Pixel Level Smoke Detection Model with Deep Neural Network

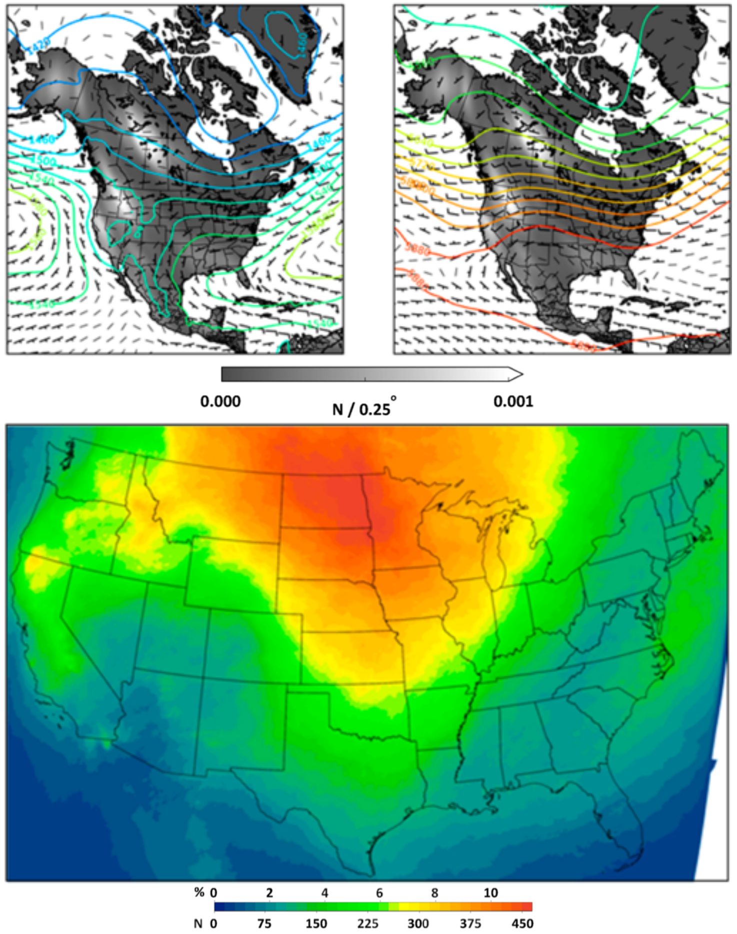
Muthukumaran Ramasubramanian[1], Aaron Kaulfus[1] , Manil Maskey[2], Rahul Ramachandran[2], Iksha Gurung[1] , Brian Freitag[1], Sundar Christopher[1]

1-University of Alabama in Huntsville
2-NASA/Marshall Space Flight Center

SPIE Remote Sensing 2019. September 9-12, 2019. Strasbourg, France

Introduction

- Biomass burning smoke has numerous detrimental environmental and ecological impacts
    - Respiratory and cardiovascular illnesses
    - Radiation budget
    - Nutrient availability
- Impacts realized both near source and potentially thousands of kilometers downwind depending on
    - Fire duration
    - Amount and type of biomass burned
    - Meteorological and fuel conditions
    - Vertical distribution in the atmosphere



Spatial distribution of MODIS fire occurrence and NOAA HMS smoke for summer 2006-2015. From Kaulfus et al. 2017 Figure 2.

Introduction

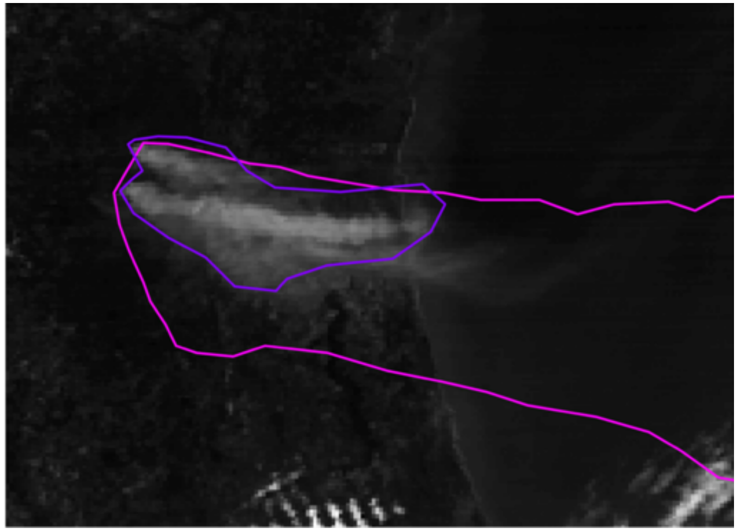
- Current detection methods present challenges for continuous smoke detection and monitoring
  - In-situ monitoring
    - Temporal, spatial, and tracer monitoring limitations
  - Remote sensing
    - Polar orbiting, once-daily overpass
    - Manual or computational intensive multispectral analysis
    - Large data volumes
    - Multiple class multispectral classification

Objectives

- Deploy a smoke detection model using machine learning on satellite remote sensing observations
  - Leverage observations from the new generation of geostationary satellite
    - High spatial and temporal resolutions over large domains
  - Alternative to multispectral analysis
  - Eliminate time consuming, subjective manual analysis

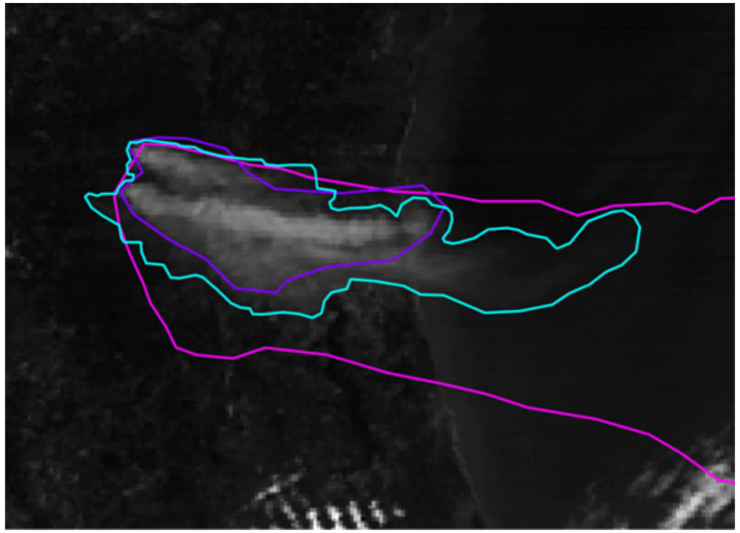
Truth Dataset

- Geostationary Operational Environmental Satellite 16 shortwave reflectance data
  - Bands 1-6 (0.47, 0.64, 0.86, 1.37, 1.6 and 2.2 μm)
  - Access L1B radiance data from AWS
  - Convert to reflectance
  - Spatially resample to 1km
- National Oceanic and Atmospheric Administration (NOAA) Hazard Mapping System (HMS) smoke analysis
  - Satellite based operational daily analysis of smoke extent over the US and surrounding areas
  - Manual quality controlled by subject matter expert to correctly match smoke extent in GOES 16 image



Truth Dataset

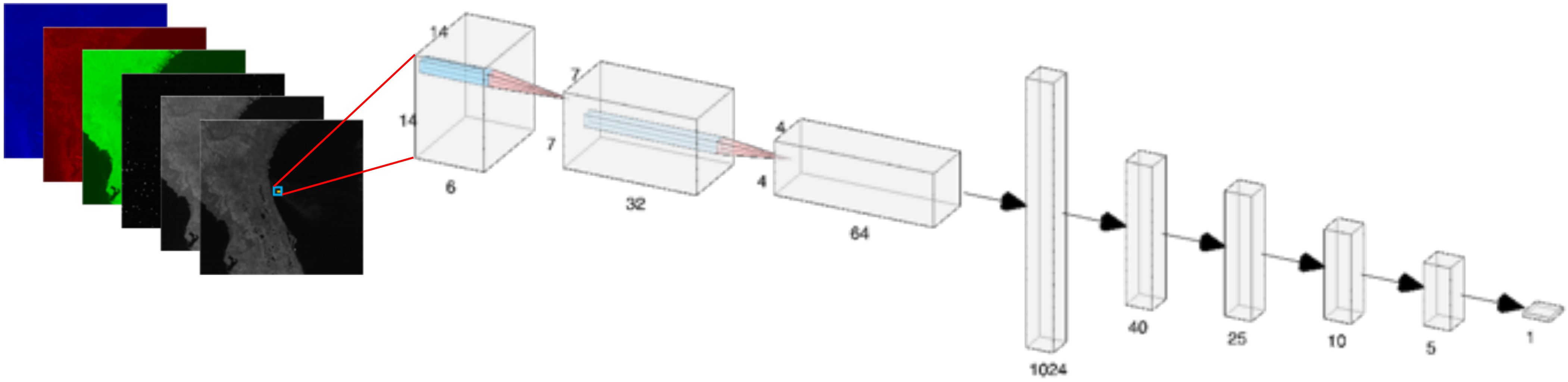
- Geostationary Operational Environmental Satellite 16 shortwave reflectance data
  - Bands 1-6 (0.47, 0.64, 0.86, 1.37, 1.6 and 2.2 μm)
  - Access L1B radiance data from AWS
  - Convert to reflectance
  - Spatially resample to 1km
- National Oceanic and Atmospheric Administration (NOAA) Hazard Mapping System (HMS) smoke analysis
  - Satellite based operational daily analysis of smoke extent over the US and surrounding areas
  - Manual quality controlled by subject matter expert to correctly match smoke extent in GOES 16 image



