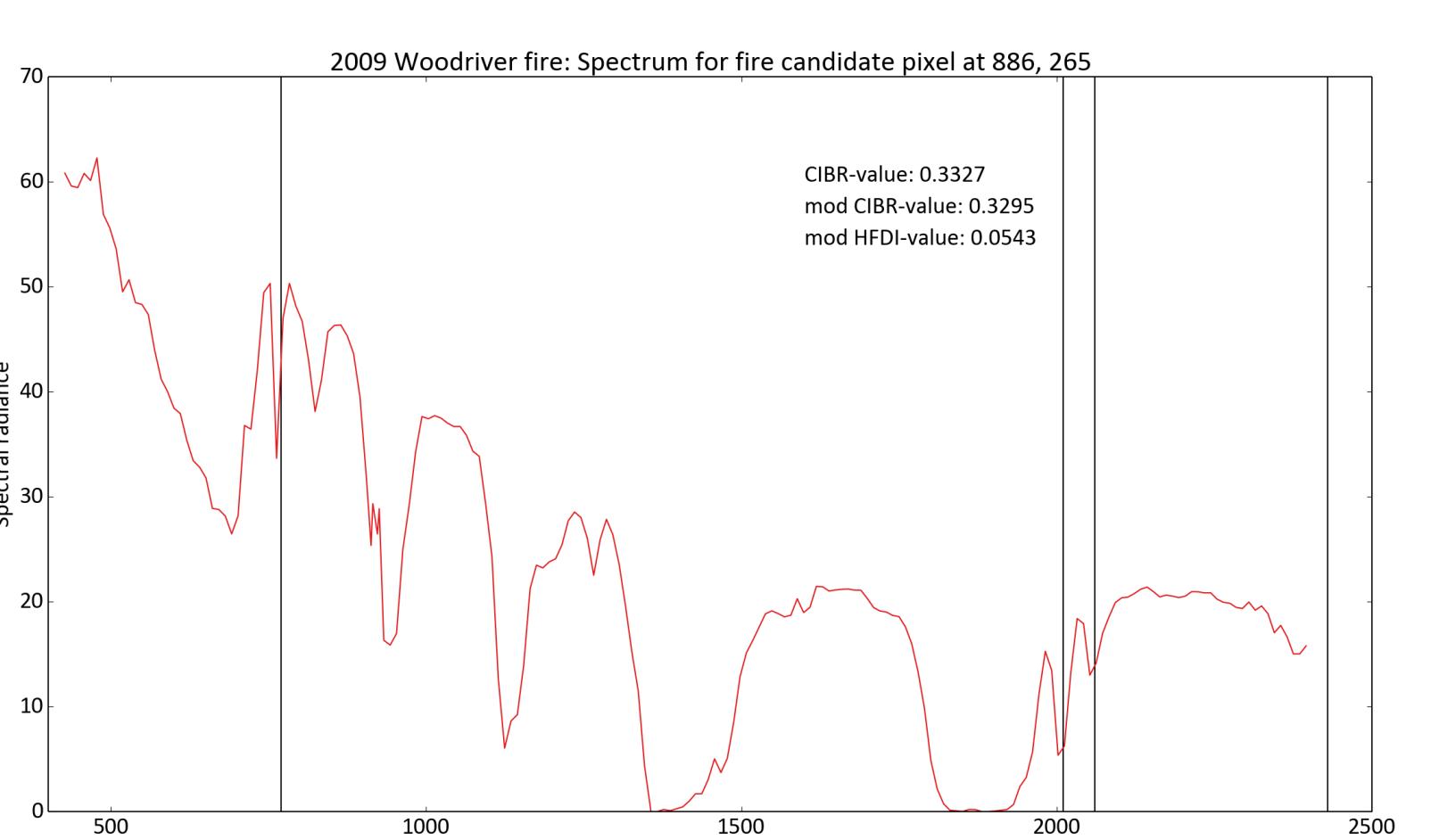
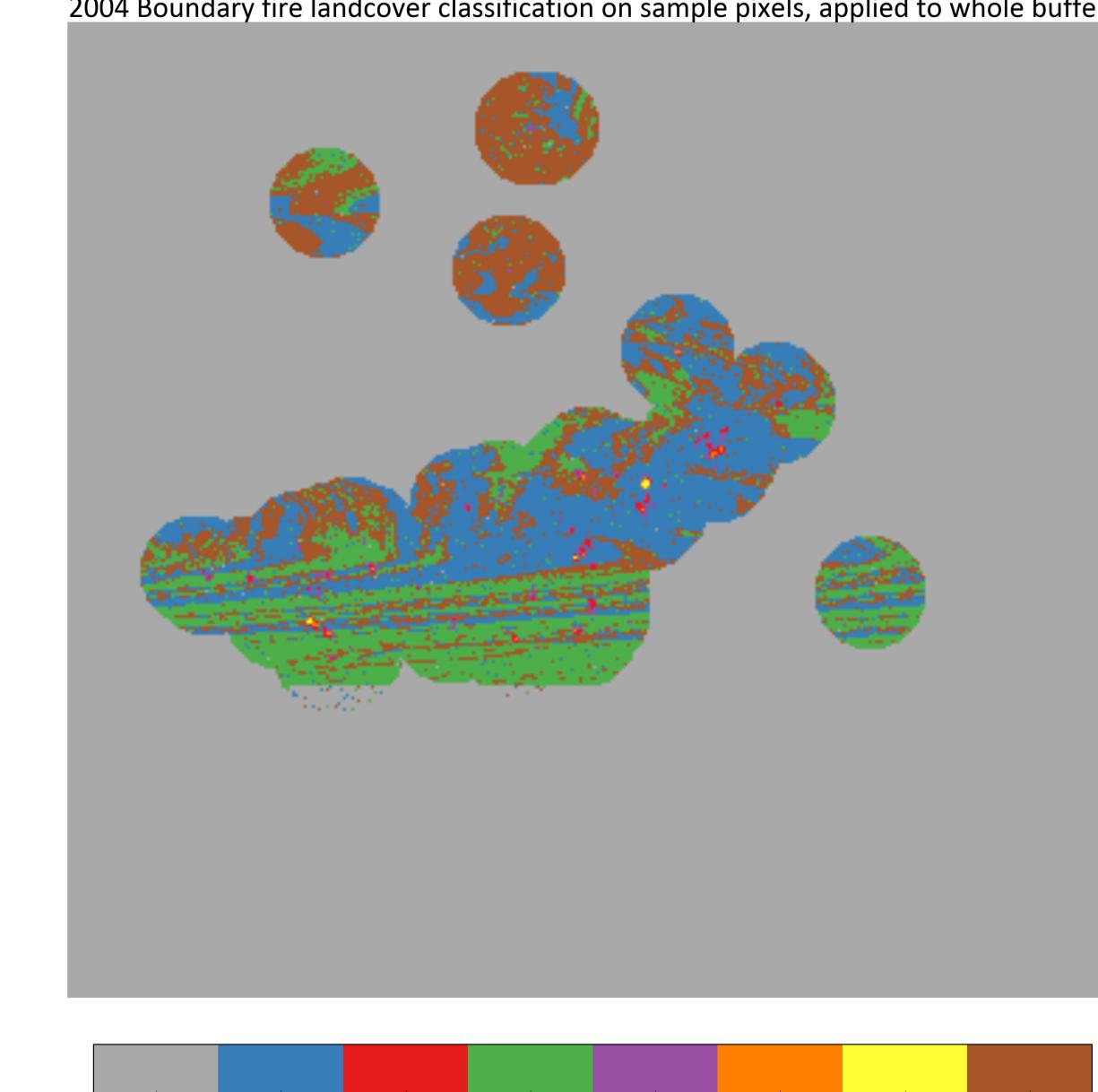
Results



