GISC 7365: Advanced Remote Sensing

Analyzing forest fires using Active Forest Fire Detection Algorithm from Landsat 8 OLI/TRS Data – A case study of Thomas Fire occurred in Santa Barbara, Ventura Counties CA.

May 1st 2018

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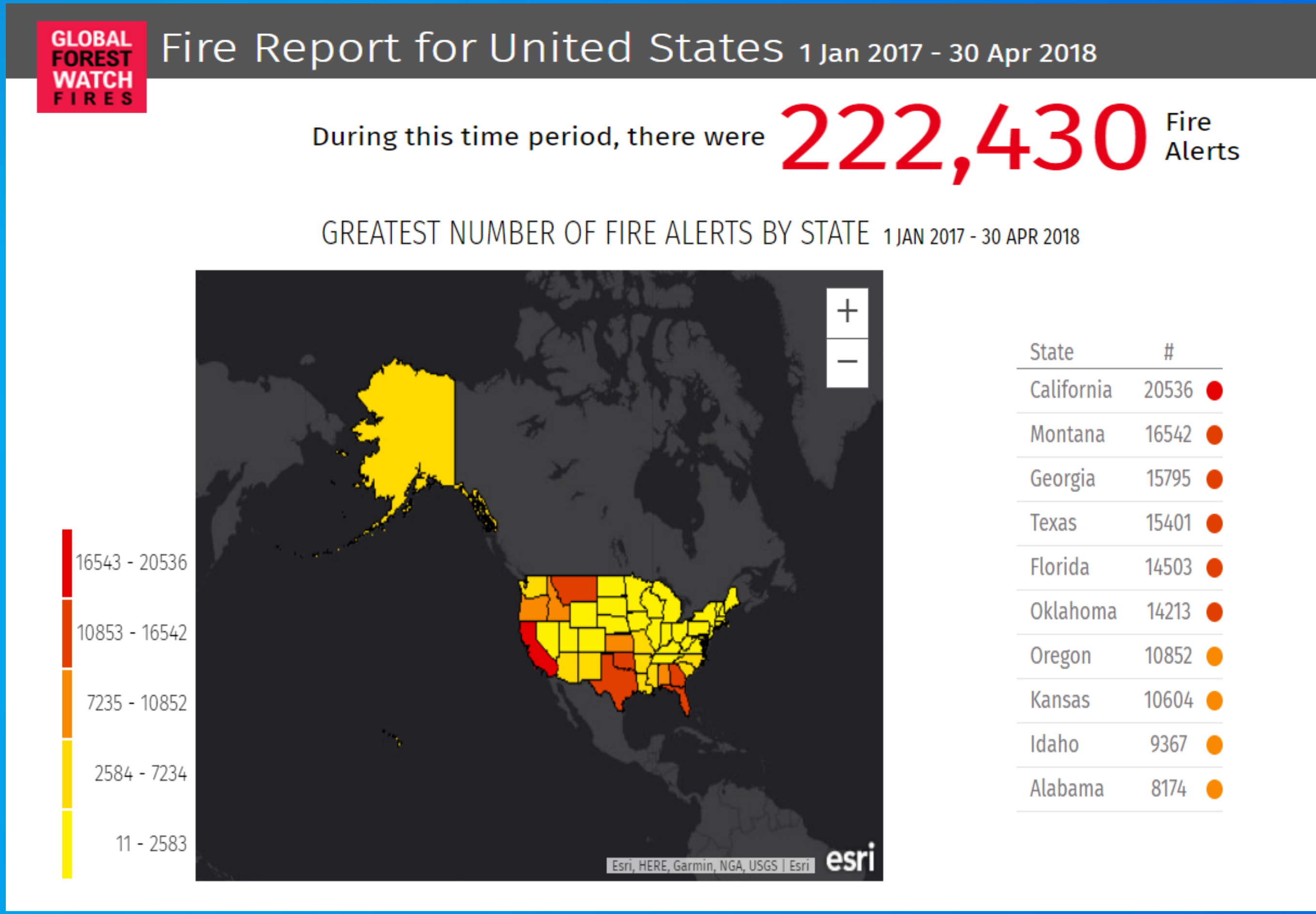
Contents

Background :
Forest Fires

- Most common hazard in forests.
- As old as forests themselves.
- Analyzing forest fire help us to determine many important
- 2017 wild fire assessment – More than 40,000 acres burnt.
- Dangerous spread rate.
- Affects environment, human health.
- Recent Thomas fire loss - $123,836,000.
- It is essential to monitor and control their vast spread