Truth Dataset

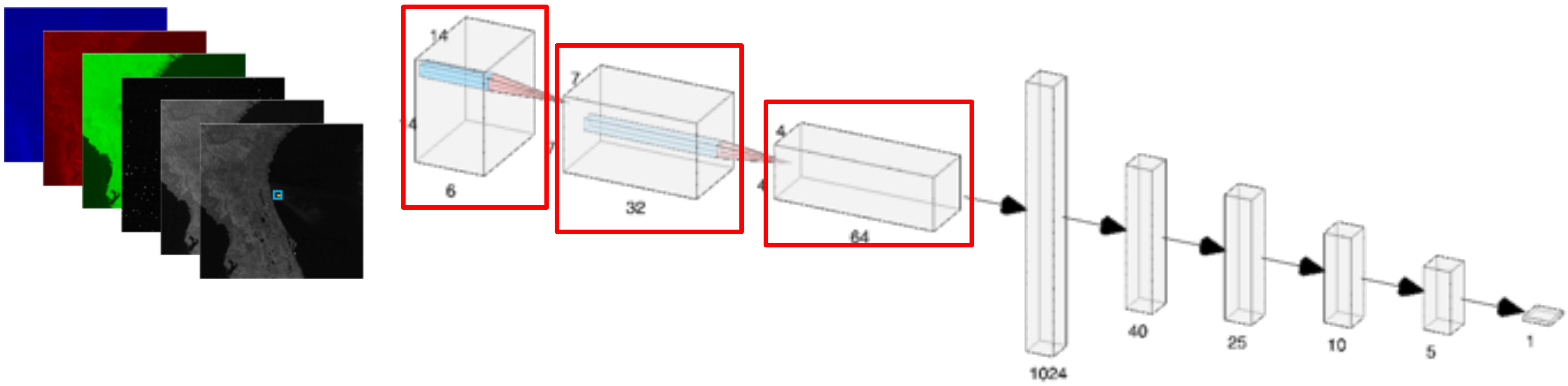
- Analyze 122 scenes containing smoke
  - 962691 smoke pixels
  - Smoke over low and high background reflectances (land and ocean)
  - Contain relevant classes to discriminate smoke from
    - Snow and ice
    - Clouds
    - Dust
  - 60% - 20% - 20% distribution of smoke pixels between training, validation and testing datasets

Model Architecture



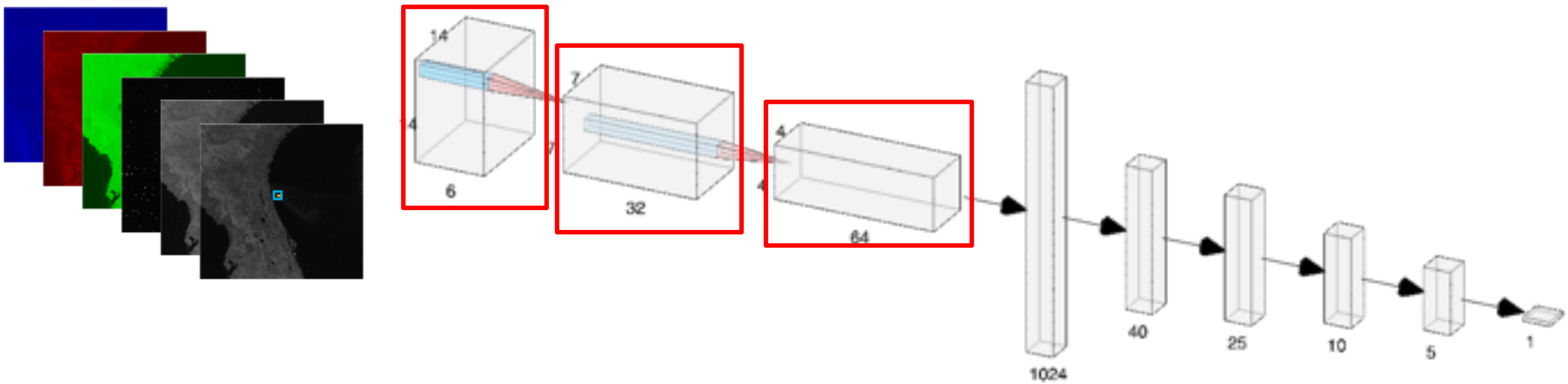
- Apply a pixel based Convolutional Neural Network (CNN)
  - Input (N*2)*(N*2) neighborhood of reflectance values surrounding a center pixel (sample)
  - 3 convolutional layers
  - Each convolutional layer followed by max-pooling layer
  - Convolutional outputs are flattened into vectors

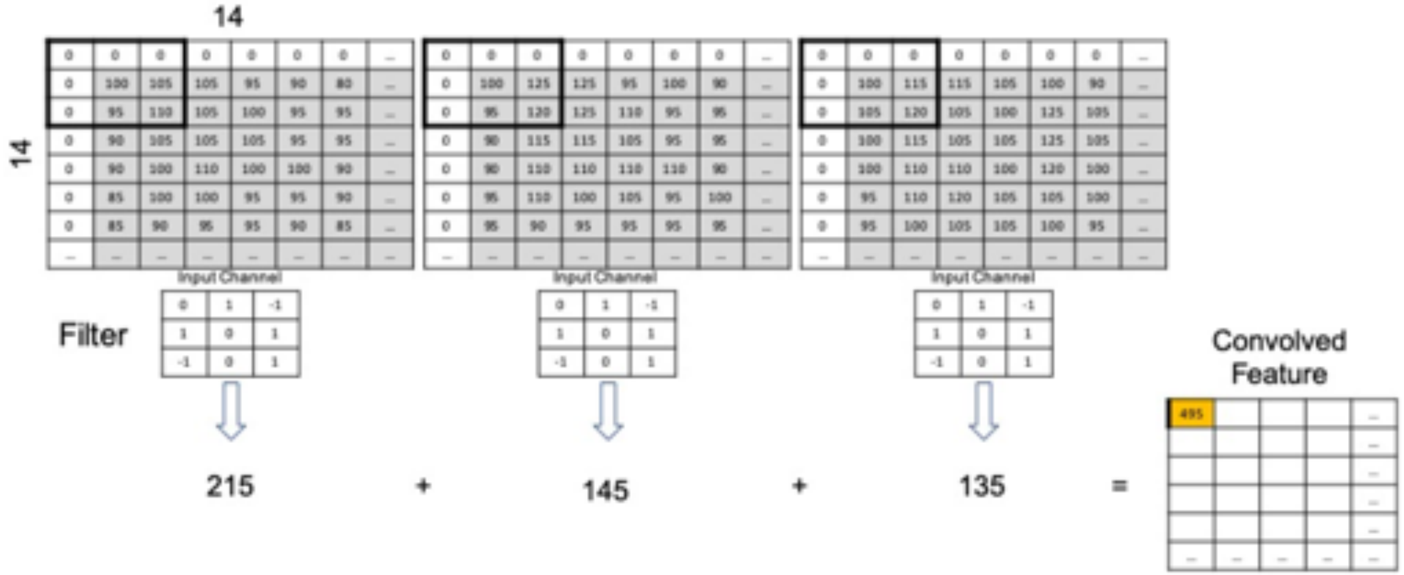
Model Architecture



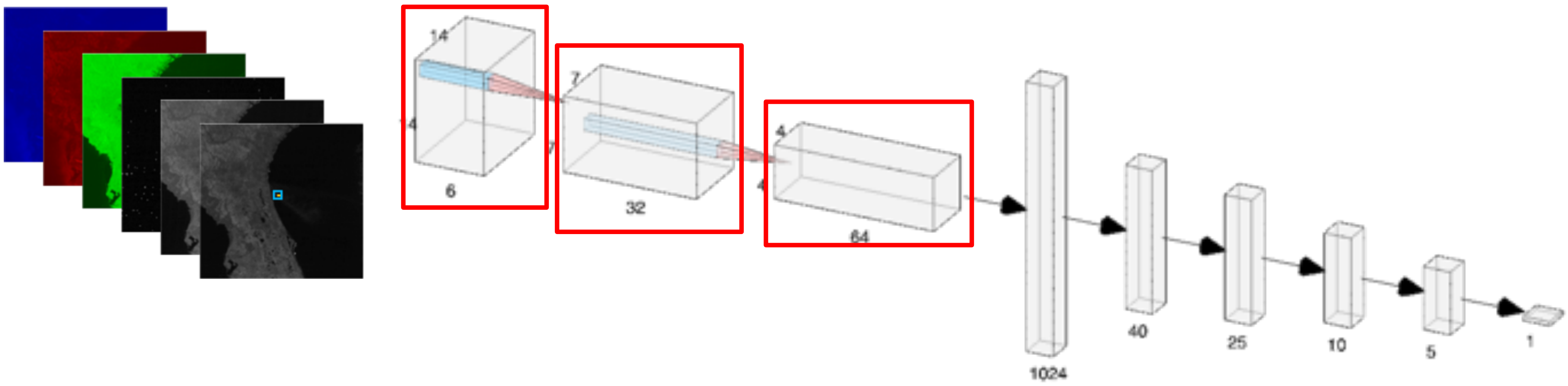
- Apply a pixel based Convolutional Neural Network (CNN)
  - Input (N*2)*(N*2) neighborhood of reflectance values surrounding a center pixel (sample)
  - 3 convolutional layers
  - Each convolutional layer followed by max-pooling layer
  - Convolutional outputs are flattened into vectors