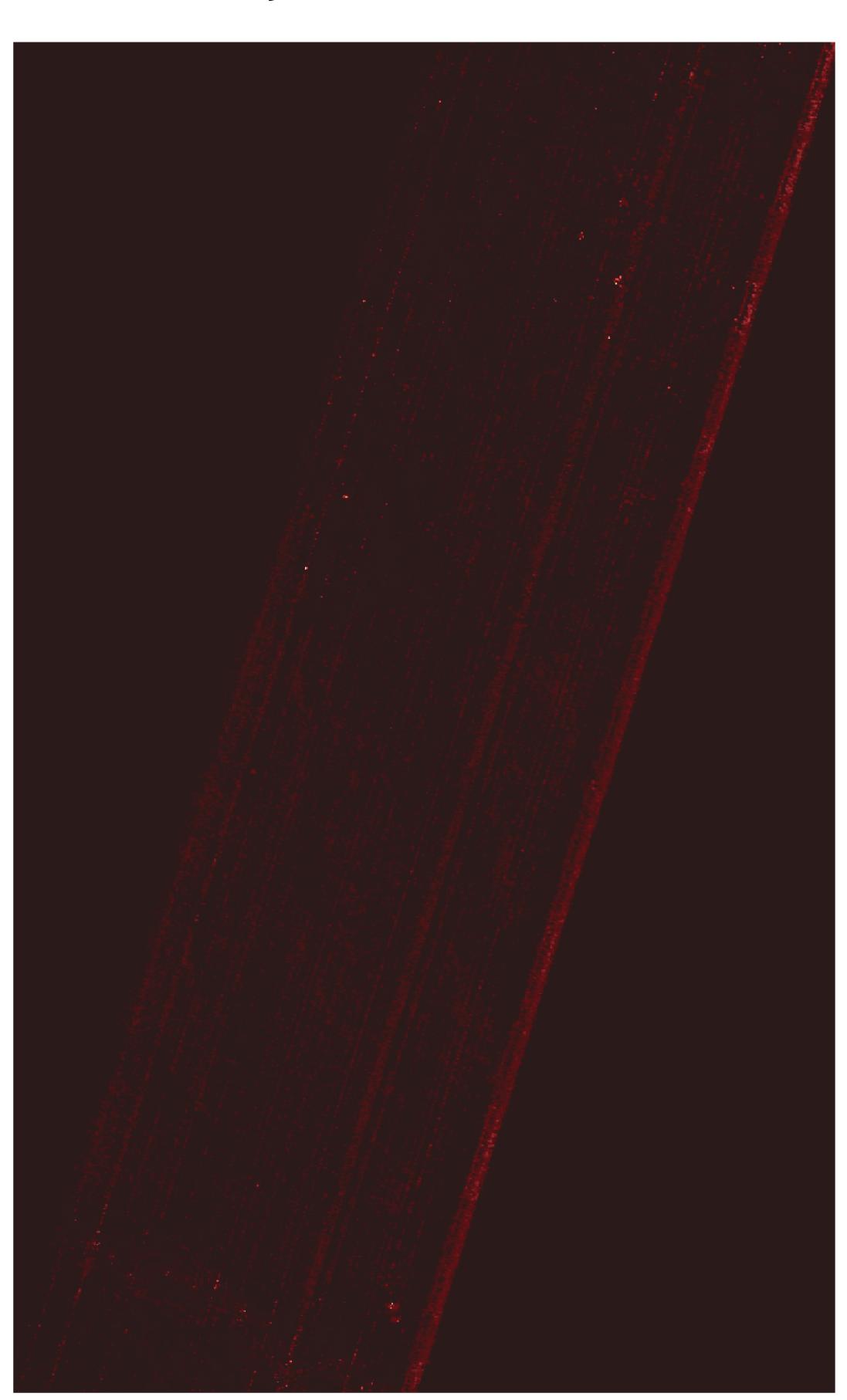
Example of cluster centers after K-Means clustering based on mixed sample of fire and vicinity pixels



