NASA Intelligent Systems (IS) Program

Intelligent Data Understanding (IDU)

Automated Wildfire Detection and Prediction Through Artificial Neural Networks

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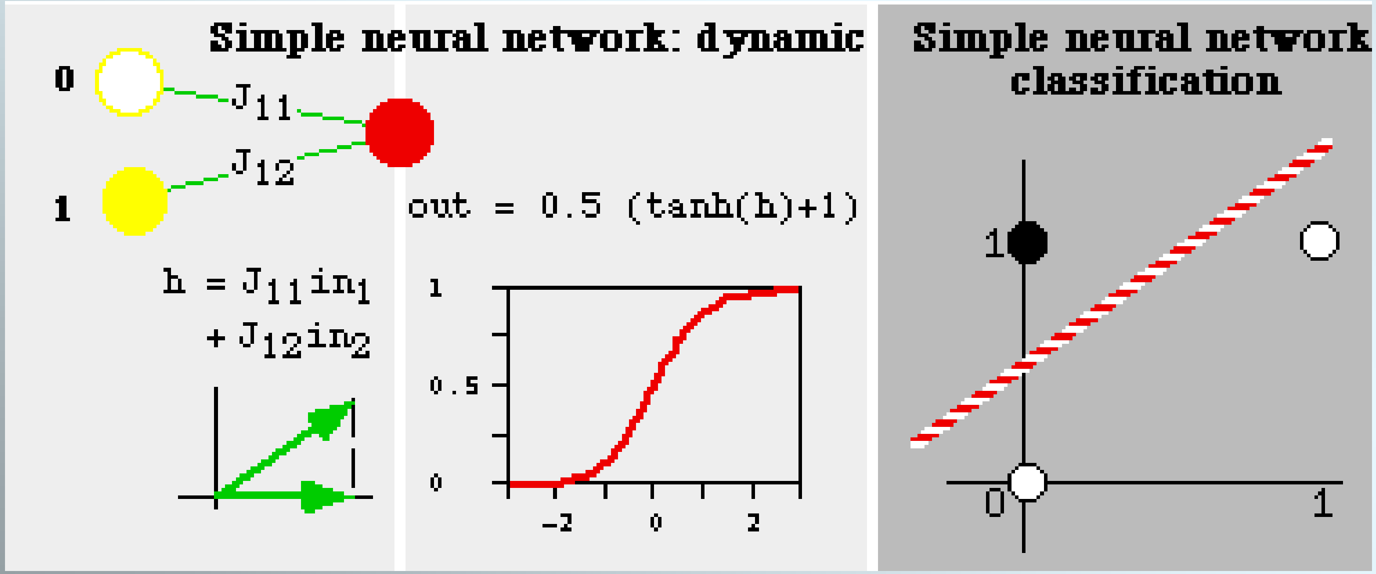
Short Description of Wildfire Project

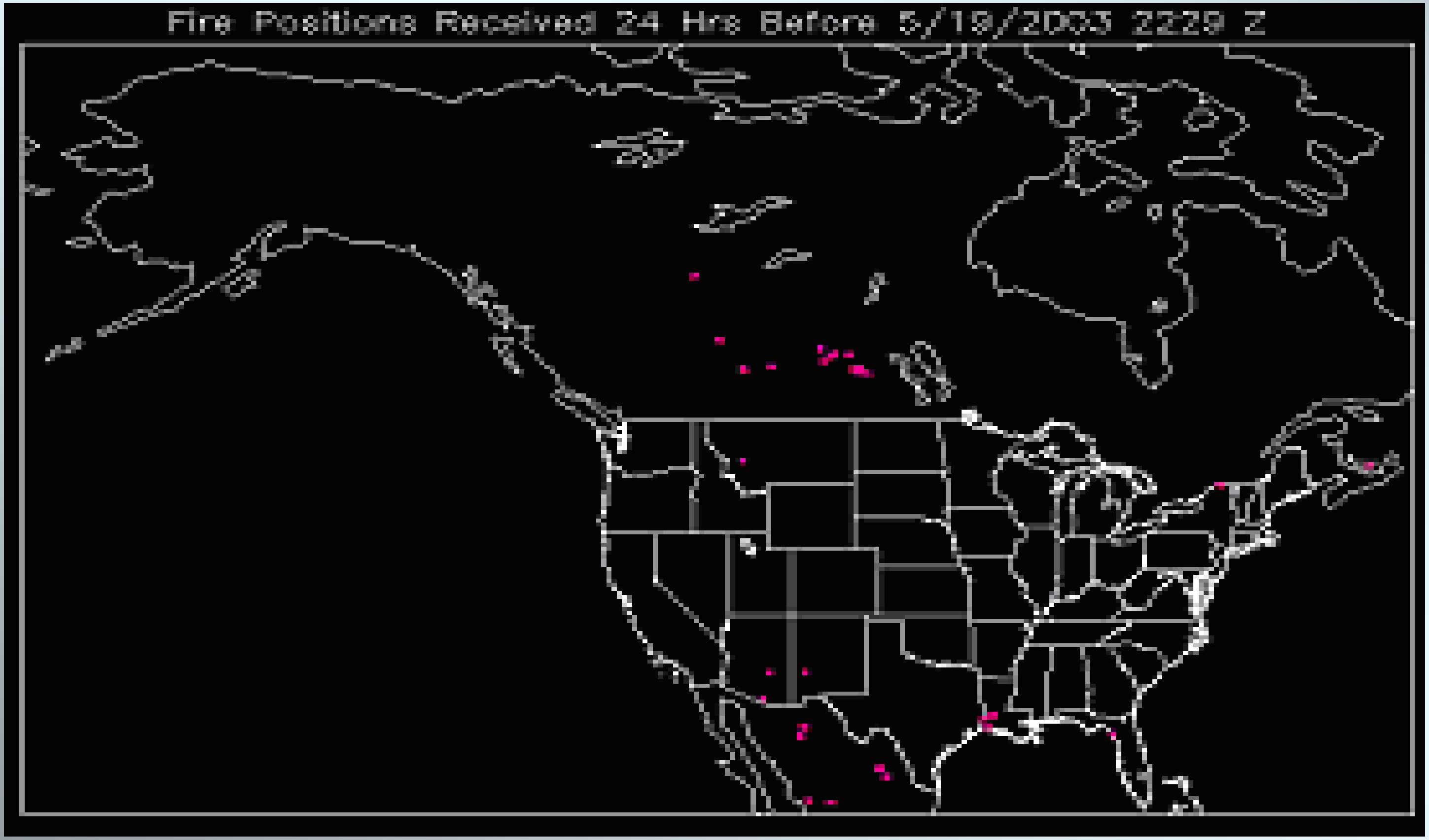
- **Automated Wildfire Detection (and Prediction) through Artificial Neural Networks *(ANN)***
  - Identify all wildfires in Earth-observing satellite images
  - Train ANN to mimic human analysts' classifications
  - Apply ANN to new data (from 3 remote-sensing satellites: GOES, AVHRR, MODIS)
  - Extend NOAA fire product from USA to the whole Earth