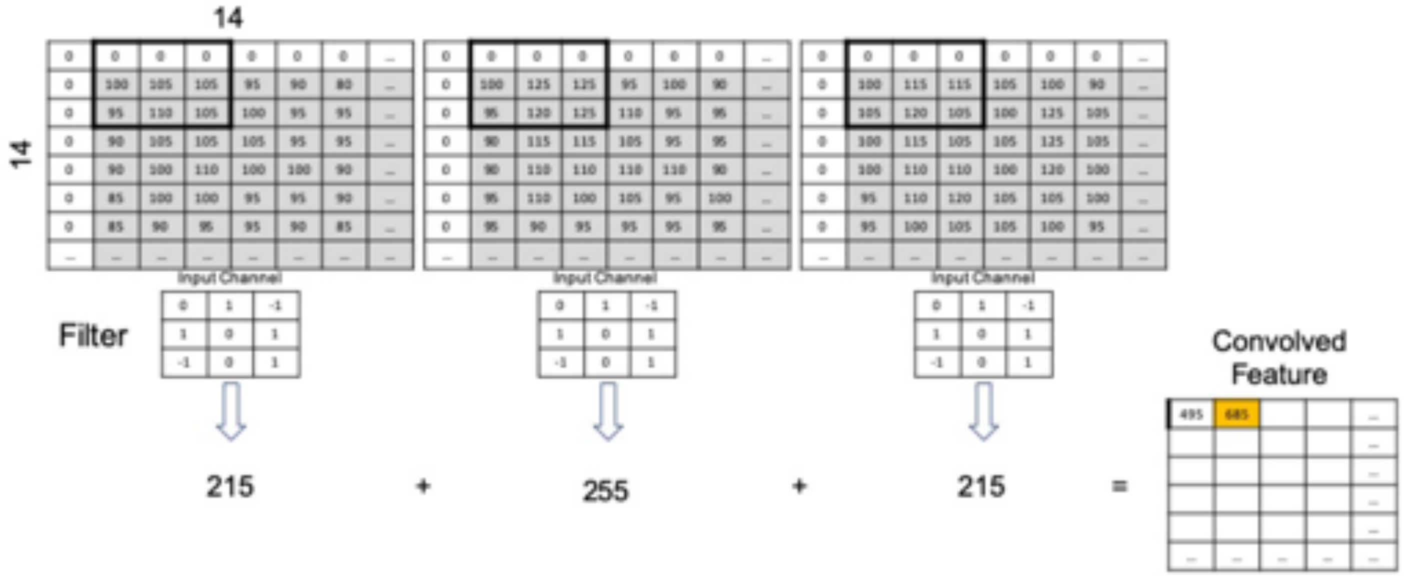
Model Architecture



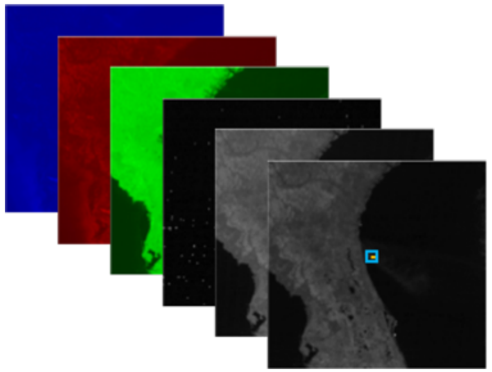


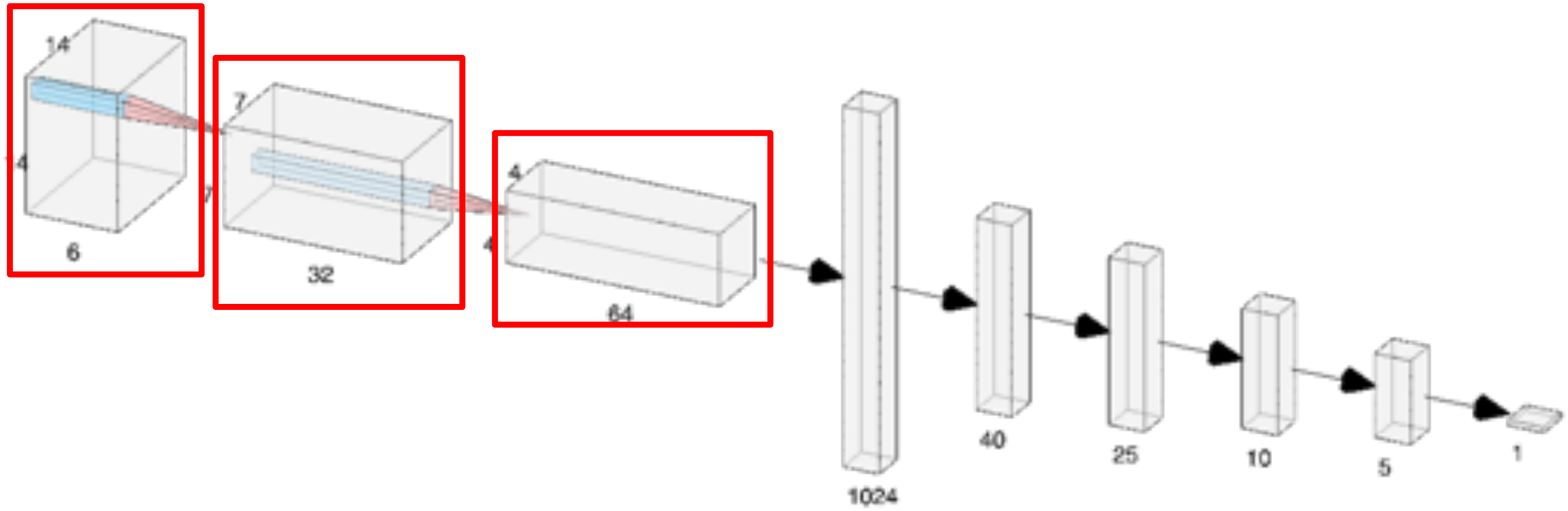
Model Architecture

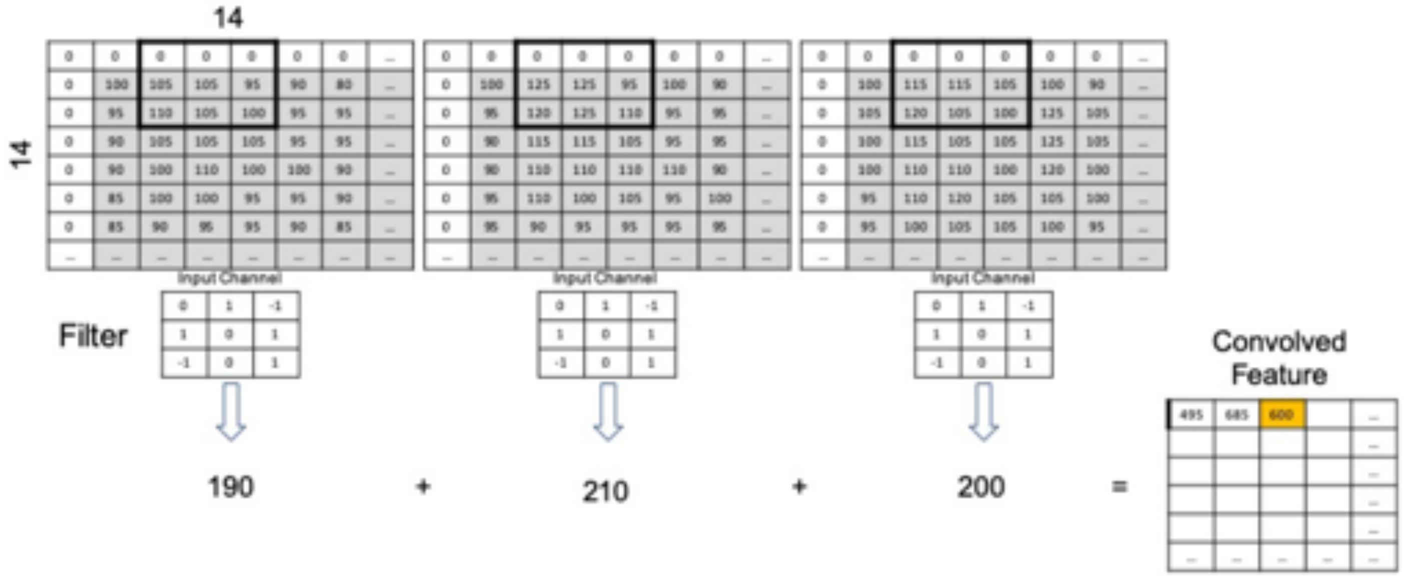




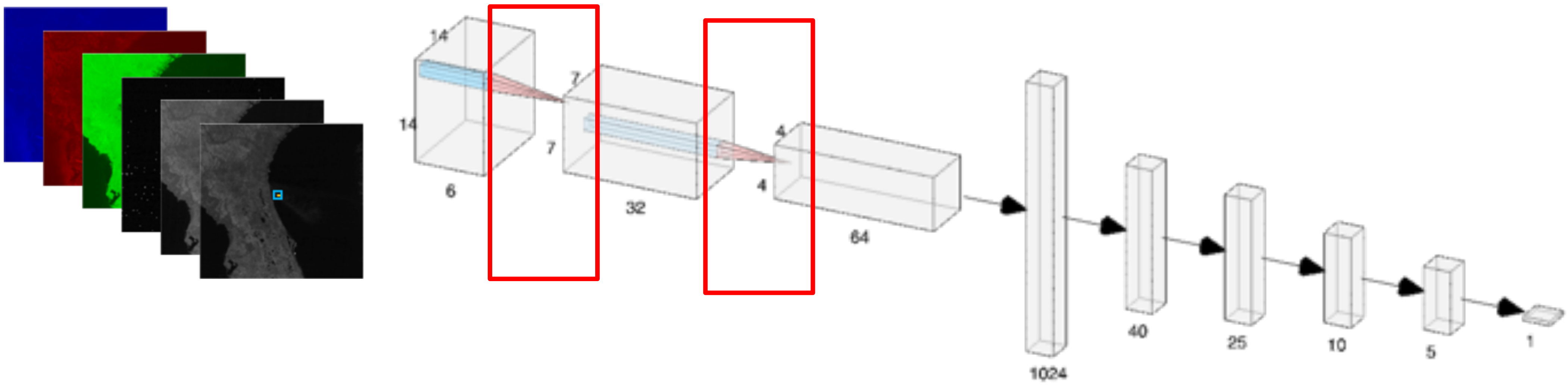
Model Architecture





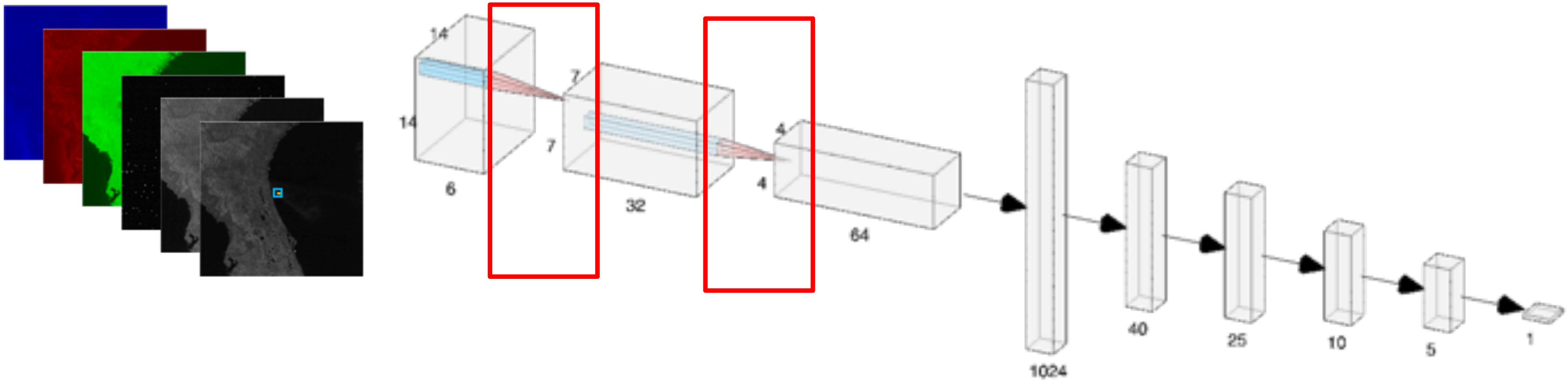


Model Architecture



- Apply a pixel based Convolutional Neural Network (CNN)
  - Input (N*2)*(N*2) neighborhood of reflectance values surrounding a center pixel (sample)
  - 3 convolutional layers
  - Each followed by max-pooling layer
  - Convolutional outputs are flattened into vectors