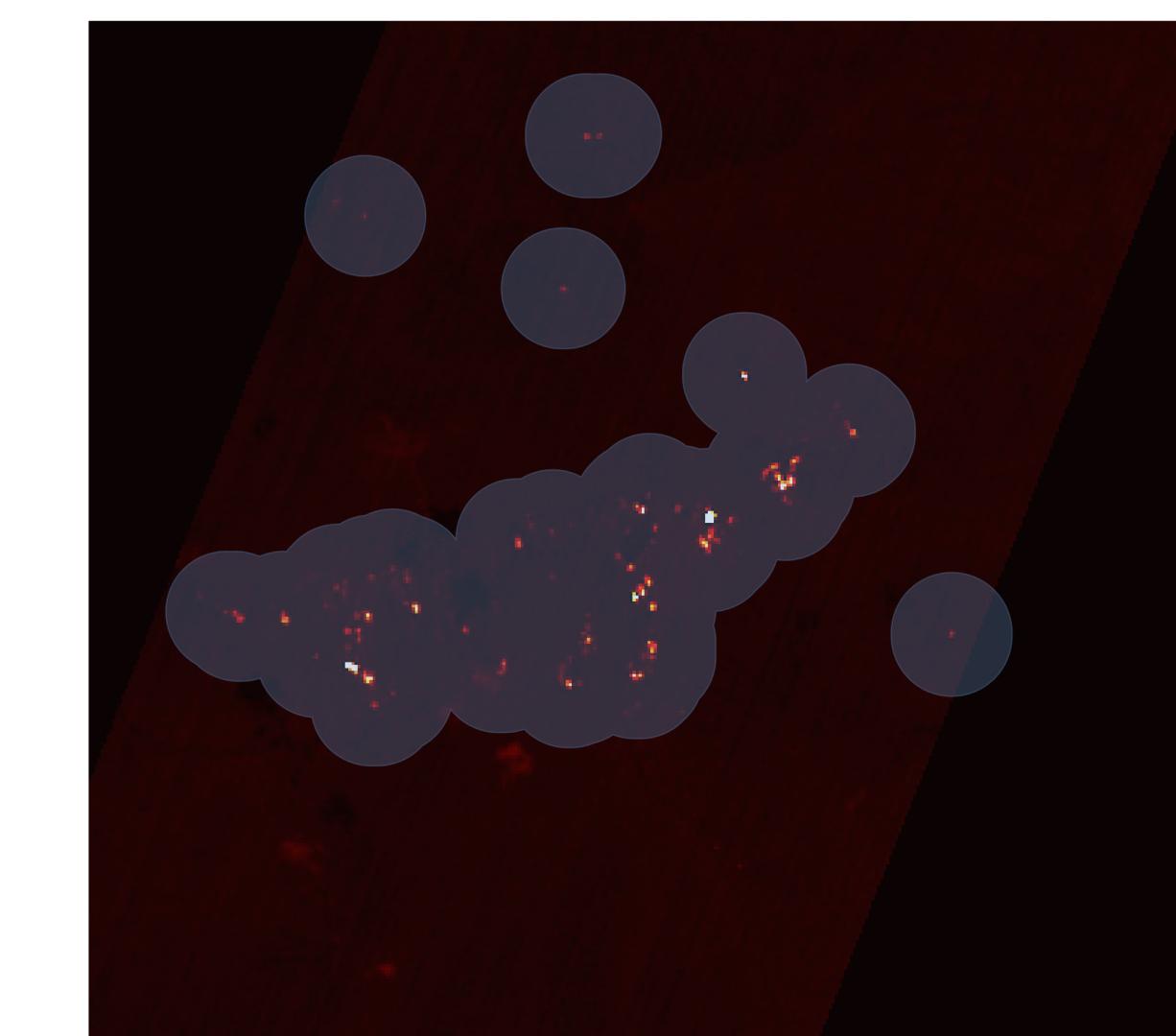
2004 Boundary fire: landcover classification on sample pixels, applied to whole buffers