NOAA'S HAZARD MAPPING SYSTEM

NOAA's Hazard Mapping System (HMS) is an interactive processing system that allows trained satellite analysts to manually integrate data from 3 automated fire detection algorithms corresponding to the GOES, AVHRR and MODIS sensors. The result is a quality controlled fire product in graphic (Fig 1), ASCII (Table 1) and GIS formats for the continental US.

Figure – Hazard Mapping System (HMS) Graphic Fire Product for day 5/19/2003



OVERALL TASK OBJECTIVES

To mimic the NOAA-NESDIS Fire Analysts' **subjective** decision-making and fire detection algorithms with a Neural Network in order to:

- remove subjectivity in results
- improve automation & consistency
- allow NESDIS to expand coverage globally

Sources of subjectivity in Fire Analysts' decision-making:

- Fire is not burning very hot, small in areal extent
- Fire is not burning much hotter than surrounding scene
- Dependency on Analysts' "aggressiveness" in finding fires
- Determination of false detects

Hazard Mapping System (HMS) ASCII Fire Product

OLD FORMAT

Lon,	Lat
-80.531,	25.351
-81.461,	29.072
-83.388,	30.360
-95.004,	30.949
-93.579,	30.459
-108.264,	27.116
-108.195,	28.151
-108.551,	28.413
-108.574,	28.441
-105.987,	26.549
-106.328,	26.291
-106.762,	26.152
-106.488,	26.006
-106.516,	25.828

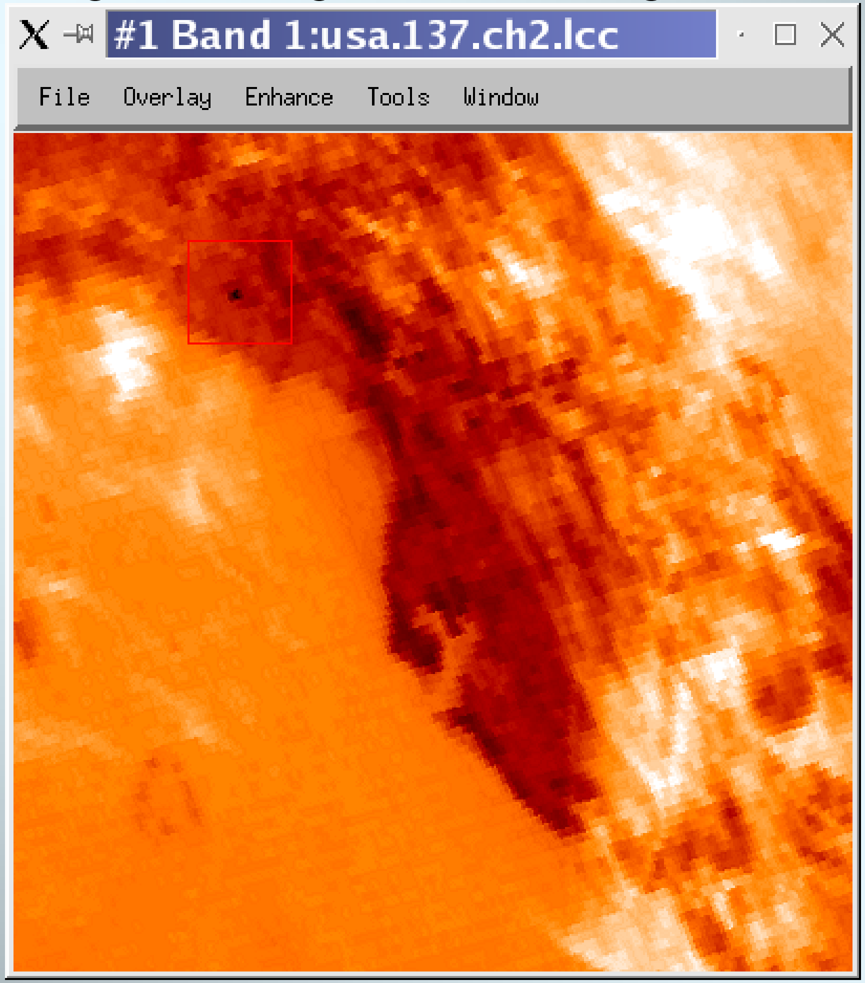
NEW FORMAT (as of May 16, 2003)