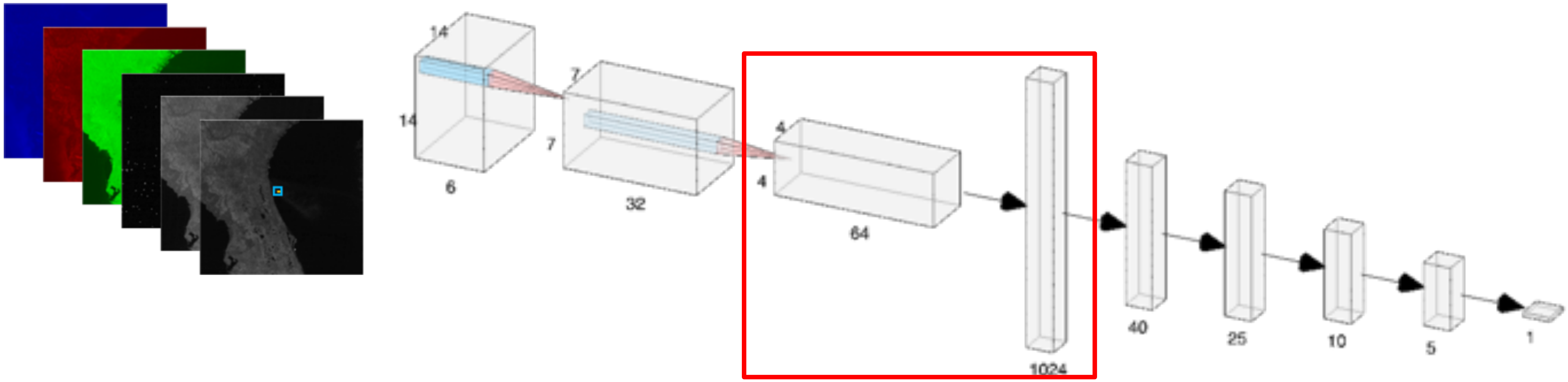
Model Architecture



495	685	600	595	...
515	665	595	550	...
510	650	710	675	...
490	705	675	625	...
450	555	600	620	...
...	...	...	...	...

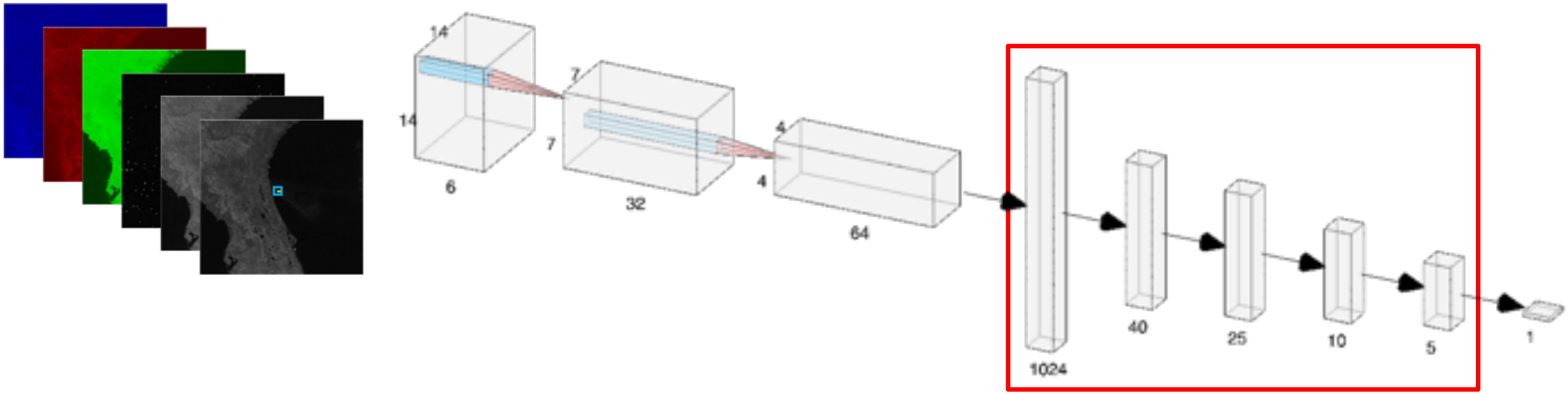
685	600	...
705	710	...
...	...	...

Model Architecture



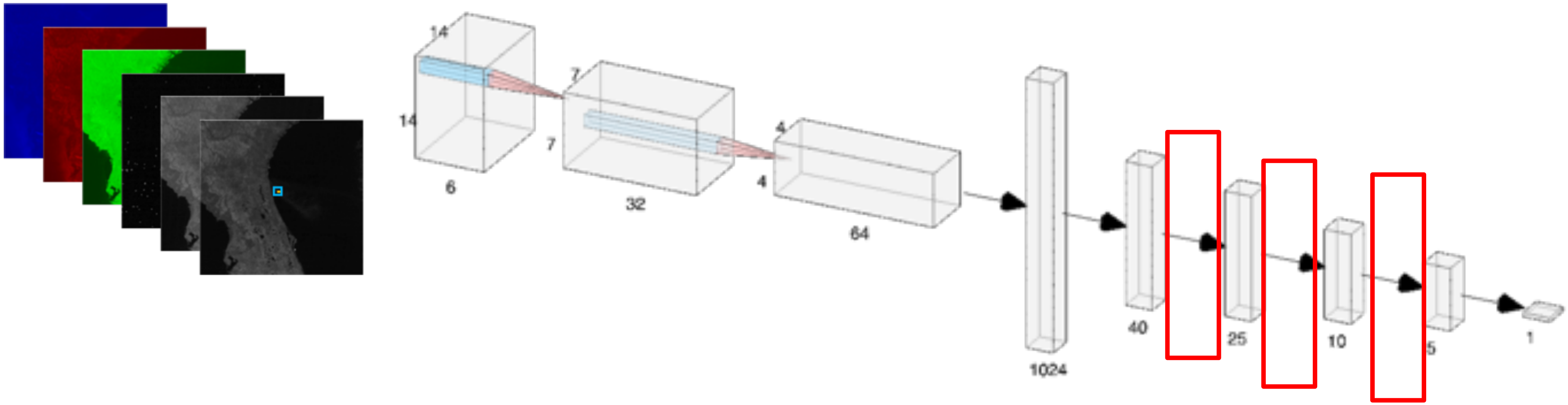
- Apply a pixel based Convolutional Neural Network (CNN)
  - Input (N*2)*(N*2) neighborhood of reflectance values surrounding a center pixel (sample)
  - 3 convolutional layers
  - Each followed by max-pooling layer
  - Convolutional outputs are flattened into vectors

Model Architecture



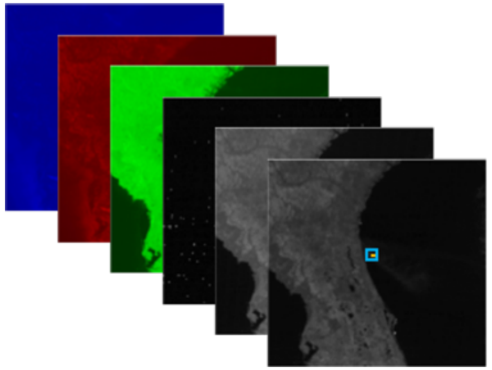
- Apply a pixel based Convolutional Neural Network (CNN)
  - 4 fully connected layers with activation function calculation g(Wx + b)
    - x is the flattened input vector
    - W is the weight matrix
    - b is the bias vector
  - Dropout for each fully connected layer