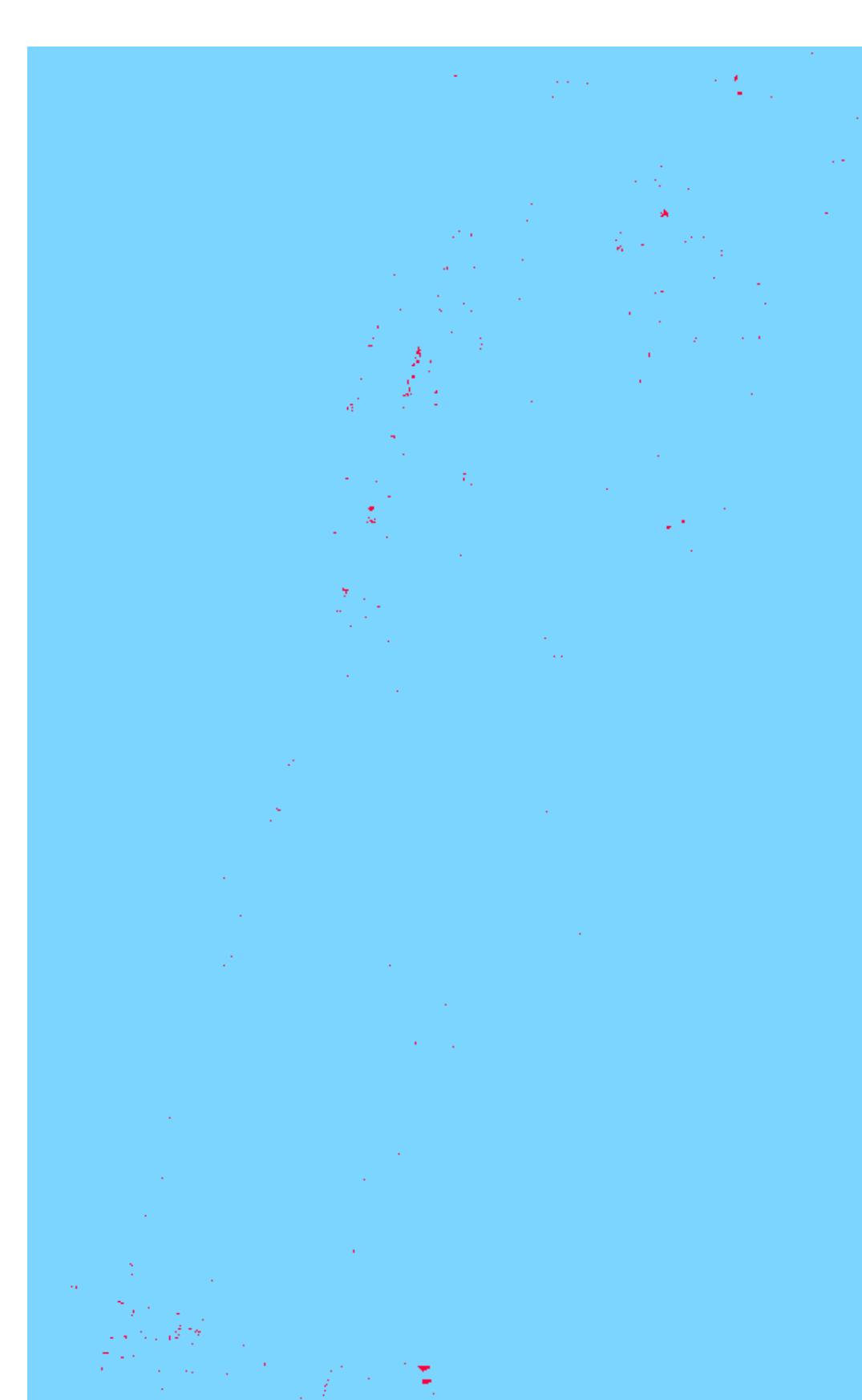
mod-CIBR map for 2009 Wood River 1 fire



Band 210, 2004 Boundary:
600m radius buffers around pixels with $L > 5W/m^2 \mu m sr$



mod- HFDI w/bands (191, 217)
threshold 0.5 STD below max



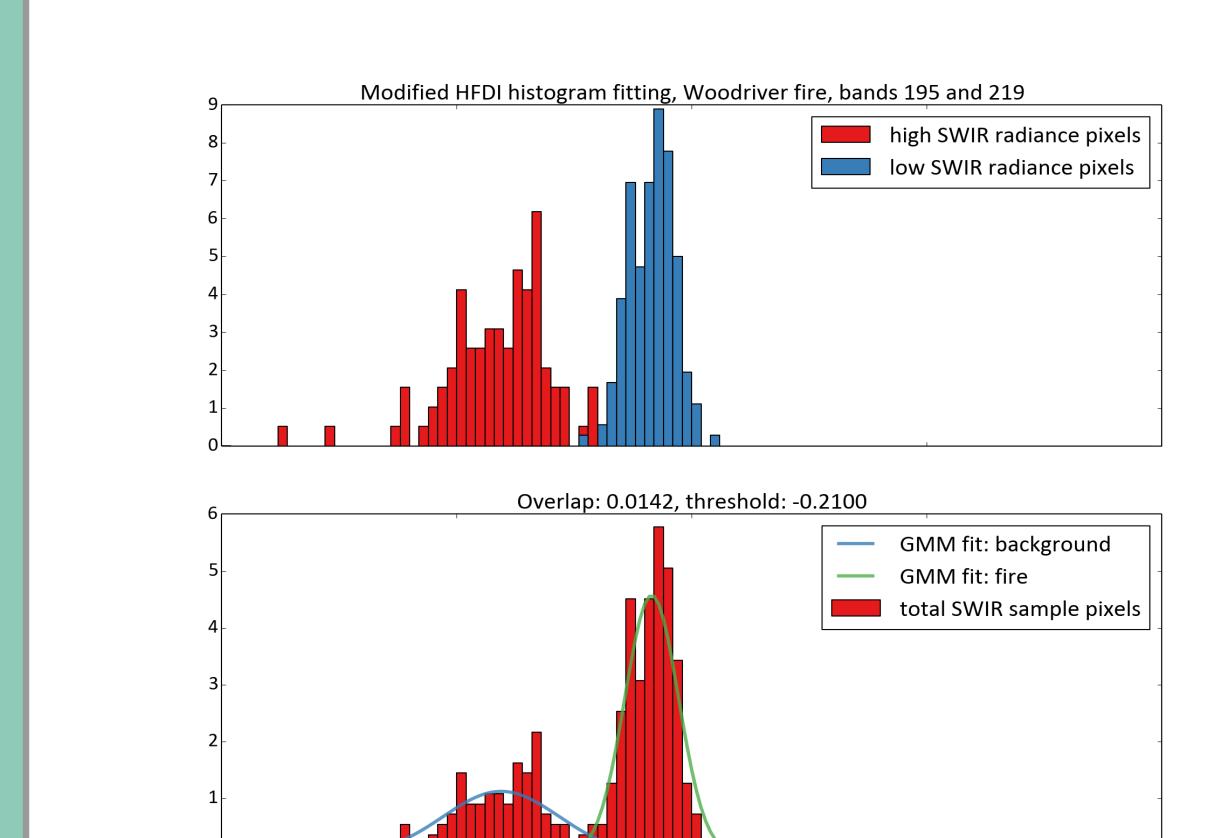
Discussion

Results:

- Fire detection using modified HFDI and CO₂ CIBR in combination is successful.
- Band selection for HFDI can be initialized from fire pixels determined by unsupervised classification.
- Iteratively, the detected fire pixels are used to refine the sample selection used as input for clustering. Initially, we used a heuristic at-sensor radiance threshold in a suitable SWIR band.
- Fire-related landcover classification with clustering (5 or 6 clusters) reveals a landcover class adjacent to and ahead of the active fire which, even though unburnt vegetation, shows distinct spectral differences from both unaffected and burnt vegetation.