Lon,	Lat,	Time,	Satellite,	Method of Detection
-80.597,	22.932,	1830,	MODIS AQUA,	MODIS
-79.648,	34.913,	1829,	MODIS,	ANALYSIS
-81.048,	33.195,	1829,	MODIS,	ANALYSIS
-83.037,	36.219,	1829,	MODIS,	ANALYSIS
-83.037,	36.219,	1829,	MODIS,	ANALYSIS
-85.767,	49.517,	1805,	AVHRR NOAA-16,	FIMMA
-84.465,	48.926,	2130,	GOES-WEST,	ABBA
-84.481,	48.888,	2230,	GOES-WEST,	ABBA
-84.521,	48.864,	2030,	GOES-WEST,	ABBA
-84.557,	48.891,	1835,	MODIS AQUA,	MODIS
-84.561,	48.881,	1655,	MODIS TERRA,	MODIS
-84.561,	48.881,	1835,	MODIS AQUA,	MODIS
-89.433,	36.827,	1700,	MODIS TERRA,	MODIS
-89.750,	36.198,	1845,	GOES,	ANALYSIS

GOES CH2 (3.78 - 4.03 μm) – Northern Florida Fire

2003: Day 126 , –82.10 Deg West Longitude, 30.49 Deg North Latitude

File: florida_ch2.png

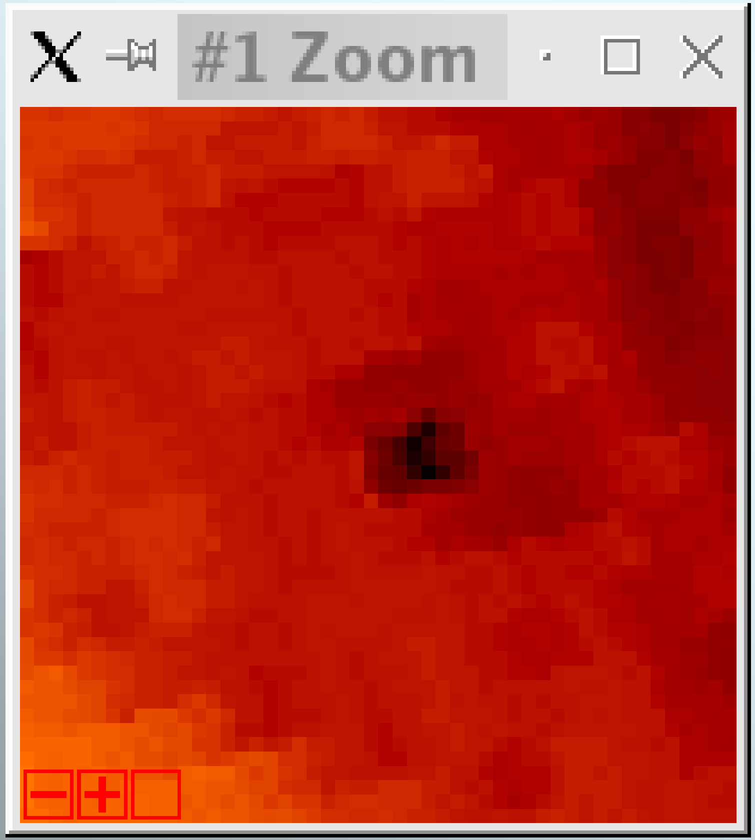


Zoom of GOES CH2 (3.78 - 4.03 μm) – Northern Florida Fire

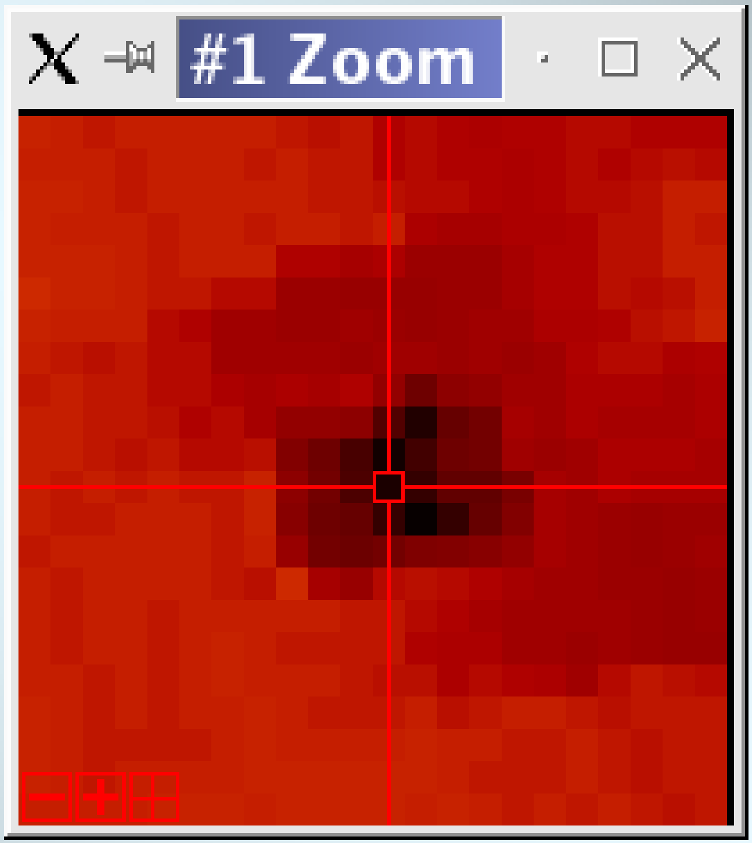
2003:Day 126, –82.10 Deg W Long, 30.49 Deg N Lat