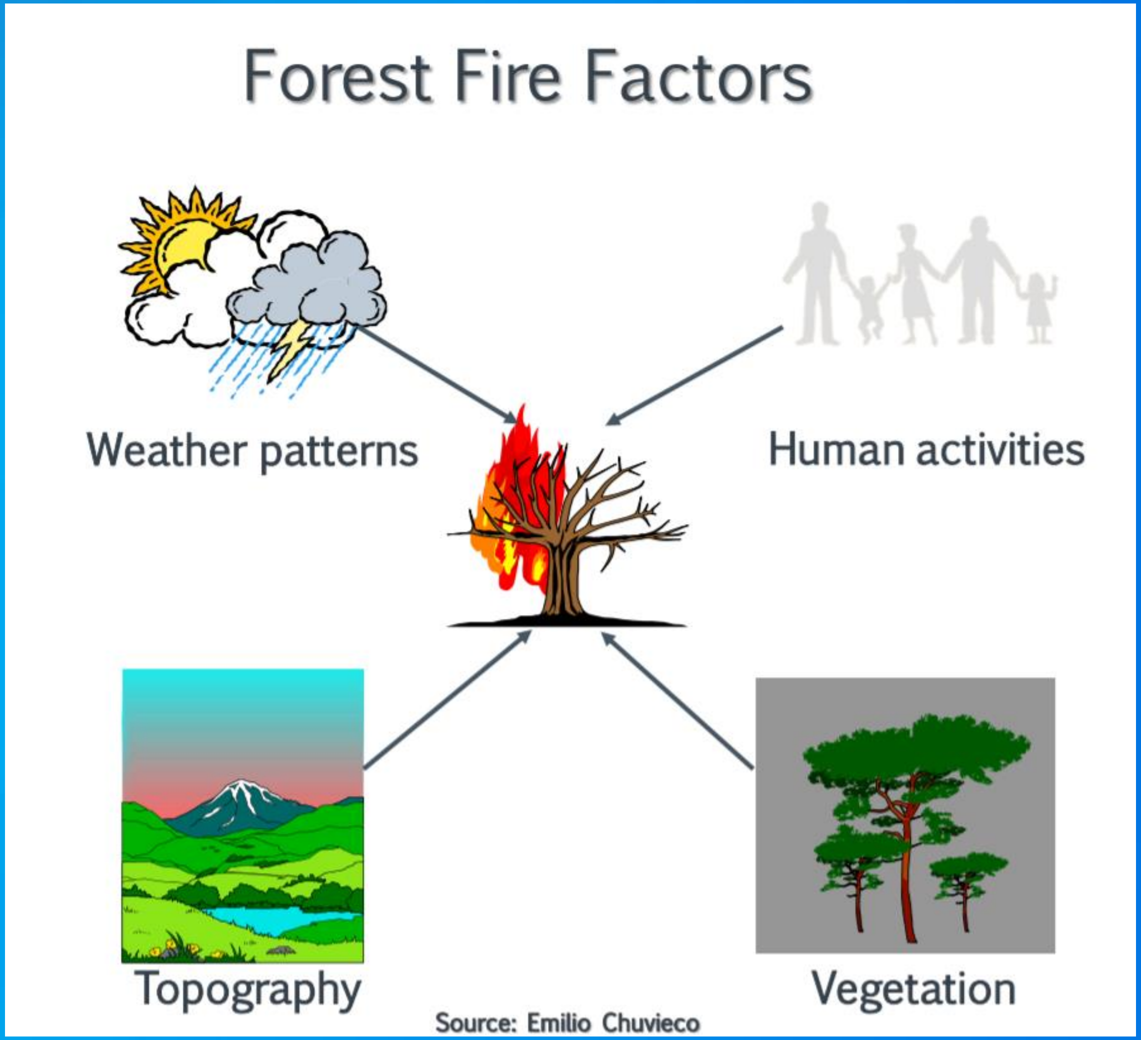


Source: globalforest.org

Major Causes:

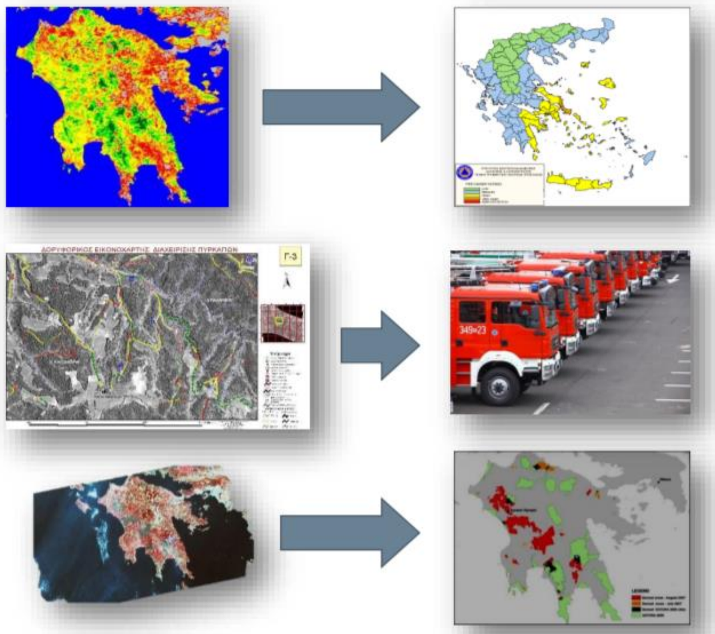
- Naturally Caused:
  - Combustion of dry fuel
  - Can be due to sandust and leaves.
  - Majority of Burnt Area
  - Not that easy to stop or control.