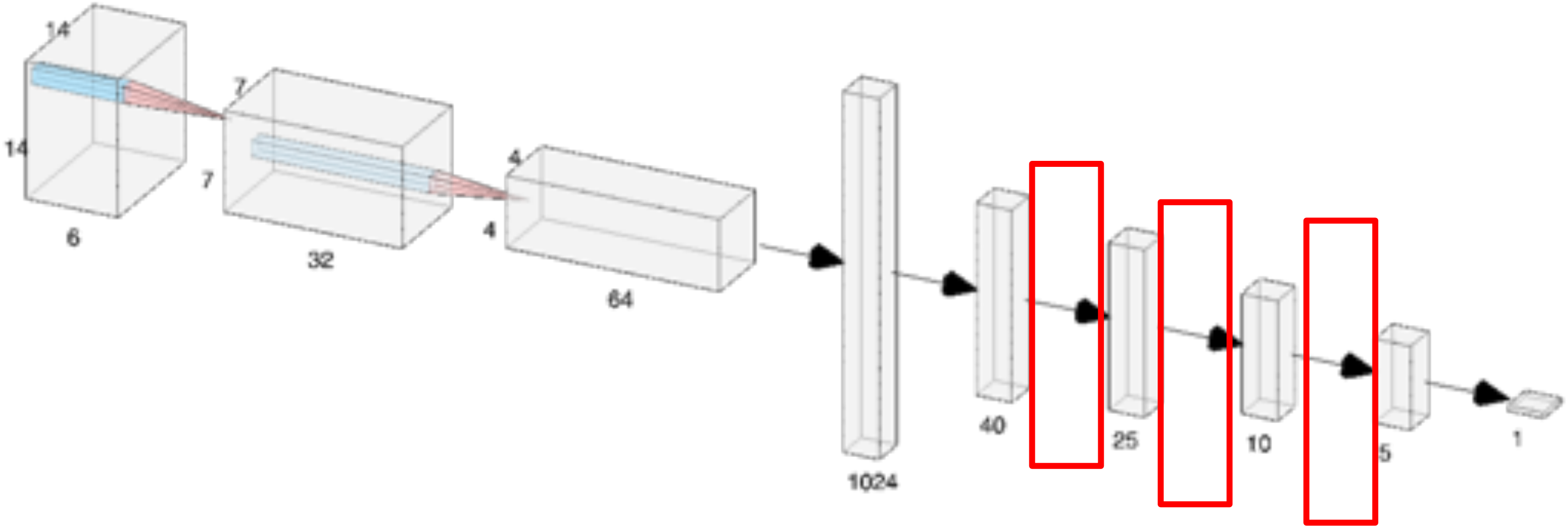
Model Architecture

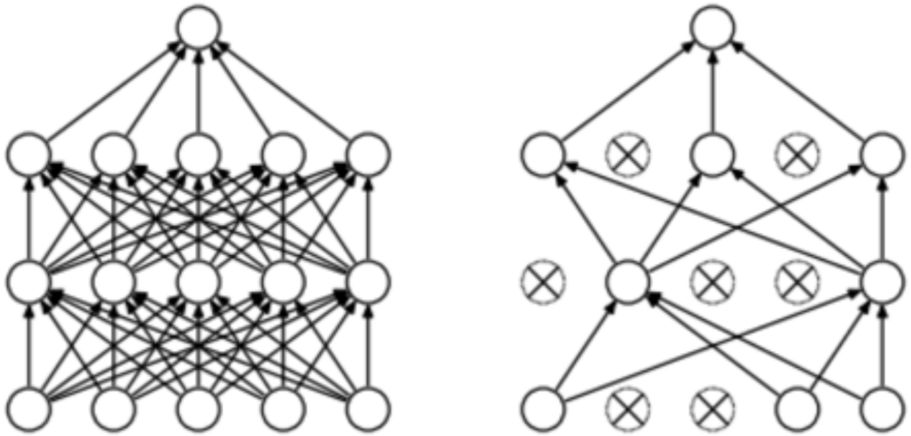


- Apply a pixel based Convolutional Neural Network (CNN)
  - 4 fully connected layers
  - Dropout randomly for each fully connected layer

Model Architecture



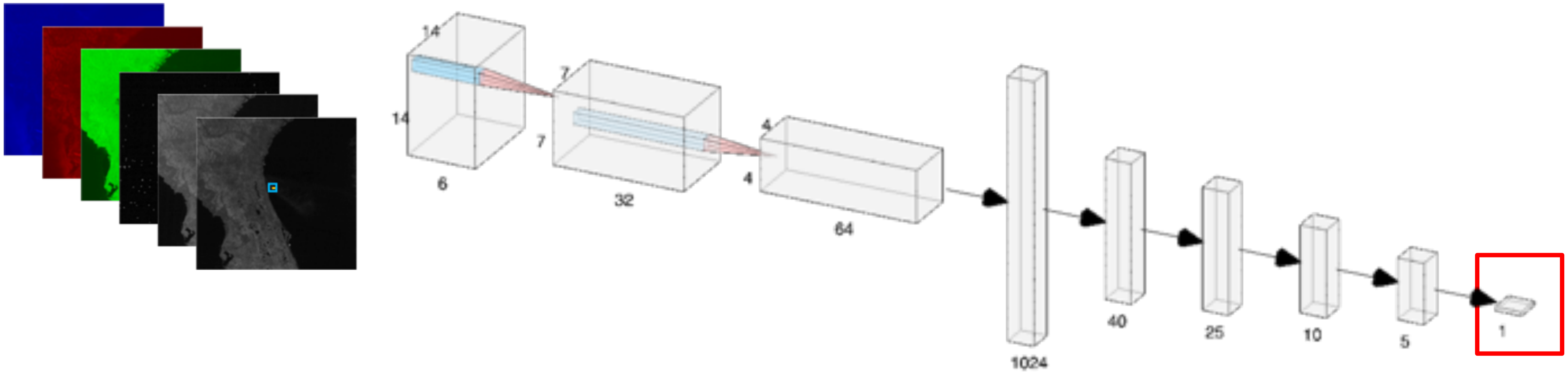




(a) Standard Neural Net

(b) After applying dropout.

Model Architecture



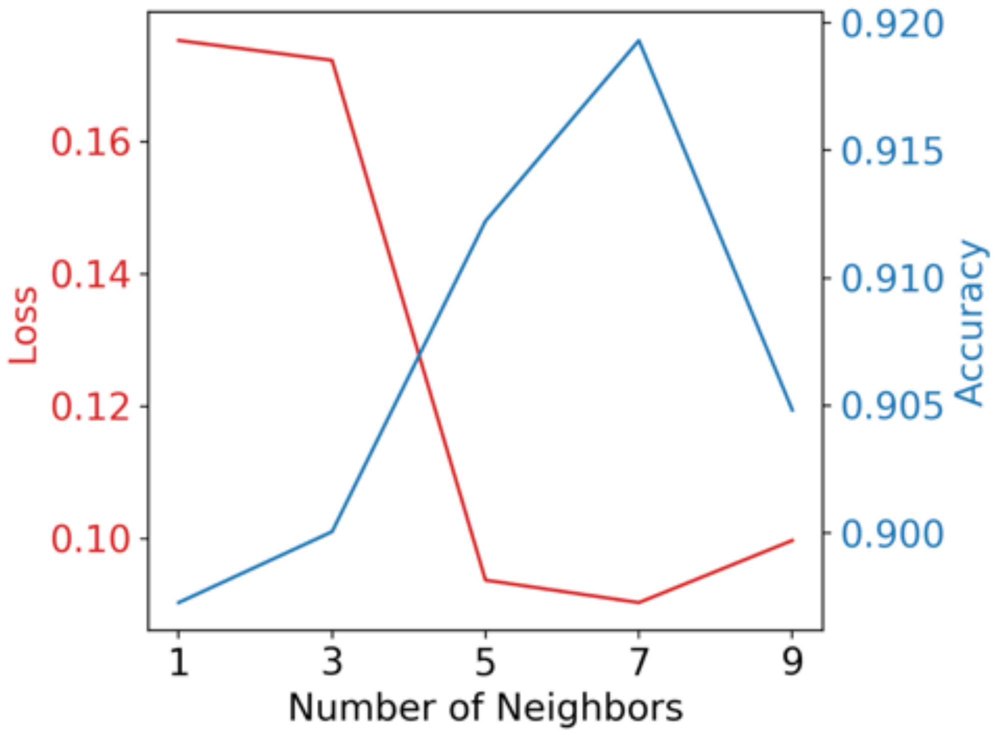
- The model outputs the probability, ranging from 0 to 1, that a pixel is smoke determined by a sigmoid function

$$p(x) = \frac{1}{1 + e^{-x}}$$

- p > 0.5 threshold applied to define smoke

Model Description

- Best neighborhood size (N) determined by iterating model development and testing for increasing N
  - All other parameters including data, learning rate and model hyper-parameters are held constant
- Best model selected when validation loss did not improve for 20 epochs



Development Testing

N	Precision	Recall	F1-Score	Accuracy
1	0.654	0.328	0.437	0.897
3	0.650	0.384	0.483	0.900
5	0.724	0.449	0.554	0.912
7	0.835	0.419	0.558	0.919
9	0.639	0.498	0.560	0.905

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$Accuracy = \frac{TP + TN}{TP + TN + TP + FN}$$

$$F1\ Score = 2 * \frac{Precision\ * Recall}{Precision + Recall}$$

- The F1 Scores, balance between Precision and Recall, for N=5,7,9 is comparable
  - Trade-off between quality and quantity of smoke predictions
- Best model has low false positive detection rate which drives high precision
  - Prefer conservative identification over incorrect classification
- Accuracy artifact of large number of True Negatives

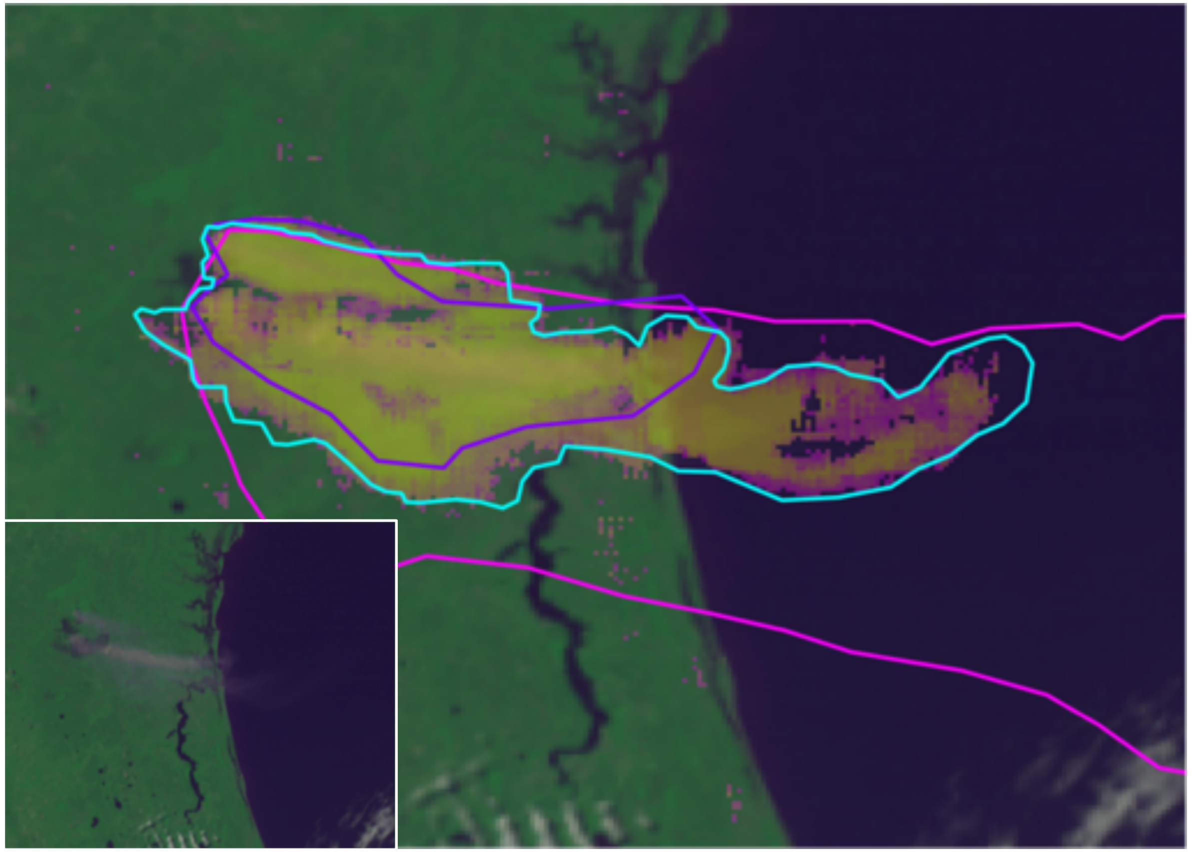
Results

- Model updated to account for variation in solar zenith angle
  - The training and testing datasets for the updated model differ from that used for the initial development
  - Results are comparable between the initial and updated models
- Better predictive capability of smoke over water
  - Compared to land, the relative decrease in true negatives over water drives a slight decrease in accuracy