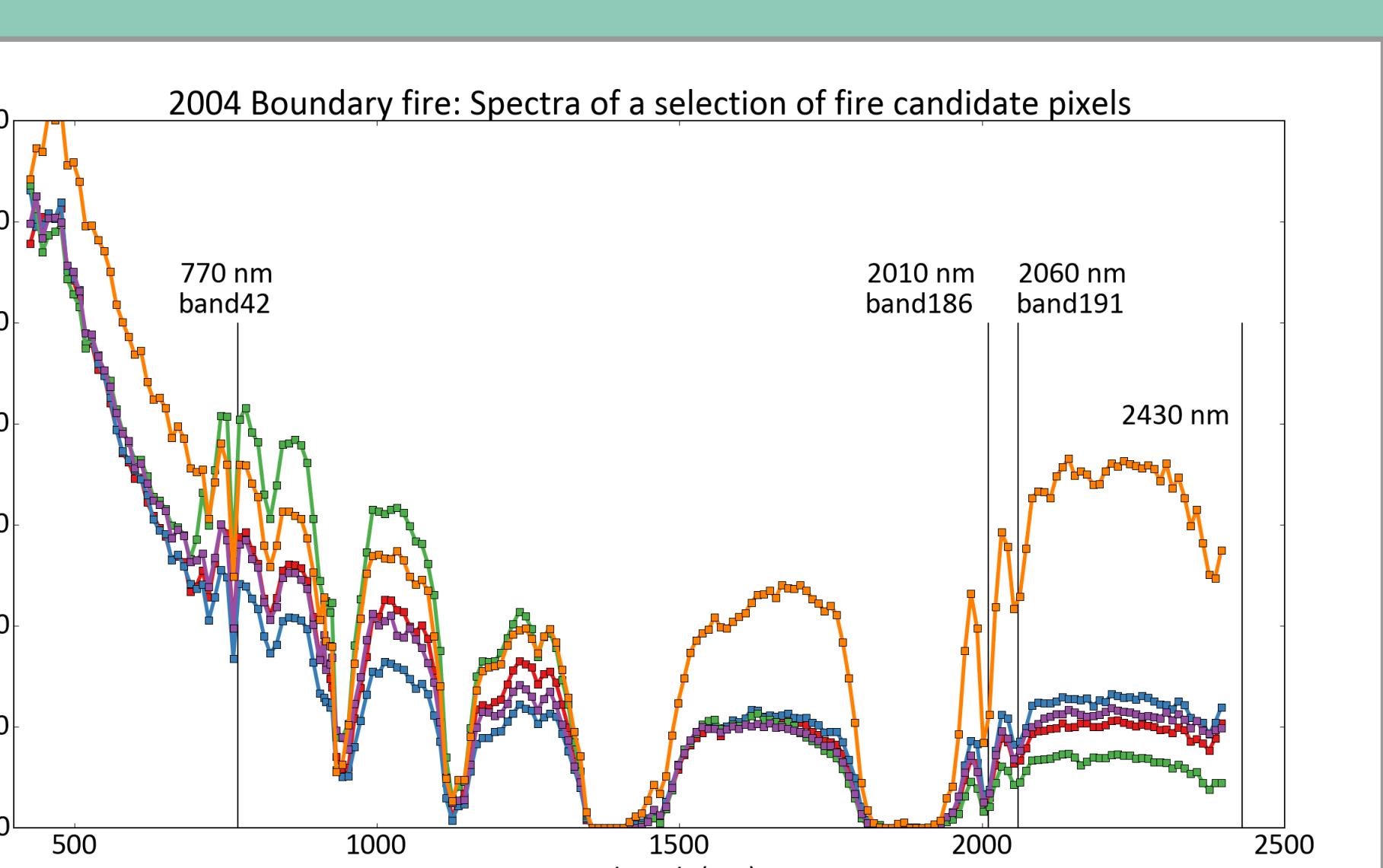
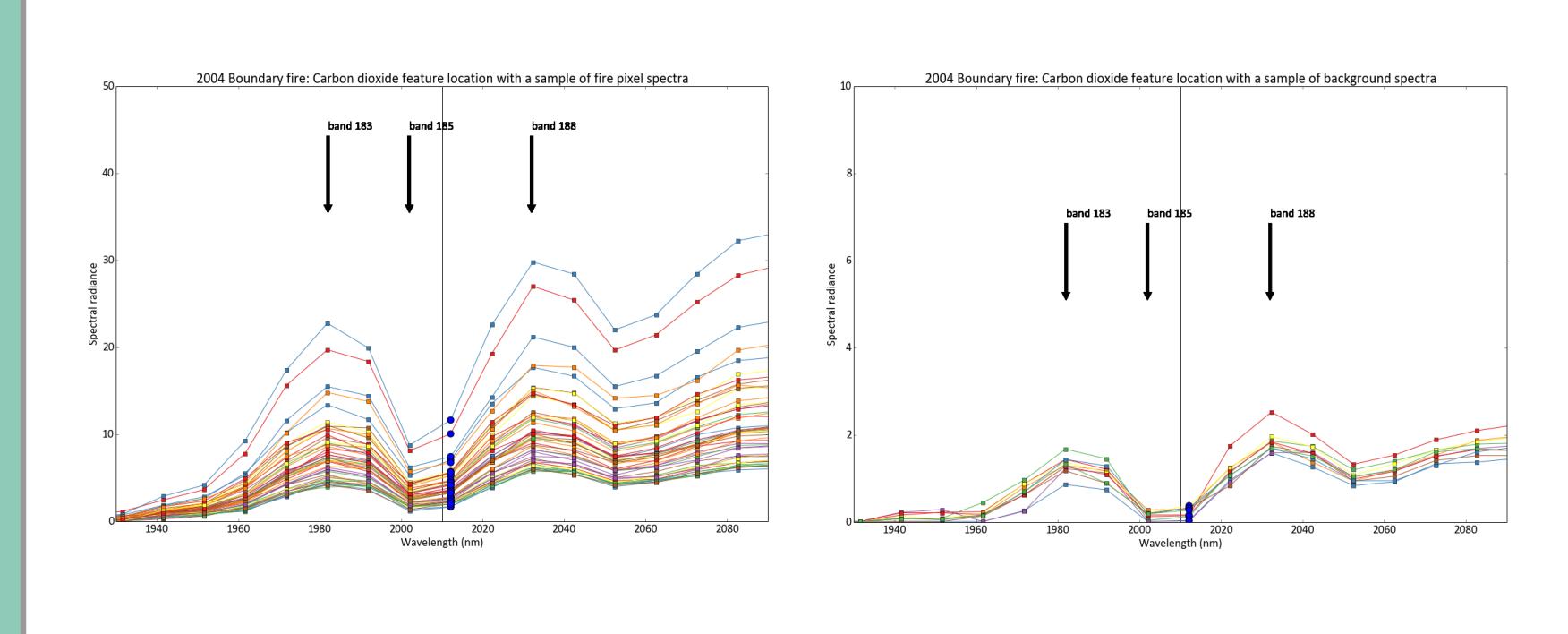
Future outlook:

- In-State capability for airborne imaging using sensors such as Hypesp and FLIR, and data collection using aerosol particle sampler will further enhance this research.
- We will be able to better characterize low-intensity burns, unburnt forests adjacent to the fires, and emissions from flaming and smoldering fires.
- Planned hyperspectral satellite missions, such as HypSIRI, will change the way in which we currently investigate high-latitude boreal forest fires.



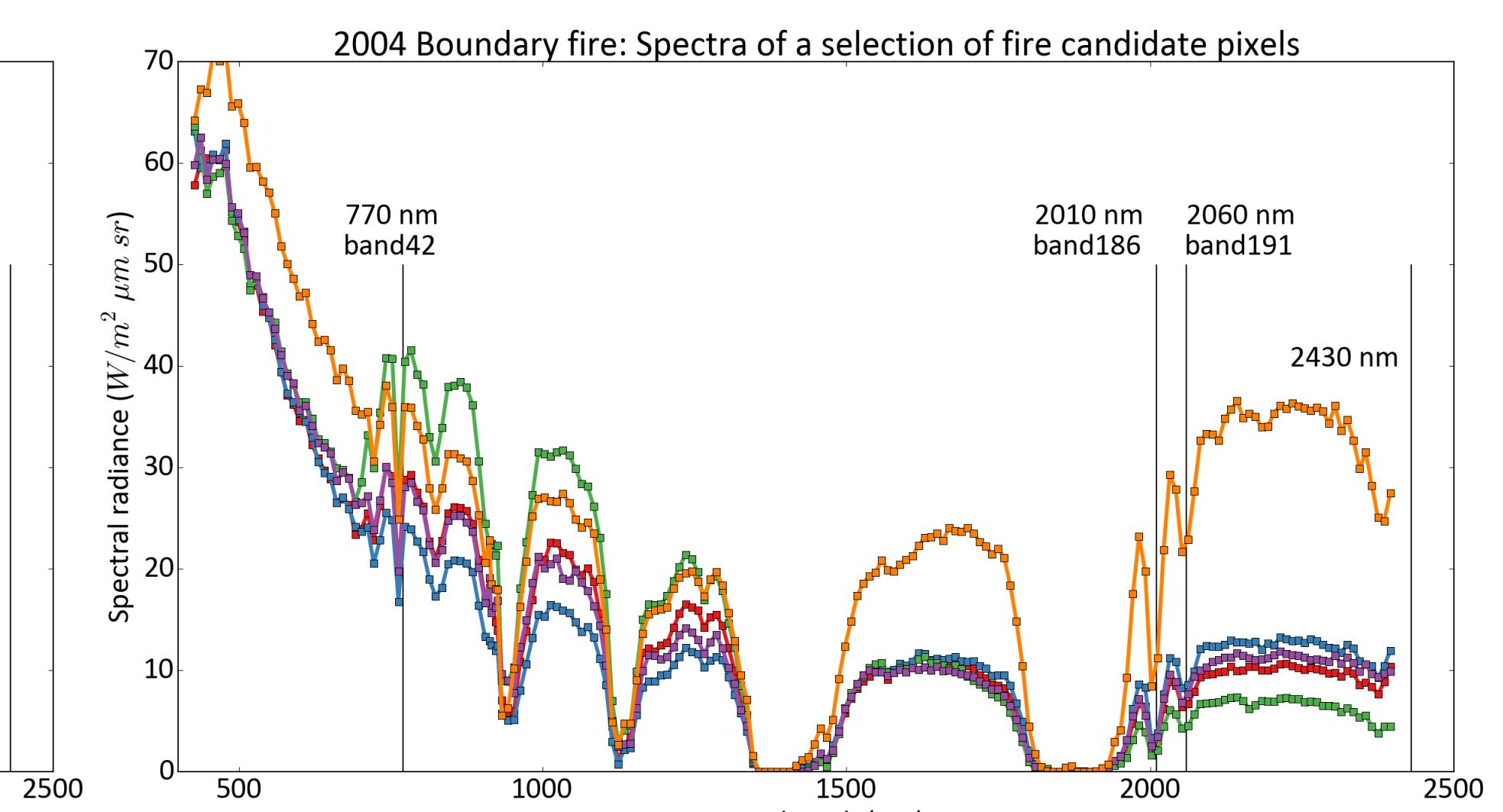
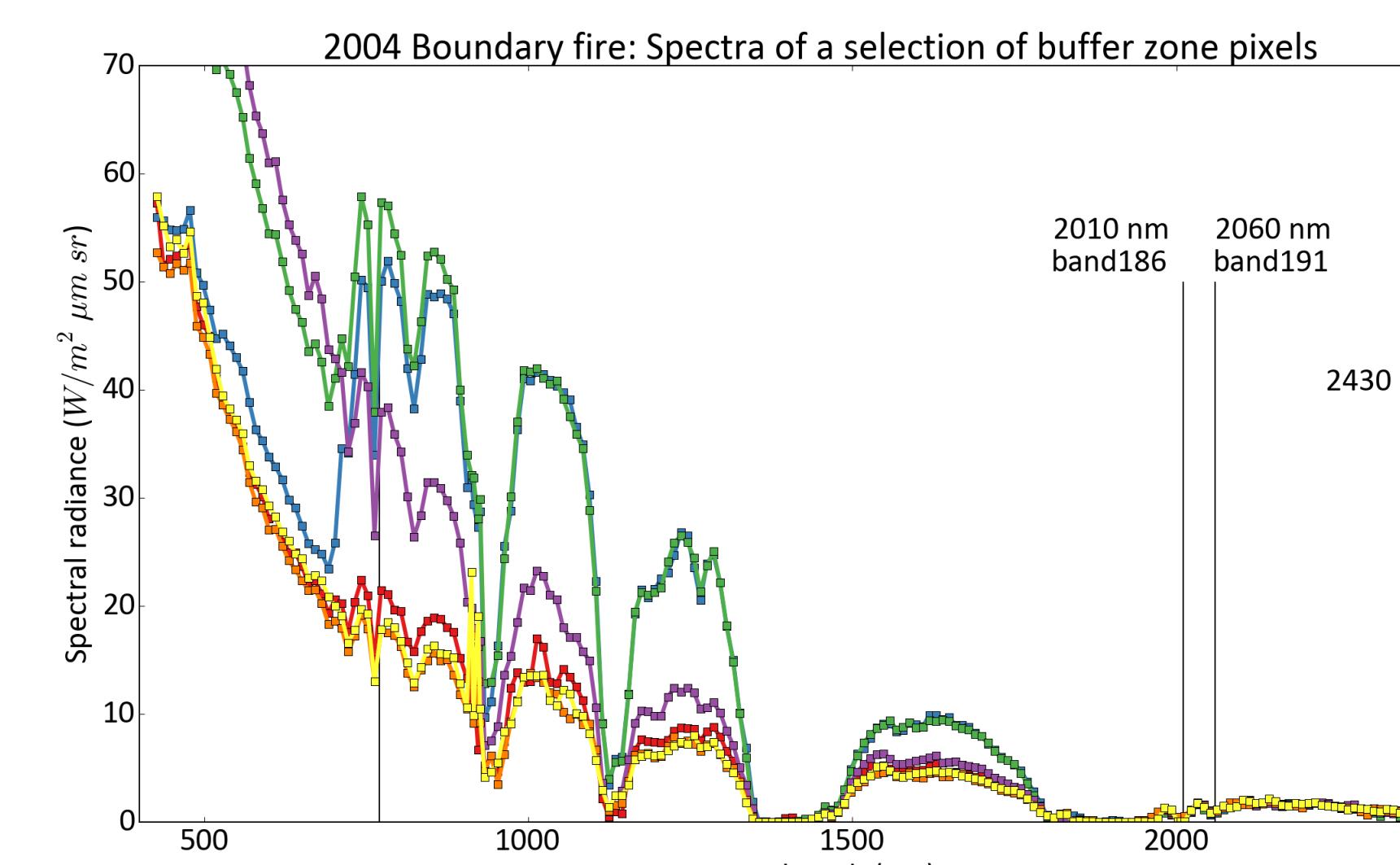
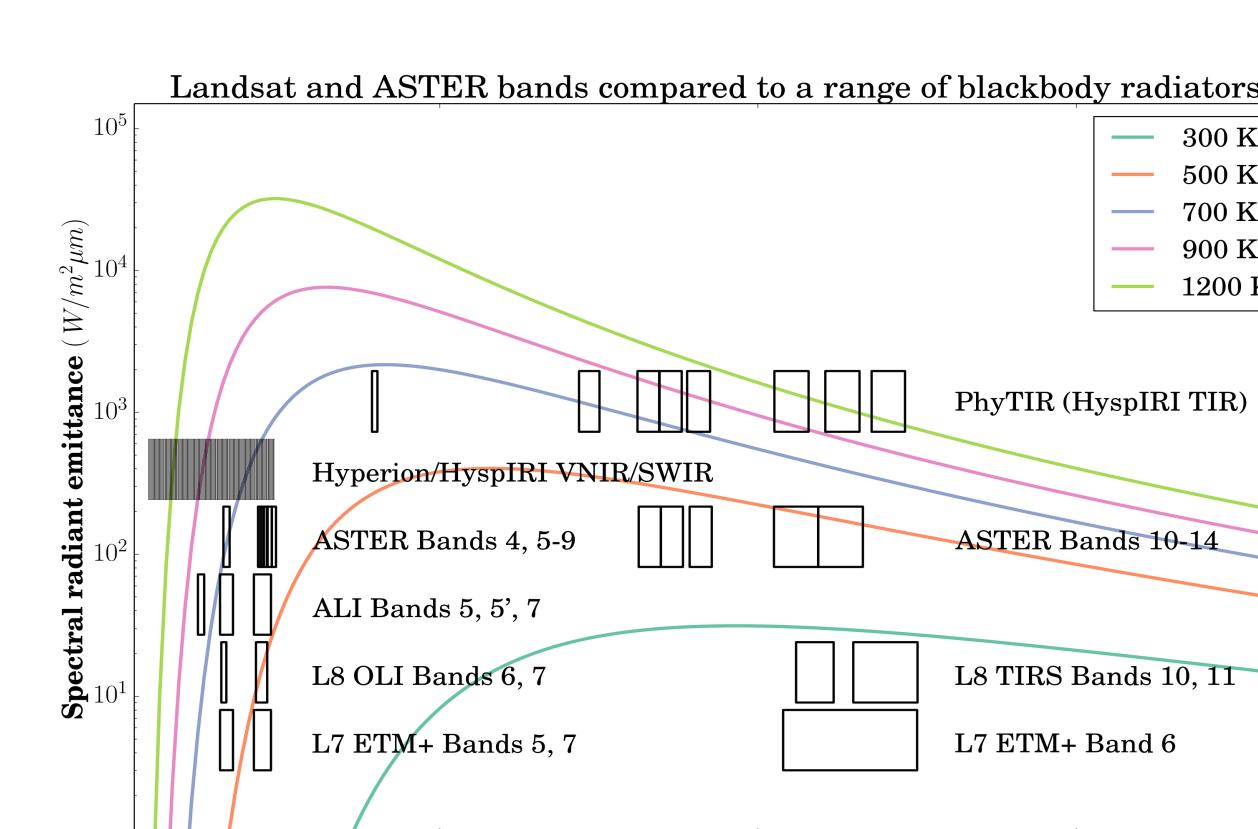
The bands selected to calculate HFDI were determined by using a 2-component Gaussian Mixture Model