- Human Caused:
  - Smoking
  - Recreation
  - Equipment generated
  - Miscellaneous
  - Detected early by fire-fighters



How Remote Sensing and GIS can be used to control this?

Remote Sensing and GIS in Forest Fire Management



Pre-fire Operations

During fire Operations

Post-fire Operations

Remotely sensed data and GIS analysis may be used in all phases of a fire management programme.

✓ **Forest Fire Management related Remote Sensing (and GIS) applications**

Pre-fire planning

- Vegetation dryness mapping and monitoring
- Fire tower visibility analysis etc.
- Fuel type mapping (eg. ArcFuel)

During fire (assist operations)

- Fire Suppression

Post-fire impact assessment

- Burned area mapping
- Operational Burned Area Mapping at National Level
- Burn Severity mapping
- Short and long term damage assessment

Source : FMRS

Major Objectives:

- Analyzing Thomas Fire Occurrences.
- Applying decision rules based on literature for identifying fire pixels.
- Automating Batch Composite Imagery Generation for Image Analysis.
- Generating burn severity map post Thomas fire using NBR.
- Comparison of obtained fire pixels with Modis Data .

STUDY AREA

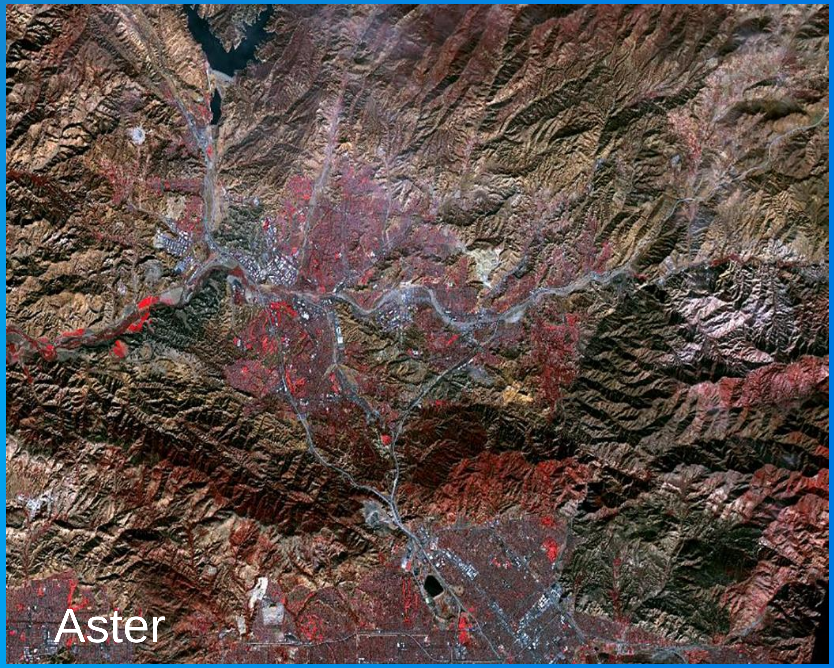

ARROYO GRANDE
Carrizo Plain
SANTA MARIA
ORCUTT
San Rafael Wilderness
Wind Wolves Preserve
Mount Pinos
GORMAN
Vandenberg Air Force Base
LOMPOC
Dick Smith Wilderness
Sespe Wilderness
Angeles National Forest
SANTA BARBARA
CARPINTERIA
FILLMORE
SANTA PAULA
VENTURA
CAMARILLO
THOUSAND OAKS
PORT HUENEME
SANTA CRUZ ISLAND
SANTA ROSA ISLAND
1
101
166
5
33
150
202

Thomas Fire Statistics and Brief Introduction:

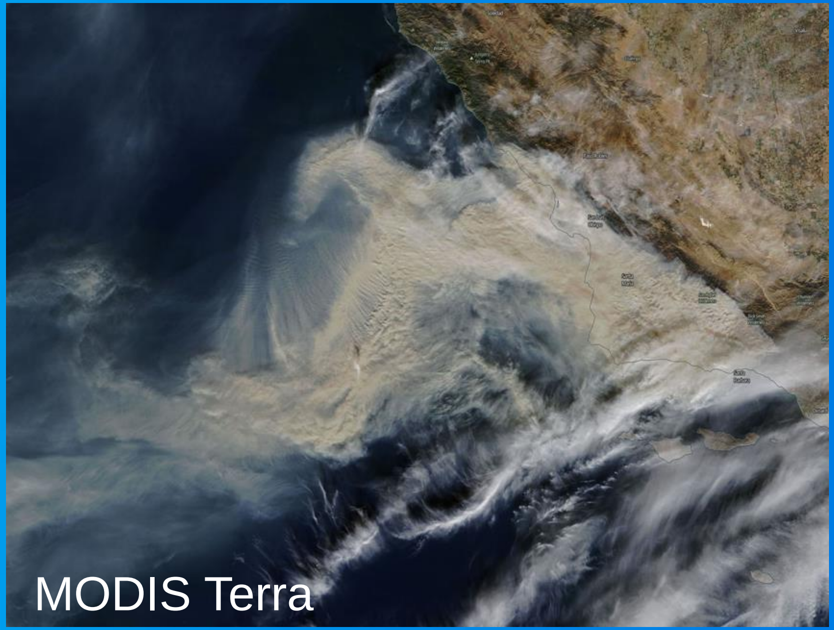
- Massive wild fire which affected Santa Barbara and Ventura Counties
- December 4th 2017 to January 12th 2018.
- Largest blaze in the history of CA.
- Nearly 282k acres burnt area. (> Dallas + Miami)
- More than 1000 structures destroyed.
- Cause still under investigation.
- One of the multiple wild fires which has ignited California in 2017.
- Other fires
  - Rye Fire
  - Creek Fire.


Burn scar
Ojai
Burn scar
Oak View
101
Ventura
Landsat

THOMAS FIRE


Aster

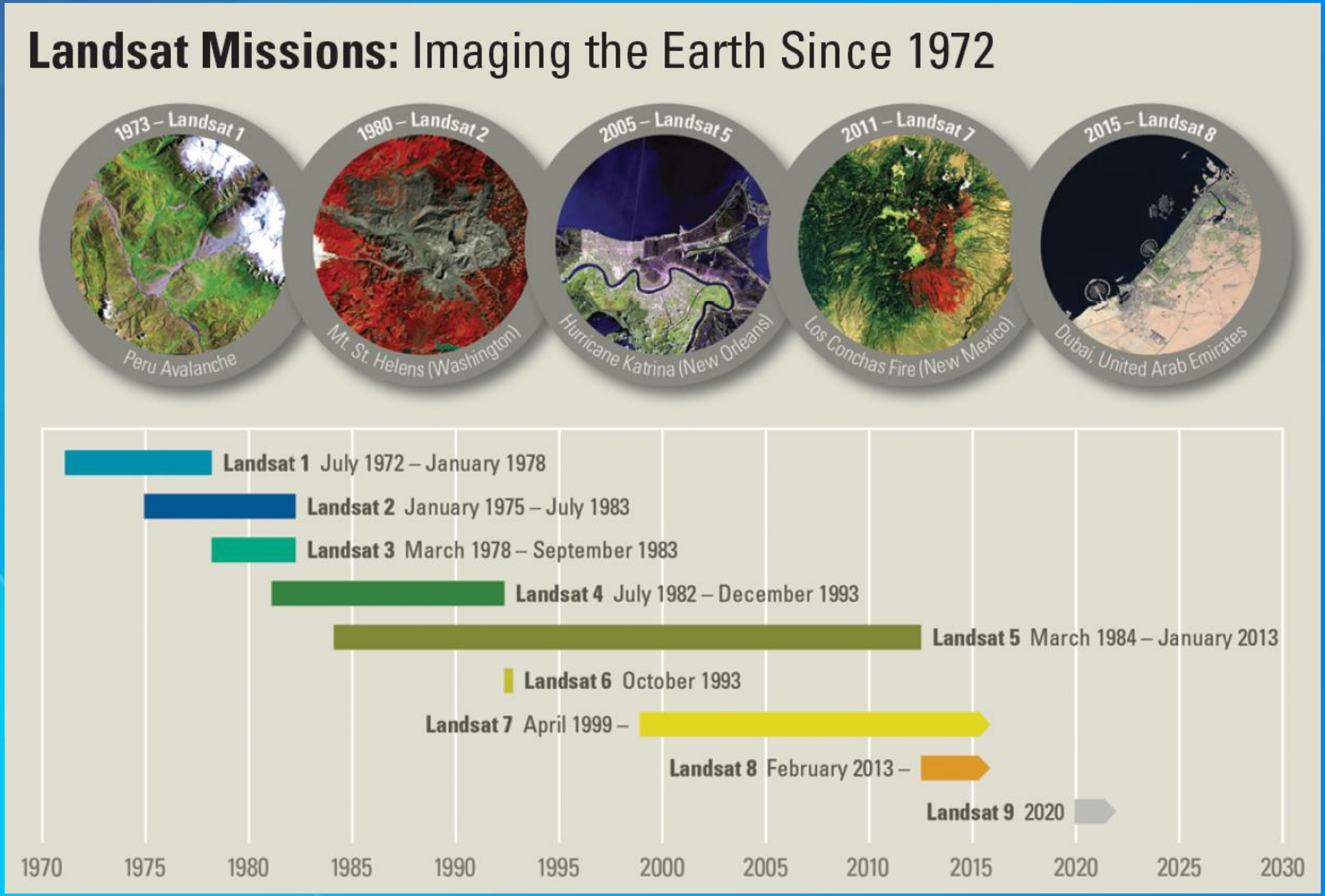

MODIS Aqua


MODIS Terra

Data Acquired:

- Landsat 8 (OLI/TRS) Level II data was acquired from USGS Earth Explorer.
- County level data was obtained
- Foot Prints were taken carefully.
- Dates Acquired
  - Before Fire : 23rd Nov
  - During Fire : 9th Dec, 25th Dec, 10th Jan
  - After Fire: 26th Jan
- WRS Path and Row : 42 and 36
- Projection System : UTM, Zone 11
- Datum : WGS 1984

Timeline and History of Landsat Missions



Source : USGS

Landsat Band Acquisitions

Table 1. Display and comparison of the bands and wavelengths of each Landsat sensor. Instrument-specific relative spectral response functions can be viewed and compared using the U.S. Geological Survey Spectral Viewer tool: https://landsat.usgs.gov/spectral-characteristics-viewer.

[OLI, Operational Land Imager; TIRS, Thermal Infrared Sensor; ETM+, Enhanced Thematic Mapper Plus; TM, Thematic Mapper; MSS, Multispectral Scanner; --, not applicable]

Band designations	Landsat band wavelength comparisons All bands 30-meter resolution unless noted									
	L8 OLI/TIRS		L7 ETM+		L4-5 TM		L4-5 MSS*		L1-3 MSS*	
Coastal/Aerosol	Band 1	0.43–0.45	--	--	--	--	--	--	--	--
Blue	Band 2	0.45–0.51	Band 1	0.45–0.52	Band 1	0.45–0.52	--	--	--	--
Green	Band 3	0.53–0.59	Band 2	0.52–0.60	Band 2	0.52–0.60	Band 1	0.5–0.6 *	Band 4	0.5–0.6 *
Panchromatic	Band 8**	0.50–0.68	Band 8 **	0.52–0.90	--	--	--	--	--	--
Red	Band 4	0.64–0.67	Band 3	0.63–0.69	Band 3	0.63–0.69	Band 2	0.6–0.7 *	Band 5	0.6–0.7 *
Near-Infrared	Band 5	0.85–0.88	Band 4	0.77–0.90	Band 4	0.76–0.90	Band 3	0.7–0.8 *	Band 6	0.7–0.8 *
Near-Infrared	--	--	--	--	--	--	Band 4	0.8–1.1 *	Band 7	0.8–1.1*
Cirrus	Band 9	1.36–1.38	--	--	--	--				
Shortwave Infrared-1	Band 6	1.57–1.65	Band 5	1.55–1.75	Band 5	1.55–1.75				
Shortwave Infrared-2	Band 7	2.11–2.29	Band 7	2.09–2.35	Band 7	2.08–2.35				
Thermal	Band 10 T1	10.60–11.19	Band 6 T2	10.40–12.50	Band 6 T2	10.40–12.50				
Thermal	Band 11 T1	11.50–12.51	--	--	--	--				

* Acquired at 79 meters, resampled to 60 meters
** 15-meter (panchromatic)
T1 = Thermal (acquired at 100 meters, resampled to 30 meters)
T2 = Thermal (acquired at 120 meters, resampled to 30 meters)

Source : USGS

Landsat Band Usage

Table 2. The bands of each Landsat satellite and descriptions of how each band is best used.

[--, not applicable]

	Uses of Landsat bands					
Band name	**L8 OLI/TIRS**	**L7 ETM+**	**L4-5 TM**	**L4-5 MSS**	**L1-3 MSS**	**Description of use**
Coastal/Aerosol	Band 1	--	--	--	--	Coastal areas and shallow water observations; aerosol, dust, smoke detection studies.
Blue (B)	Band 2	Band 1	Band 1	--	--	Bathymetric mapping; soil/vegetation discrimination, forest type mapping, and identifying manmade features.
Green (G)	Band 3	Band 2	Band 2	Band 1	Band 4	Peak vegetation; plant vigor assessments.
Red (R)	Band 4	Band 3	Band 3	Band 2	Band 5	Vegetation type identification; soils and urban features.
Near-Infrared (NIR)	Band 5	Band 4	Band 4	Band 3	Band 6	Vegetation detection and analysis; shoreline mapping and biomass content.
	--	--	--	Band 4	Band 7	
Shortwave Infrared-1 (SWIR-1)	Band 6	Band 5	Band 5	--	--	Vegetation moisture content/drought analysis; burned and fire-affected areas; detection of active fires.
Shortwave Infrared-2 (SWIR-2)	Band 7	Band 7	Band 7	--	--	Additional detection of active fires (especially at night); plant moisture/drought analysis.
Panchromatic (PAN)	Band 8	Band 8	--	--	--	Sharpening multispectral imagery to higher resolution.
Cirrus	Band 9	--	--	--	--	Cirrus cloud detection.
Thermal (T)	Band 10	Band 6	Band 6	--	--	Ground temperature mapping and soil moisture estimations.
	Band 11			--	--	

Source : USGS

Why SWIR is considered over TIR?