N=7	Precision	Recall	F1-Score	Accuracy
All	0.736	0.453	0.561	0.923
Land	0.631	0.383	0.476	0.928
Water	0.923	0.585	0.717	0.900

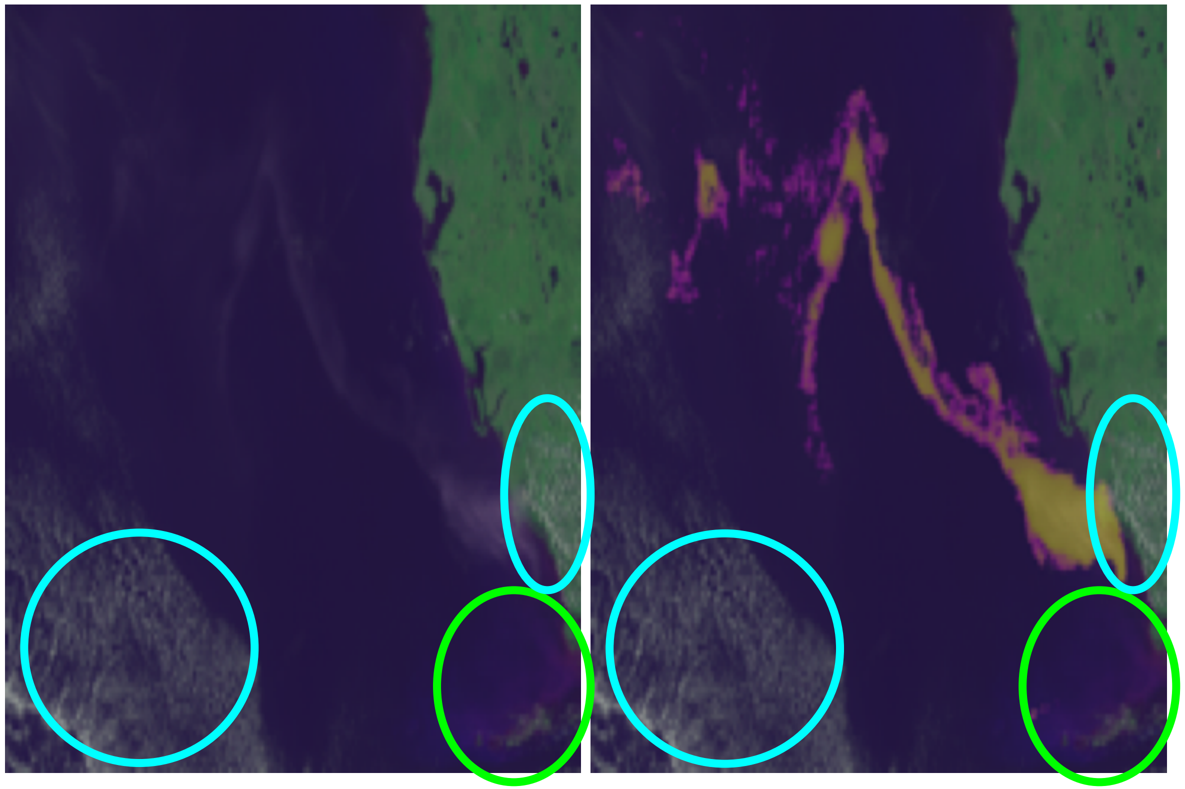
2 May 2018 - Southern Florida

- Smoke identified over both land and ocean
  - Model identifies well defined plumes for scenes with absence of complex features
  - Probabilities resemble visually observed optical thickness
- Predictions closer resemblance to quality controlled shapefiles



24 March 2018 - Southern Florida

- Distinguishable from chlorophyll commonly found in coastal settingsFair weather cumulus cloud discrimination
- Spectral information for other classes not provided to the model

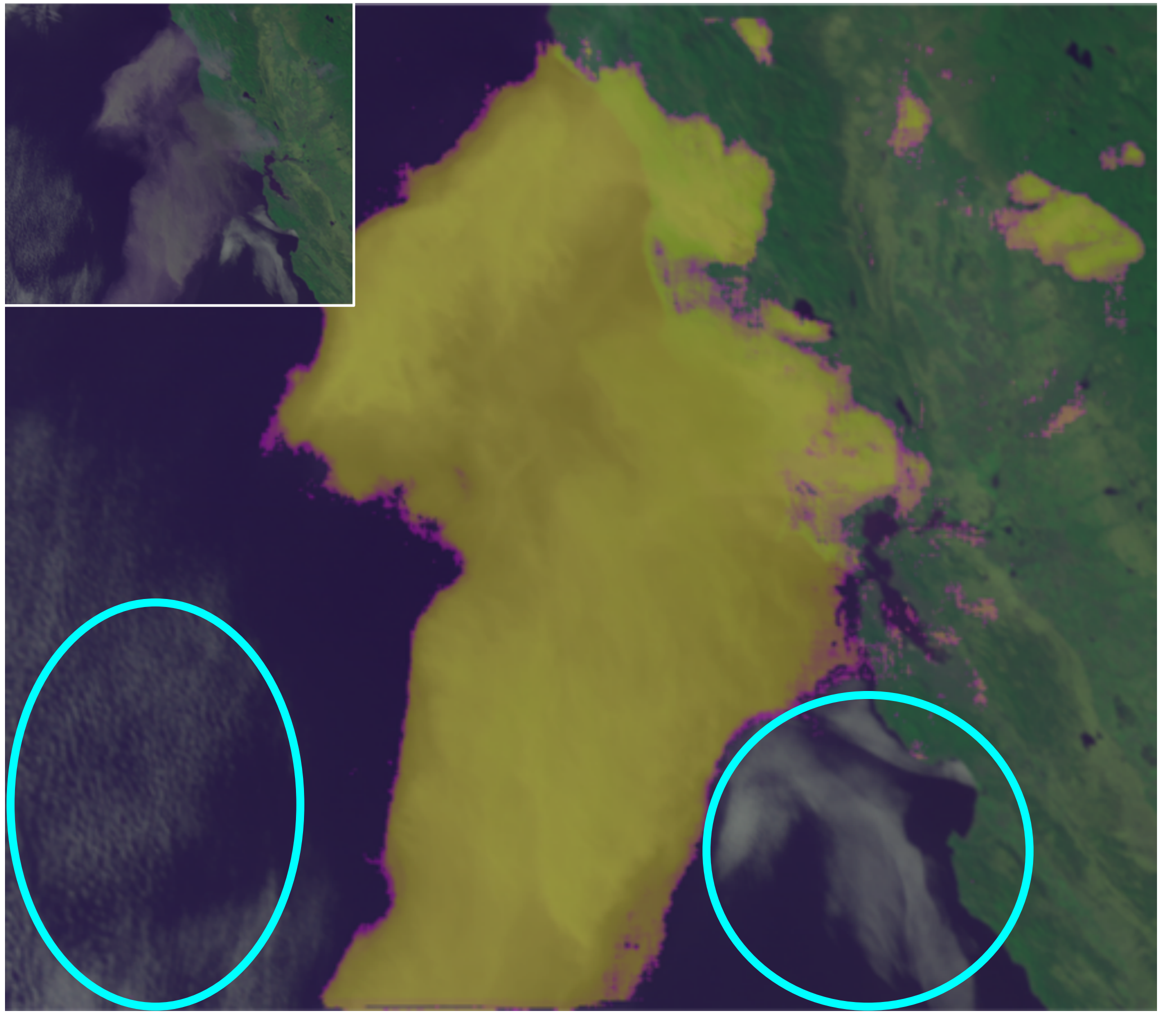


	Precision	Recall	F1-Score	Accuracy
All	0.744	0.604	0.666	0.948
Land	0.847	0.244	0.379	0.976
Water	0.742	0.623	0.677	0.943

9 October 2017 - Central California

- Large and small plumes
- Identification over both land and ocean
- Coastal stratus clouds