Local minimum in vicinity of core pixel used as fire location.

File: florida_fire_ch2_zoom.png

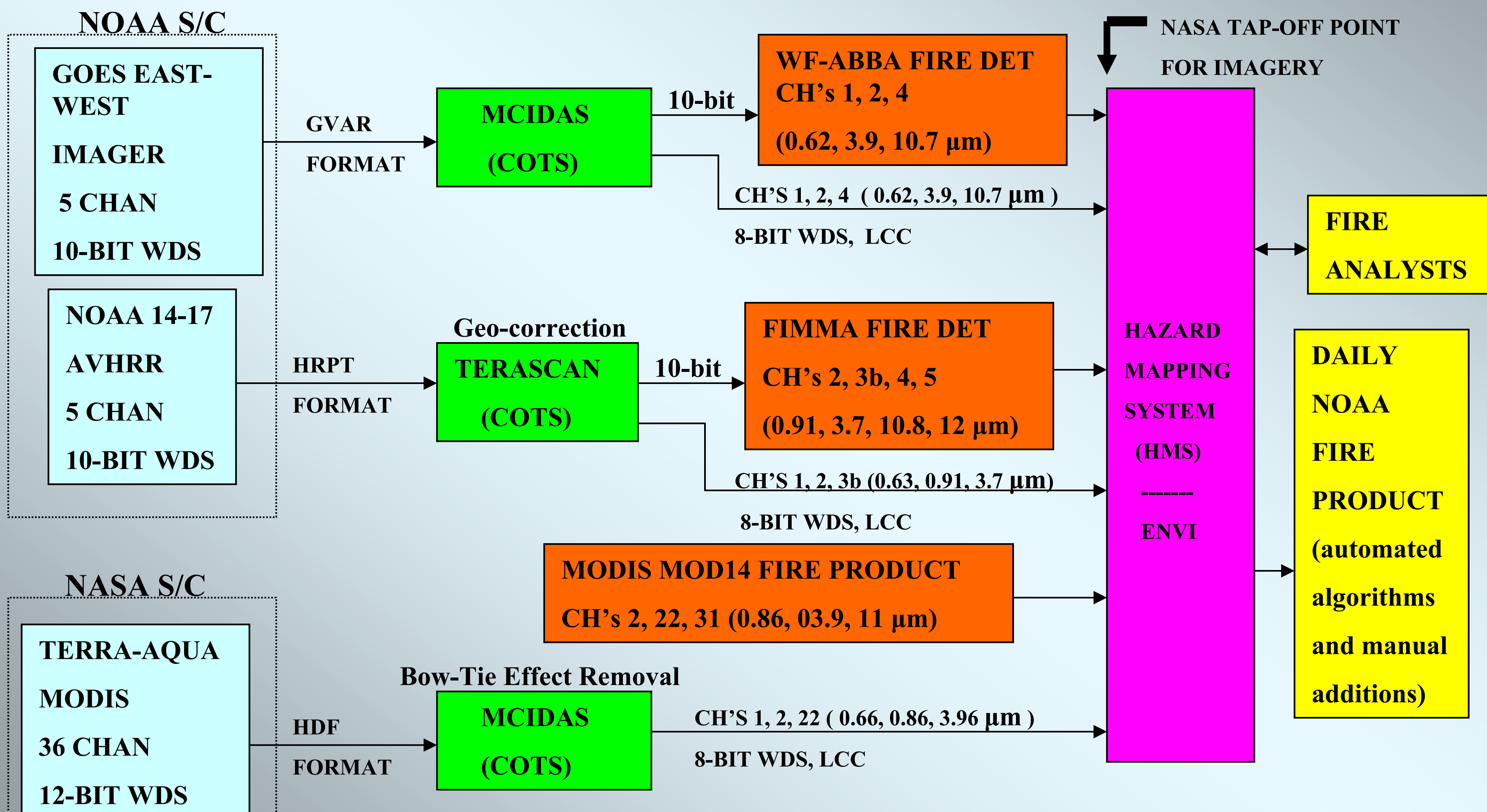


File: florida_ch2_zoom.png



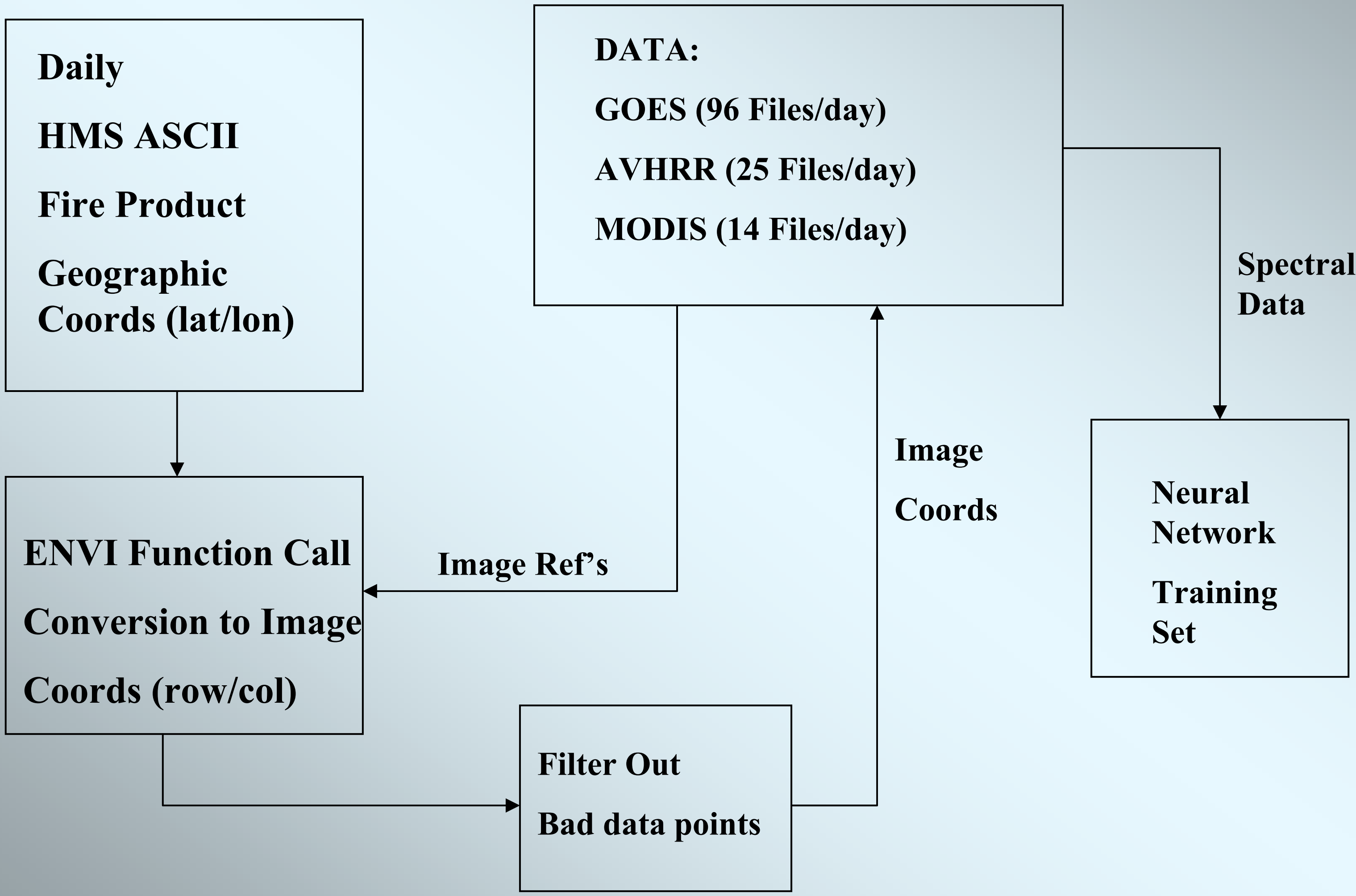
NOAA-NESDIS FIRE DETECTION SYSTEM

WF-ABBA = Wildfire Automated Biomass Burning Alg **FIMMA = Fire Identification Mapping and Monitoring Alg**