TIR:

- Thermal sensors detect warm object over a cool background.
- May not detect accurately because of high resolution 100m in Landsat 8.

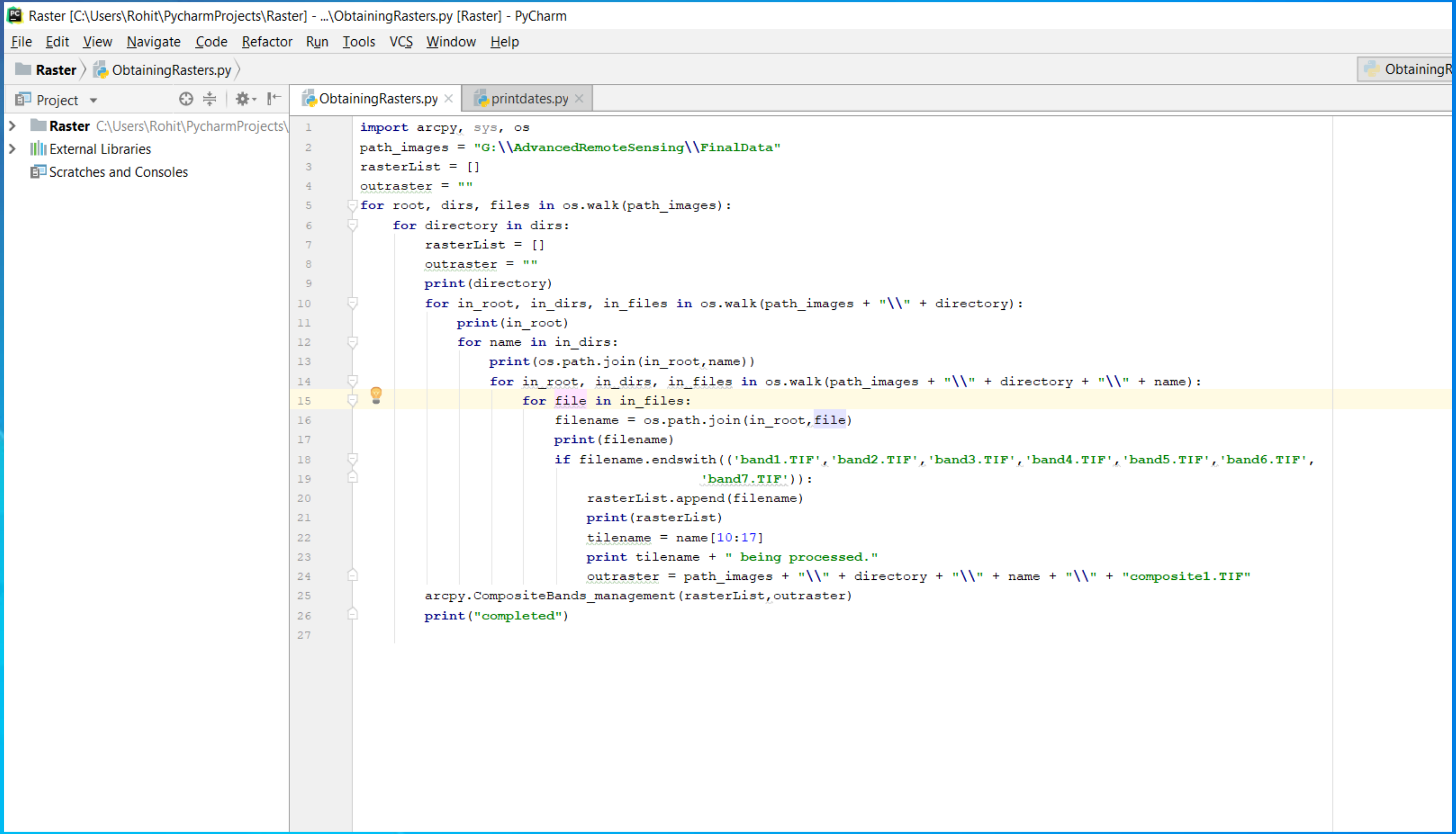
SWIR:

- Provides high resolution (30m)
- Pin points sites of active burning.
- Detect hot spots and estimate where the fire is burning the hottest