Band Selection for CO₂ CIBR



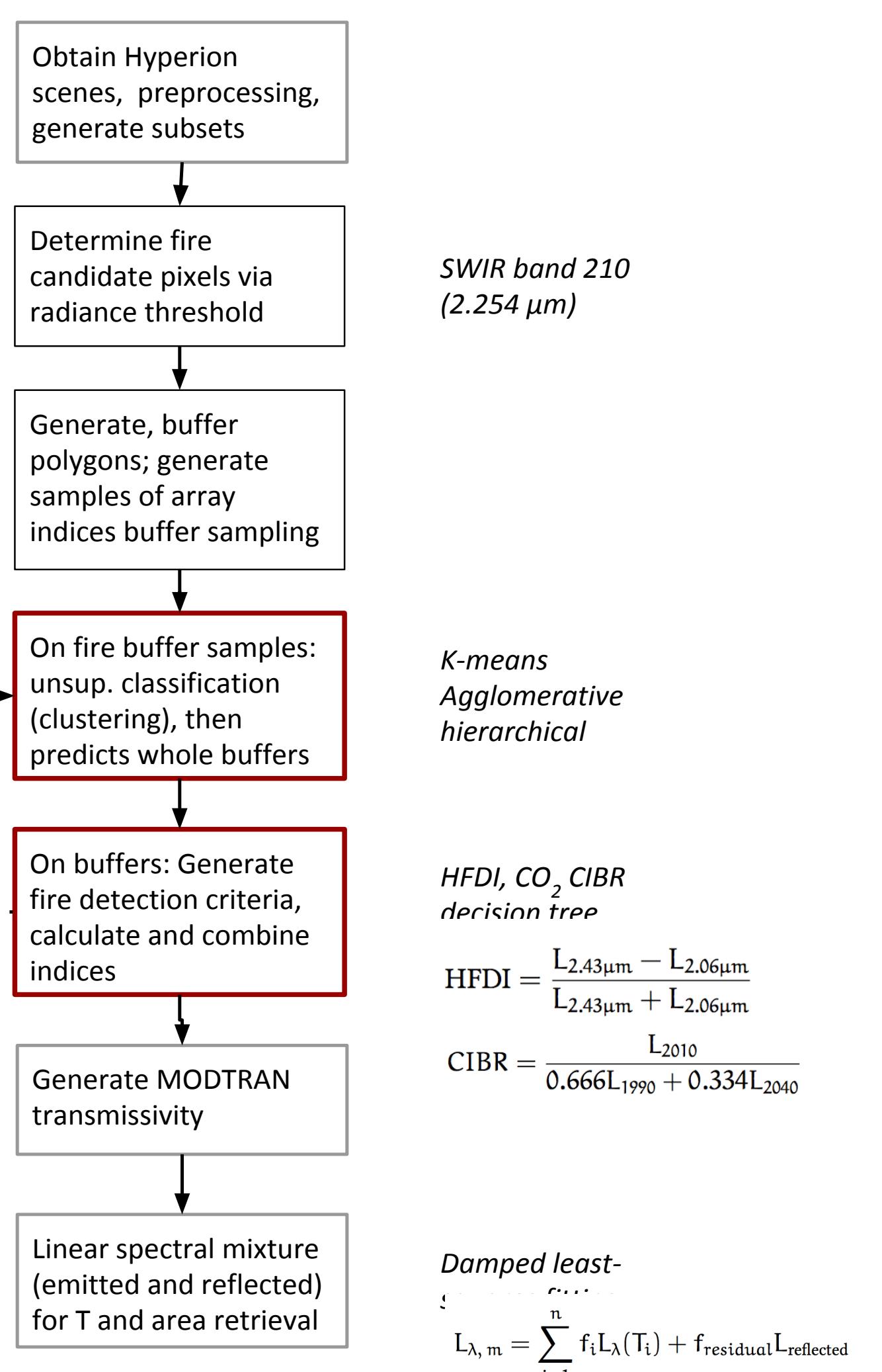
Data

- 2004 Boundary: EO-1 Hyperion EO1H0690142004201 of July 19, 2004 (and L7 ETM+ LE70690142004201EDC01); moderately dense black spruce (*Picea mariana*) on hilly topography, some alpine tundra.
- 2009 Wood River 1 : EO-1 Hyperion EO1H0690142009214 of August 2, 2009 (and L7 ETM+ LE70690152009214EDC00); sparser black spruce and brushwork and located on the Tanana River floodplain on military land.



Methods

Processing workflow
The highlighted steps are the object of this presentation



The work is currently in progress. The scope is:

- Fire-related landcover classification uses a machine-learning approach and only the SWIR part of the spectra: K-means and hierarchical clustering (agglomerative) are suitable. Restarting the algorithm multiple (N=100) times helps escape local minima.
- Fire detection: We developed suitable modifications to the Hyperspectral Fire Detection Index (HFDI). Mod-HFDI thresholds are determined by fitting a Gaussian Mixture Model (GMM) and selecting cut-offs based on the "fire pixel" HFDI standard deviation.
- The CO₂ Continuum Interpolated Band Ratio (CIBR) is affected by sensor noise. High-intensity fire is detected, but there are false positives. CIBR and HFDI can be combined using machine learning (decision tree).
- Ka-emission based fire detection did not yield results, likely due to excessive sensor noise.
- Sub-pixel T and fractional area retrieval via spectral mixture model.

Acknowledgements

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References & contact

Philip E. Dennison and Dar A. Roberts. Daytime fire detection using airborne hyperspectral data. *Remote Sensing of Environment*, 113(8):1646–1657, August 2009. ISSN 0034-4257. doi:10.1016/j.rse.2009.03.010.

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