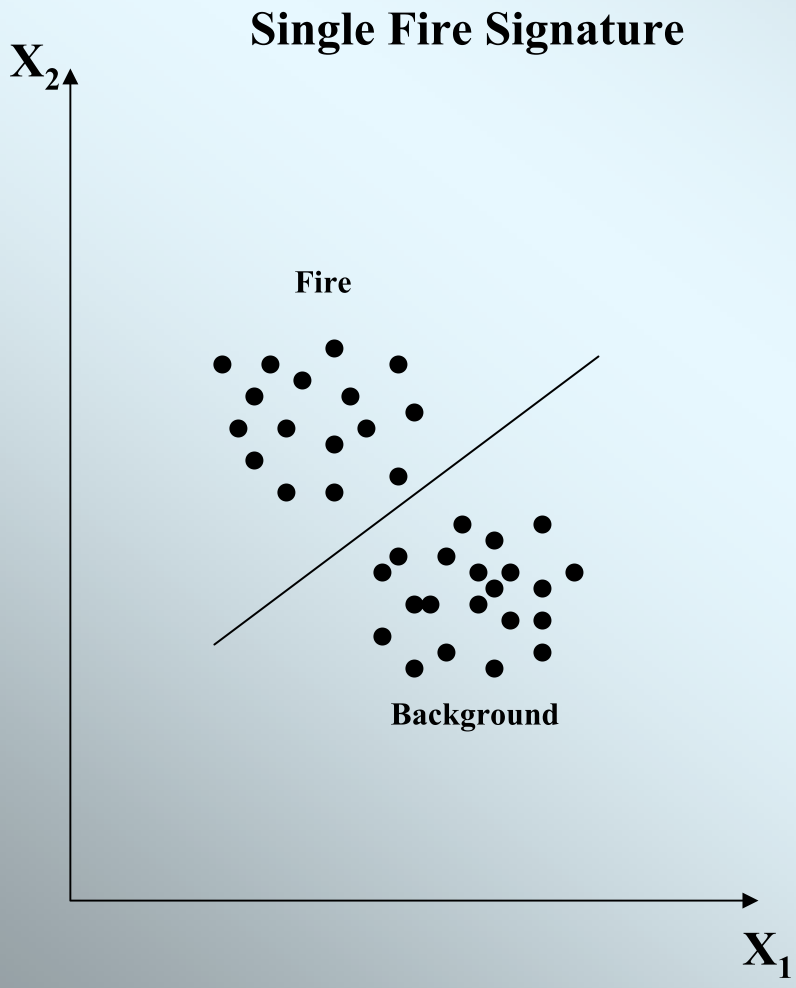


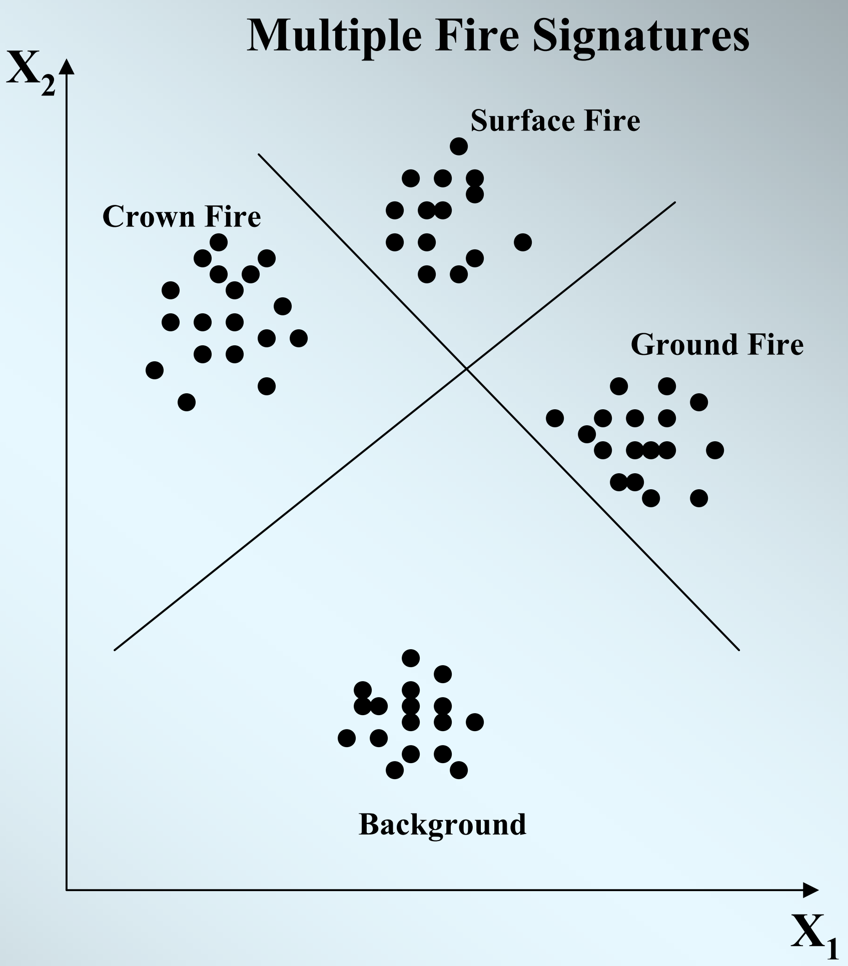
LCC = Lambert Conformal Conic Projection **MCIDAS = Man Computer Interactive Data Access System**