Source : USGS

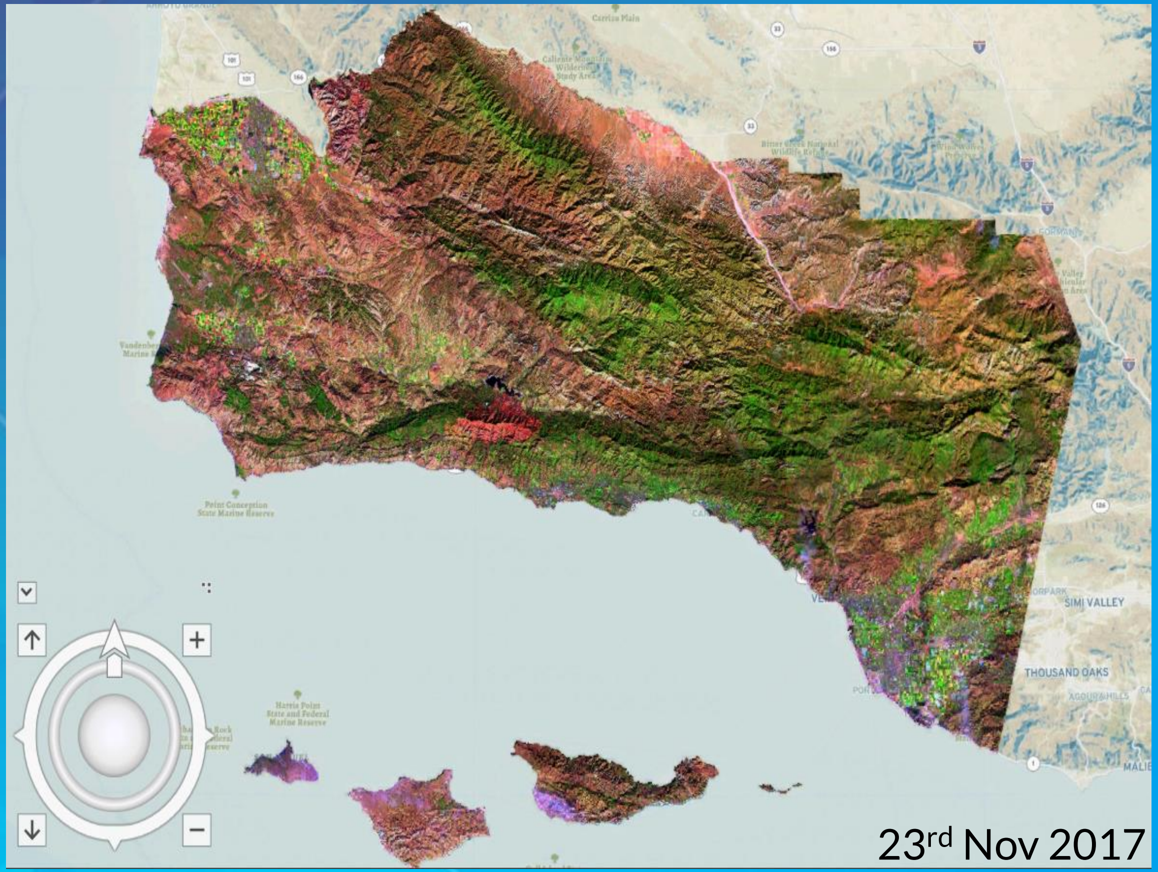
Data Prep: Making Batch Composites from Satellite Imagery Bands using ArcPy