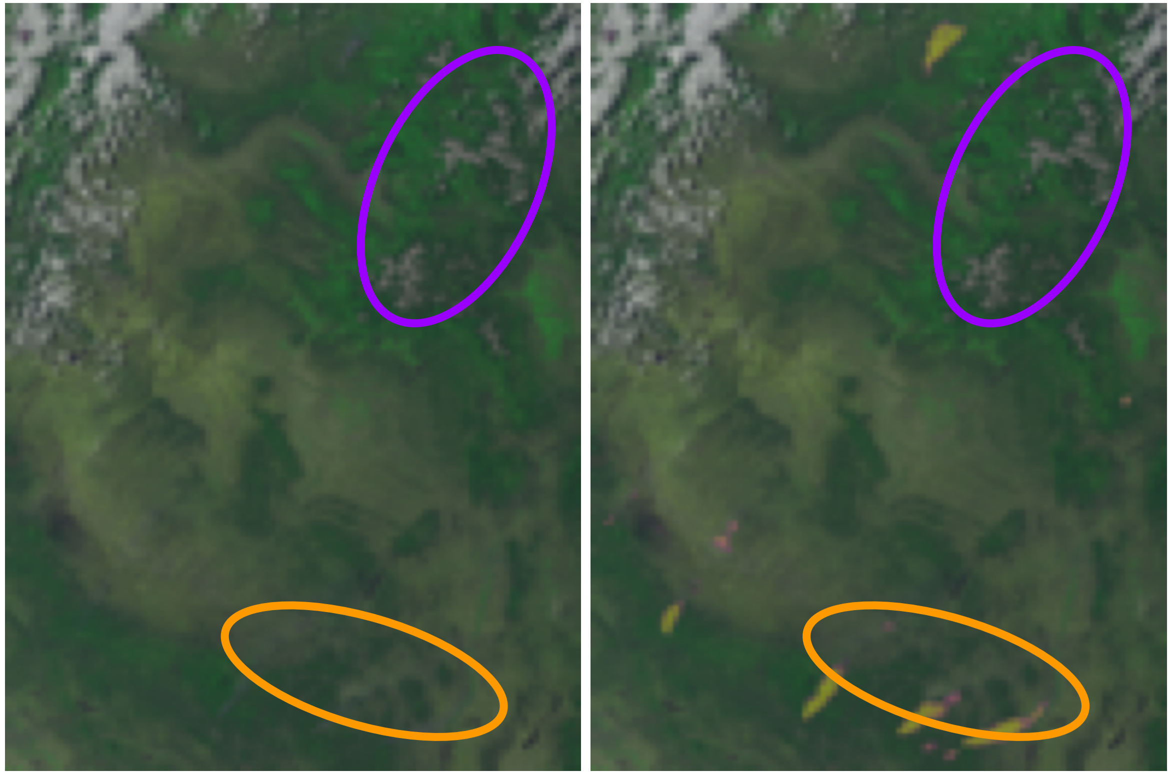
	Precision	Recall	F1-Score	Accuracy
All	0.970	0.919	0.944	0.961
Land	0.904	0.754	0.823	0.920
Water	0.986	0.965	0.975	0.980



11 June 2017 - Southern Rocky Mts. United States

- Successfully discriminates land surface snow/ice from smoke
  - Over snow capped mountains for this case
- Detection challenges for optically thin smoke over arid regions

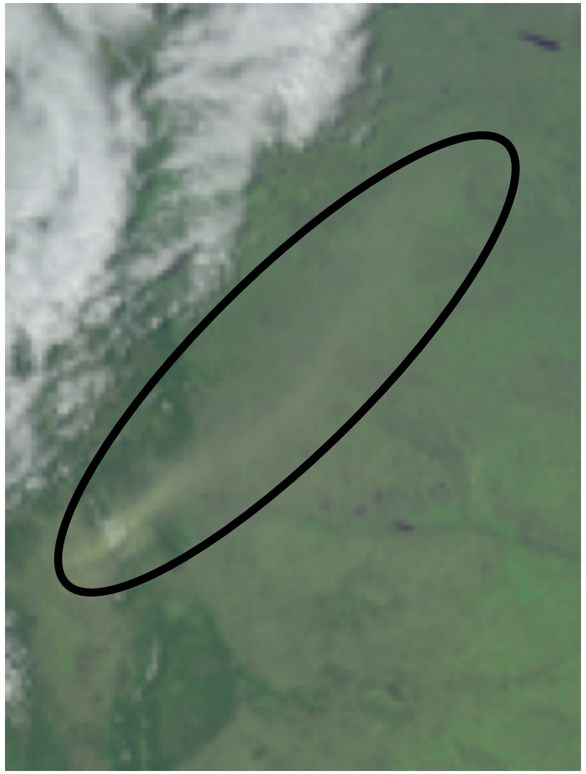
	Precision	Recall	F1-Score	Accuracy
All	0.848	0.318	0.462	0.977
Land	0.848	0.319	0.463	0.977
Water	N/A	N/A	N/A	0.984

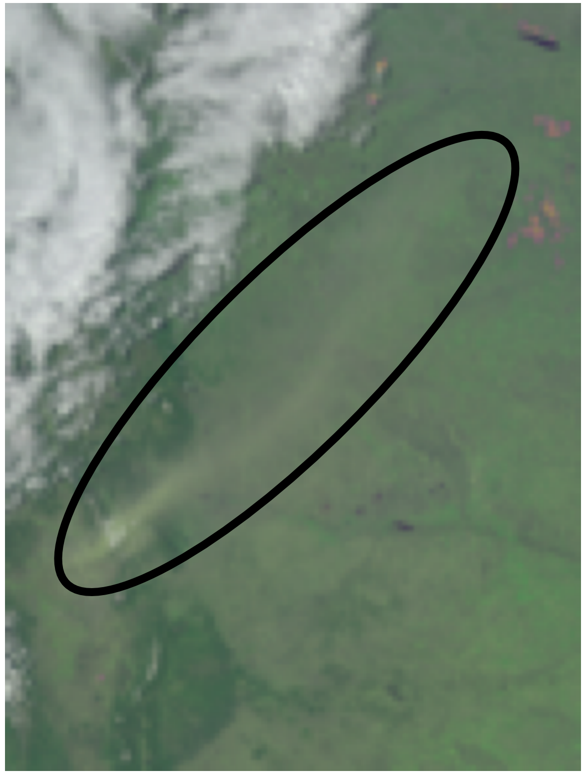


17 April 2018 - Southern Rocky Mts. United States

- Other atmospheric aerosols not classified as smoke
- Large dust storm case
  - Represents a major source of aerosols in the atmosphere
  - Expected over regions where smoke is also common

	Precision	Recall	F1-Score	Accuracy
All	N/A	N/A	N/A	0.996
Land	N/A	N/A	N/A	0.996
Water	N/A	N/A	N/A	N/A

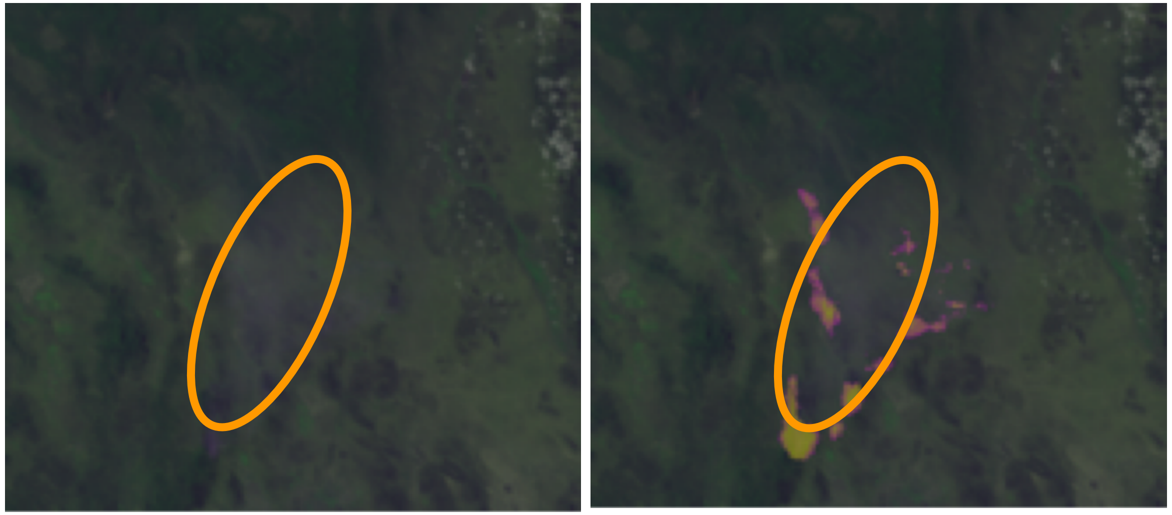




20 May 2018 - Southern Arizona

- Smoke not detected at very low sun angles
  - Compounded by low optical thickness over relatively high reflective surface
  - Probability of being smoke is low for few pixels that are identified

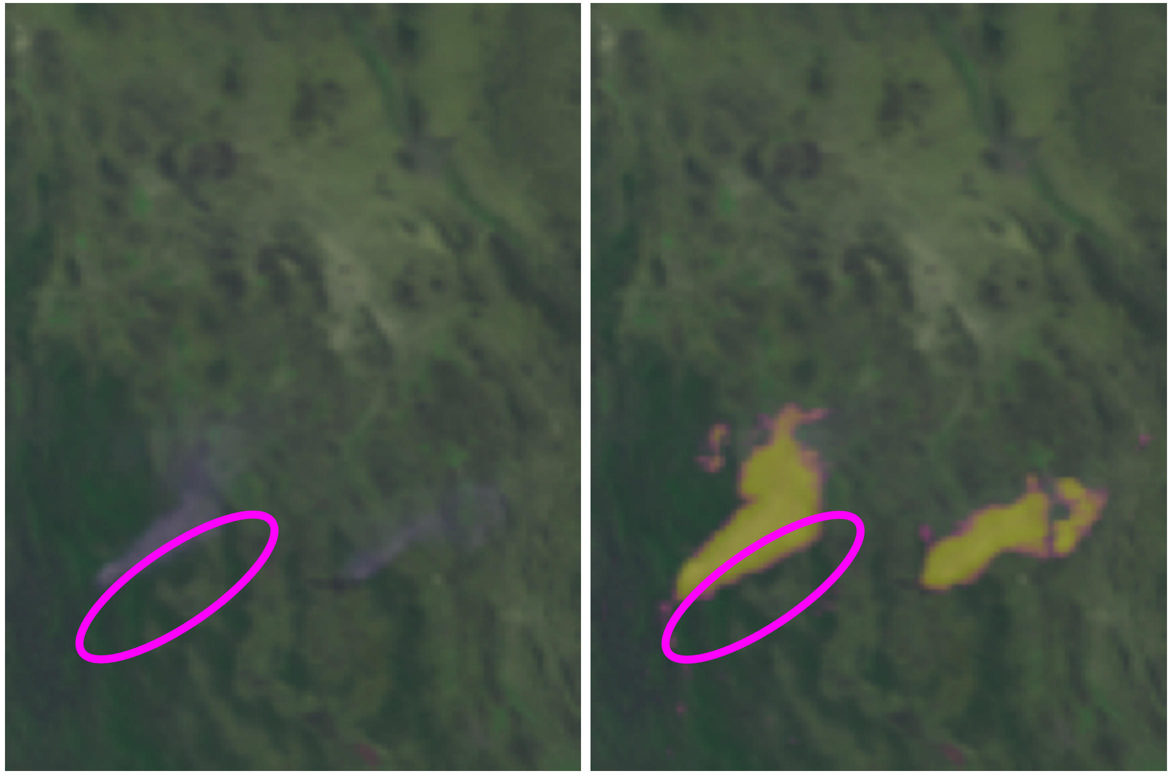
	Precision	Recall	F1-Score	Accuracy
All	0.995	0.093	0.171	0.823
Land	0.995	0.093	0.171	0.822
Water	0.923	0.585	0.717	1.000