SIMPLIFIED DATA EXTRACTION PROCEDURE



DECISION REGIONS AND BOUNDARIES FOR HIGHLY IDEAL SCATTER PLOT CLUSTERING PATTERNS



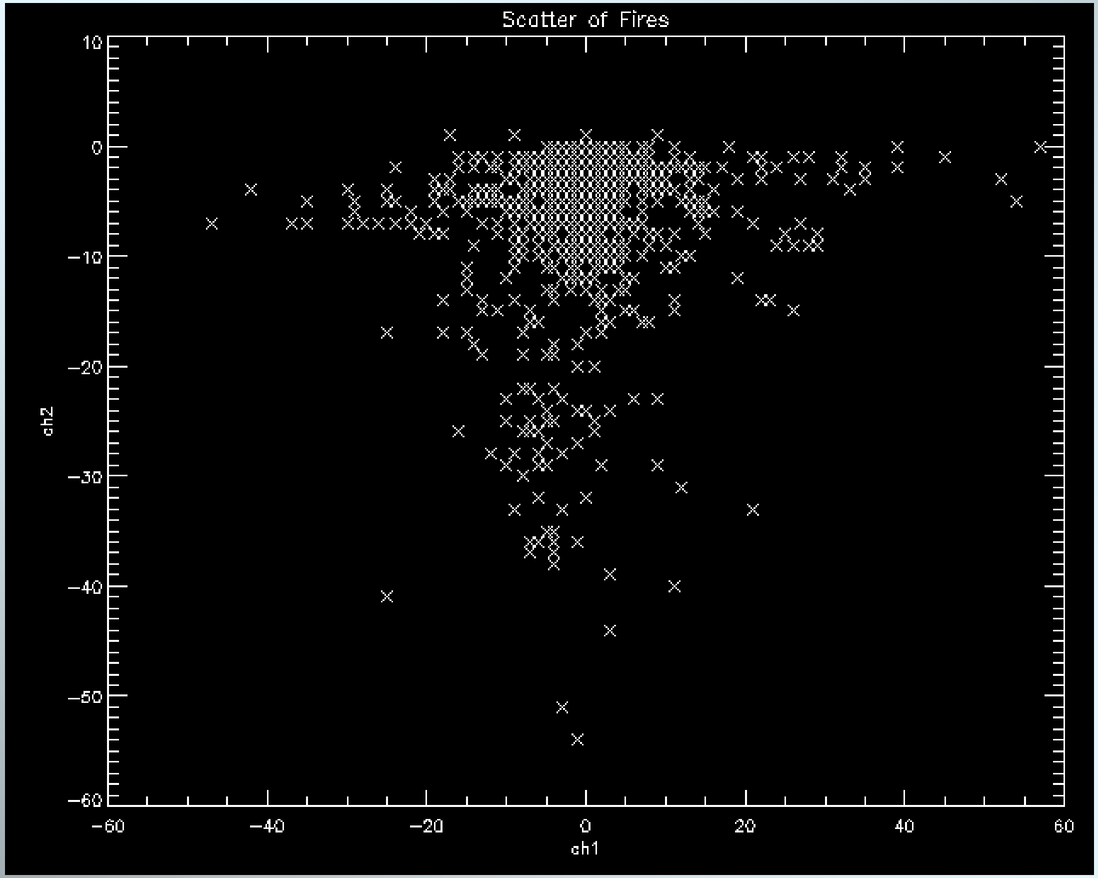


Scatter Plot of Background-Subtracted GOES CH 1 vs. CH 2

Fire (lower) and non-fire (upper) separation of clusters

2003: June 2 Northern Florida File: scatter_fires12.png

(GOES CH1, CH2, CH4 are input to neural network)