14 April 2018 - Southern Rocky Mts. United States

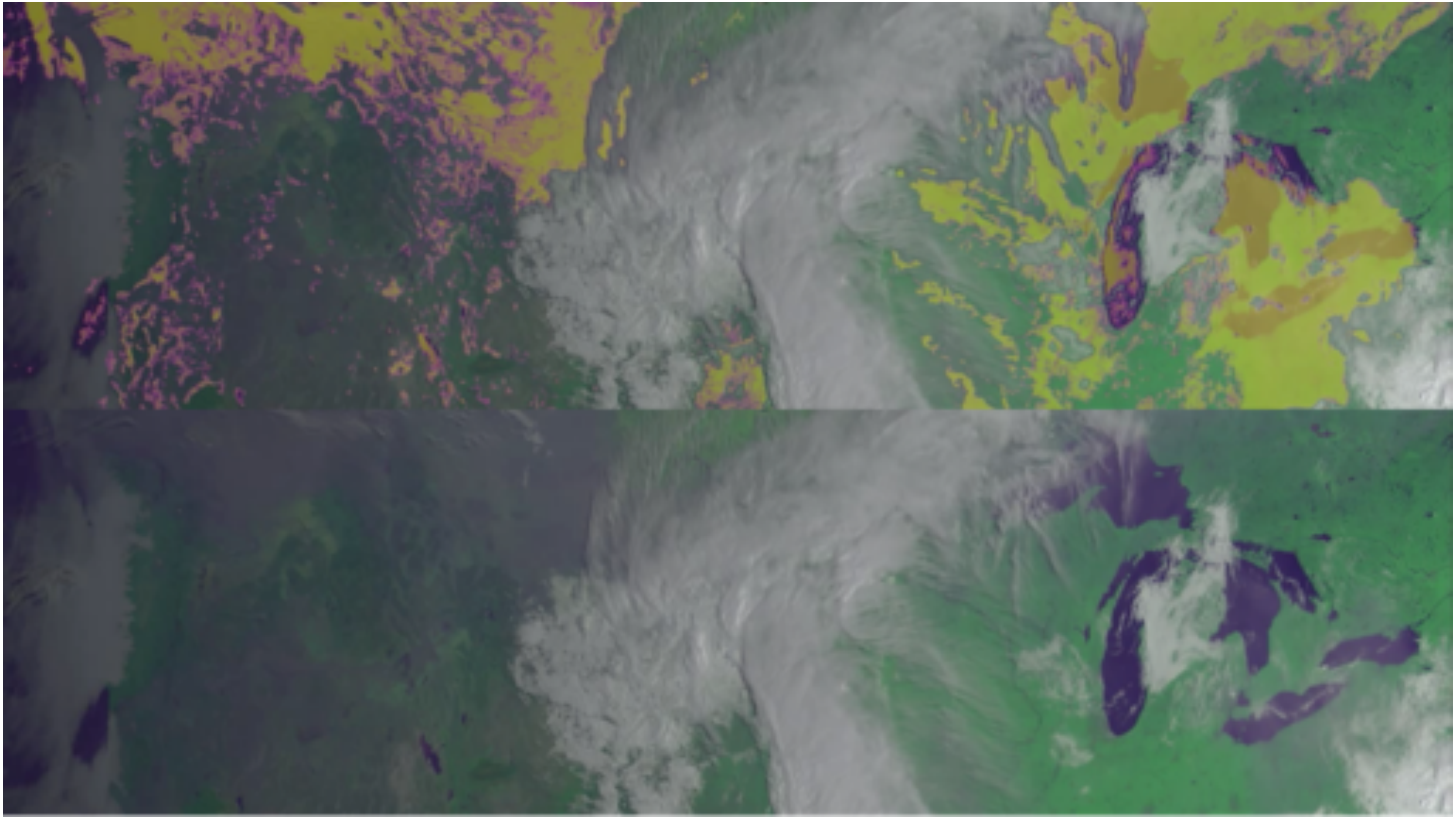
- Overprediction of plume extent
  - Artifact of large (N=7) neighborhood size
  - Non-zero floor to number of false positives

	Precision	Recall	F1-Score	Accuracy
All	0.830	0.738	0.781	0.981
Land	0.830	0.738	0.781	0.981
Water	N/A	N/A	N/A	0.993



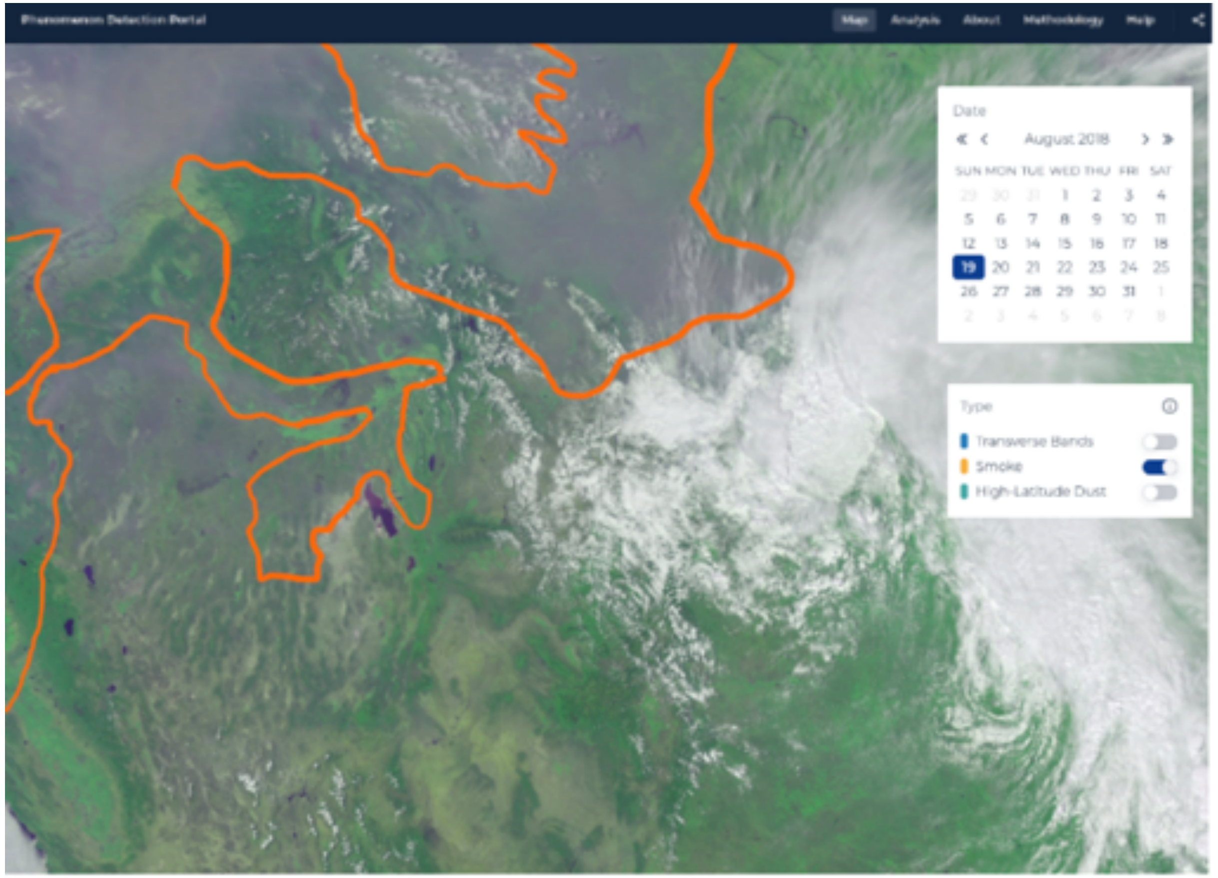
Operational Capabilities

- Currently testing new deployment in operational environment
  - Anticipate operational October 2019
- Fully deployed in cloud using Amazon S3 and Cloud Computing Services
- End-to-end analysis and visualization pipeline
  - Full disk GOES observation available ~10 min intervals
  - Model prediction available ~15 min after data availability
    - Preprocessing ~10 min
    - Prediction and Postprocessing ~5min



Operational Capabilities - Postprocessing

- Spatial grouping of predicted pixels to define plumes
  - Convert predicted pixels to bitmap image
  - Blurring to smoothen edges
  - Contour blurred image to group smoke pixels into plumes
  - Plumes visualized and geojson representation of plume extents available for download in the Phenomena Portal (http://phenomena.surge.sh)



Summary

- Developed end-to-end machine learning smoke detection pipeline for next-generation of geostationary satellites
  - Well curated smoke extent dataset
  - Scalable smoke detection deep learning model, requiring only smoke spectral information, and capable of detecting smoke with:
    - Varying optical thicknesses
    - Over low and high reflectance background surfaces
    - Discriminates from common, spectrally similar, features
  - Fully automated operational deployment of model in development
    - Plume visualization and extent data accessible in online platform

Future work

- Expand training data to account for identified weaknesses
  - Low sun angles
  - Thin smoke over arid regions
  - Thin clouds
- Refinement of the machine learning model
  - Confirmation of N=7 as best performing model
    - Explore trade-off between neighborhood size and prediction capabilities
  - Stepwise band selection considering all 16 GOES bands
  - Robust model validation
    - Band exclusion to identify contribution to feature learning
- Performance assessment for operational improvements

Thank you!

mr0051@uah.edu

aaron.kaulfus@nsstc.uah.edu

IMPACT
Interagency Implementation and Advanced Concepts Team