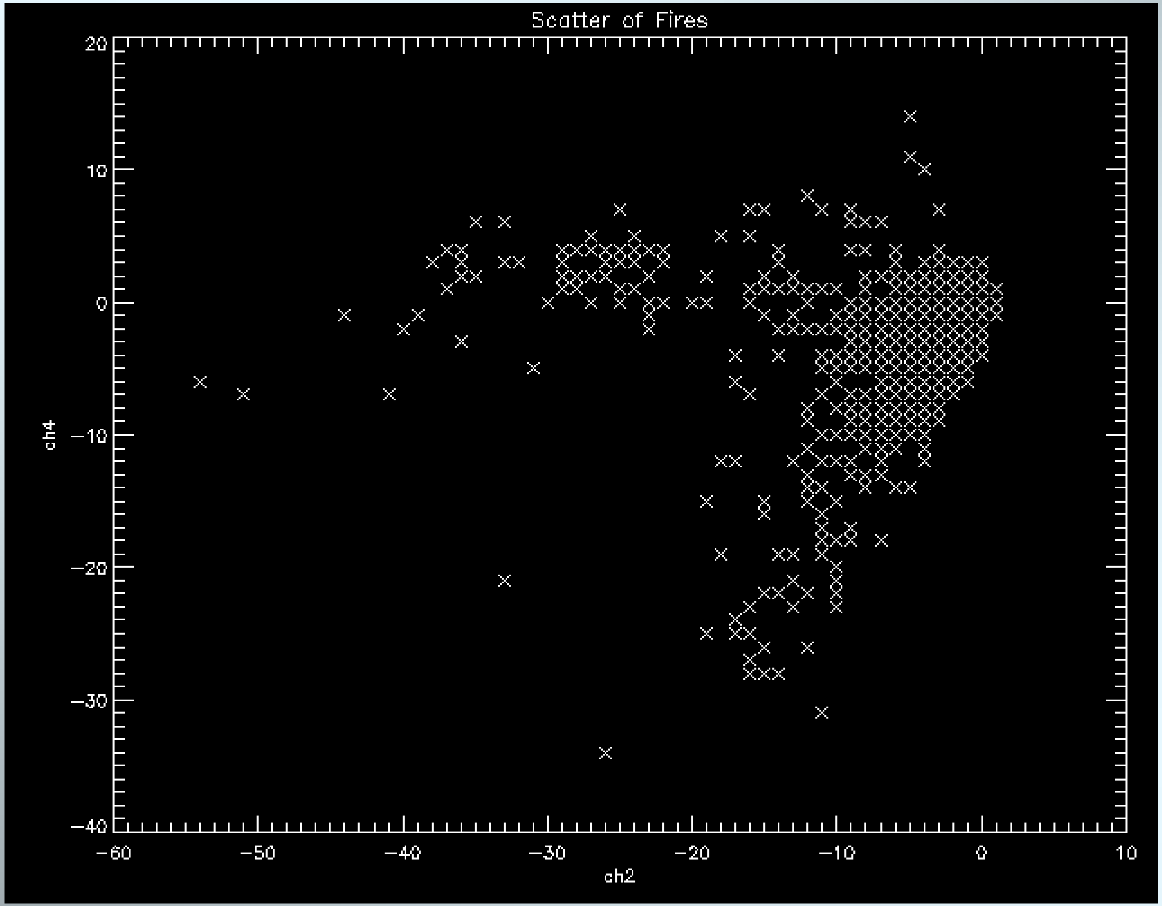


Scatter Plot of Background –Subtracted GOES CH 2 vs. CH 4

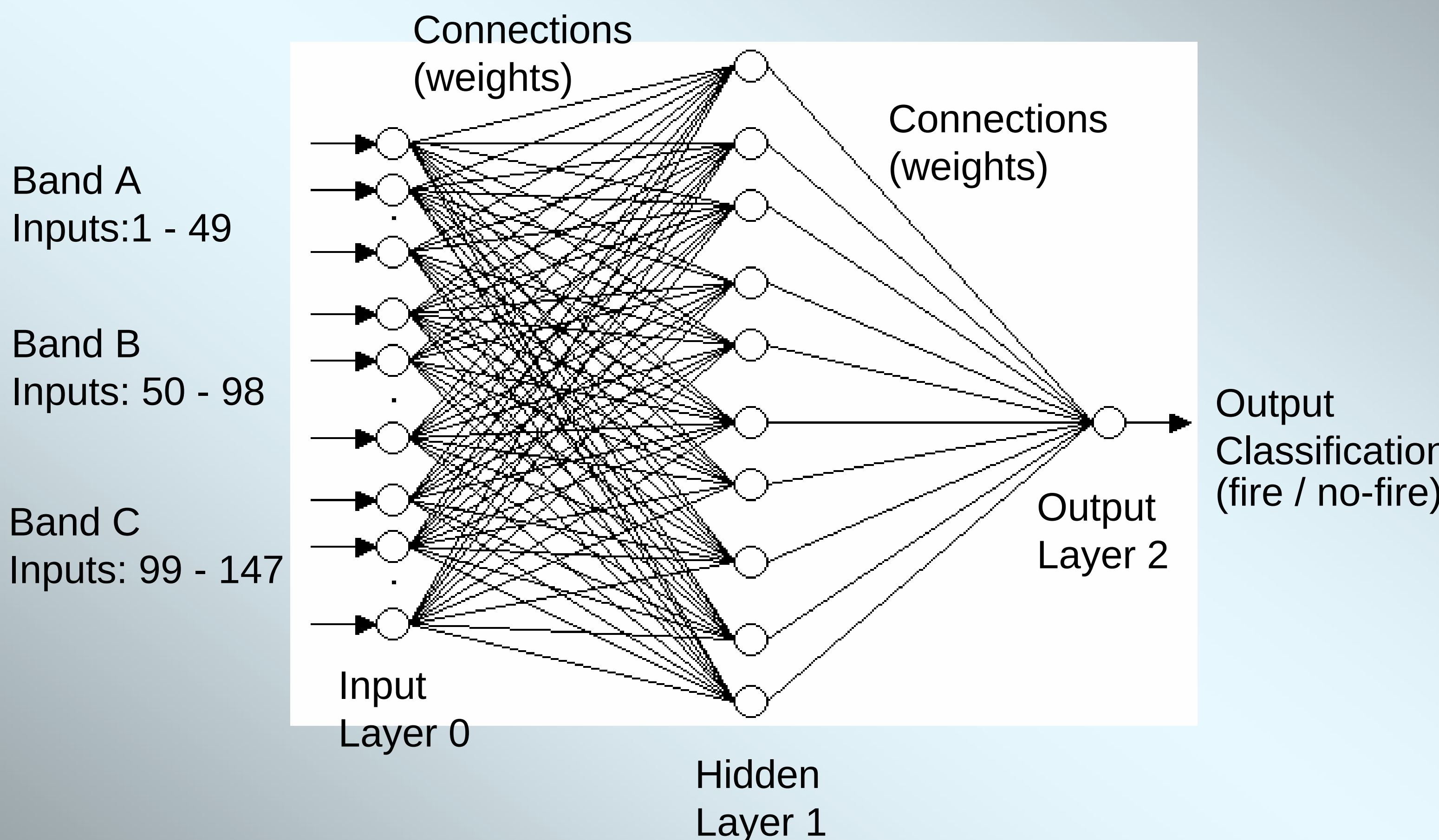
Fire (left) and non-fire (right) separation of clusters

2003: June 2 Northern Florida File:scatter_fires22.png

(GOES CH1, CH2, CH4 are input to neural network)



Neural Network Configuration for Wildfire Detection Neural Network



RESULTS

Typical Error Matrix
(for MODIS instrument)

True Positive	False Positive
False Negative	True Negative

TRAINING DATA

Neural Network Classification

	Fire	NonFire	Totals
Fire	2834 (TP)	173 (FP)	3007
NonFire	318 (FN)	3103 (TN)	3421
Totals	3152	3276	6428

Typical Measures of Accuracy

• Overall Accuracy	=	(TP+TN)/(TP+TN+FP+FN)
• Producer's Accuracy (fire)	=	TP/(TP+FN)
• Producer's Accuracy (nonfire)	=	TN/(FP+TN)
• User's Accuracy (fire)	=	TP/(TP+FP)
• User's Acuracy (nonfire)	=	TN/(TN+FN)

Accuracy of our NN Classification

• Overall Accuracy	=	92.4%
• Producer's Accuracy (fire)	=	89.9%
• Producer's Accuracy (nonfire)	=	94.7%
• User's Accuracy (fire)	=	94.2%
• User's Acuracy (nonfire)	=	90.7%