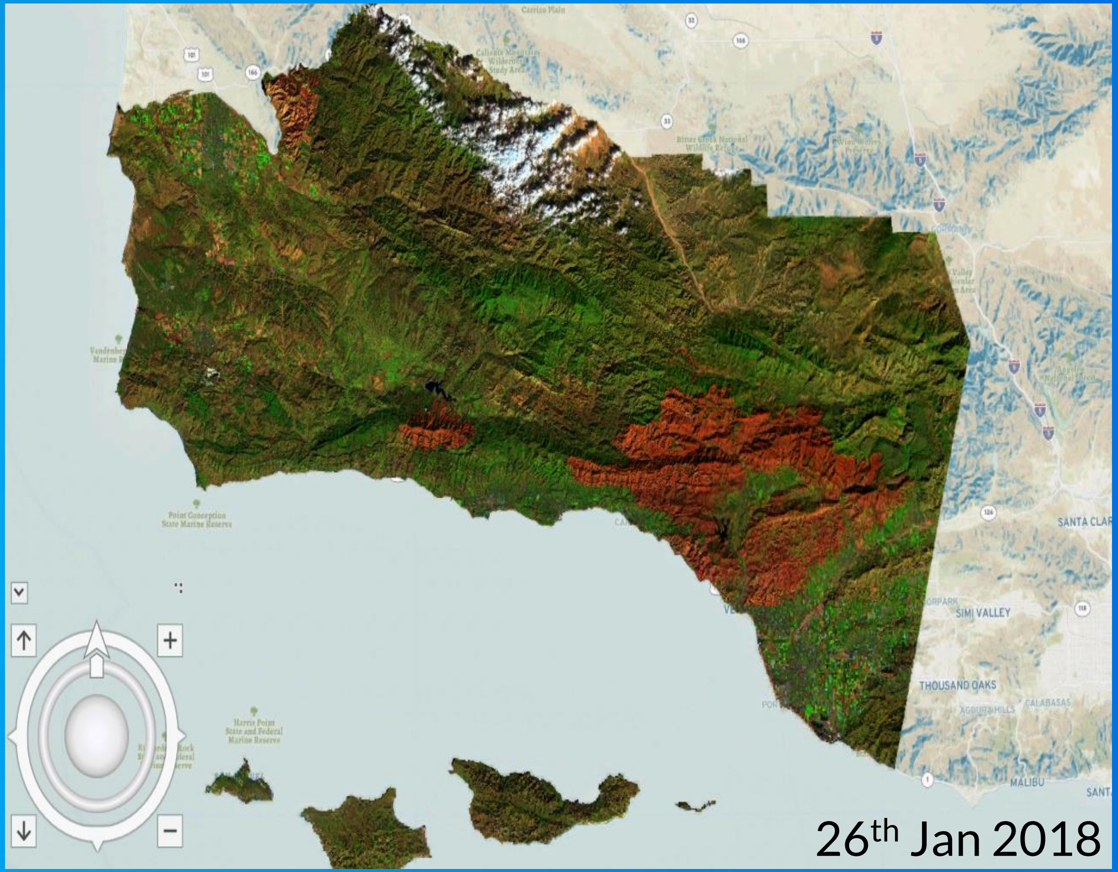
Primary task for any Satellite Image Analysis




```python
import arcpy, sys, os
path_images = "G:\\AdvancedRemoteSensing\\FinalData"
rasterList = []
outraster = ""
for root, dirs, files in os.walk(path_images):
    for directory in dirs:
        rasterList = []
        outraster = ""
        print(directory)
        for in_root, in_dirs, in_files in os.walk(path_images + "\\" + directory):
            print(in_root)
            for name in in_dirs:
                print(os.path.join(in_root,name))
                for in_root, in_dirs, in_files in os.walk(path_images + "\\" + directory + "\\" + name):
                    for file in in_files:
                        filename = os.path.join(in_root,file)
                        print(filename)
                        if filename.endswith(('band1.TIF','band2.TIF','band3.TIF','band4.TIF','band5.TIF','band6.TIF',
                                              'band7.TIF')):
                            rasterList.append(filename)
                            print(rasterList)
                            tilename = name[10:17]
                            print tilename + " being processed."
                            outraster = path_images + "\\" + directory + "\\" + name + "\\" + "composite1.TIF"
        arcpy.CompositeBands_management(rasterList,outraster)
        print("completed")
```

Landsat Imagery Band (7,5,2) Combination



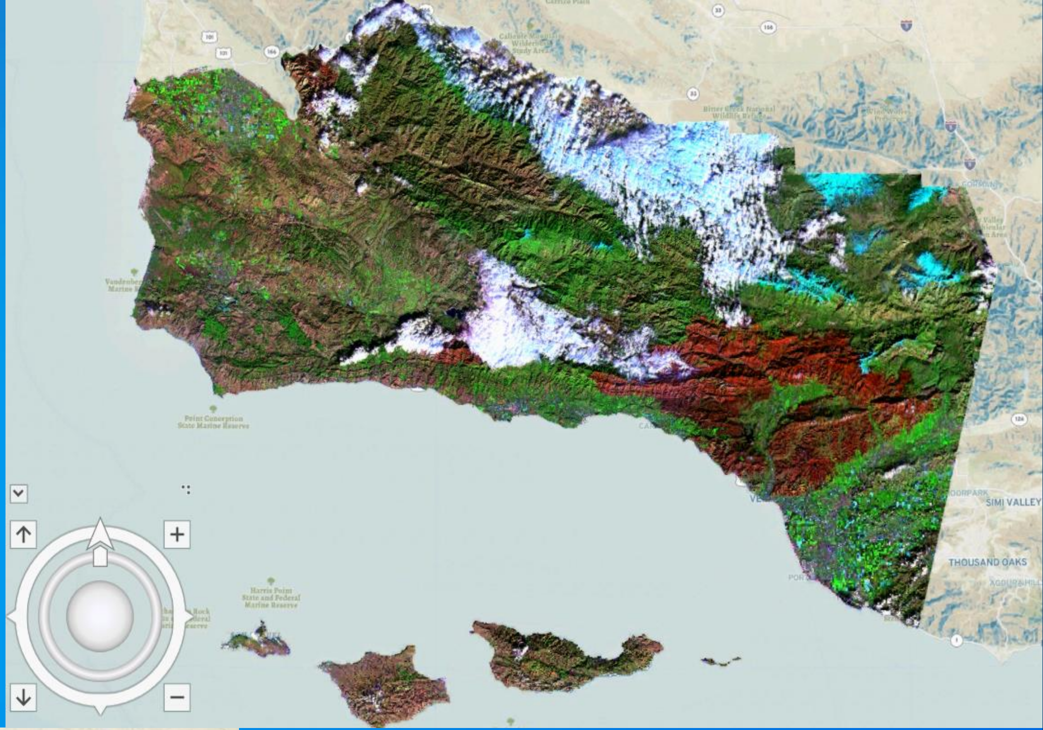


Pre Fire

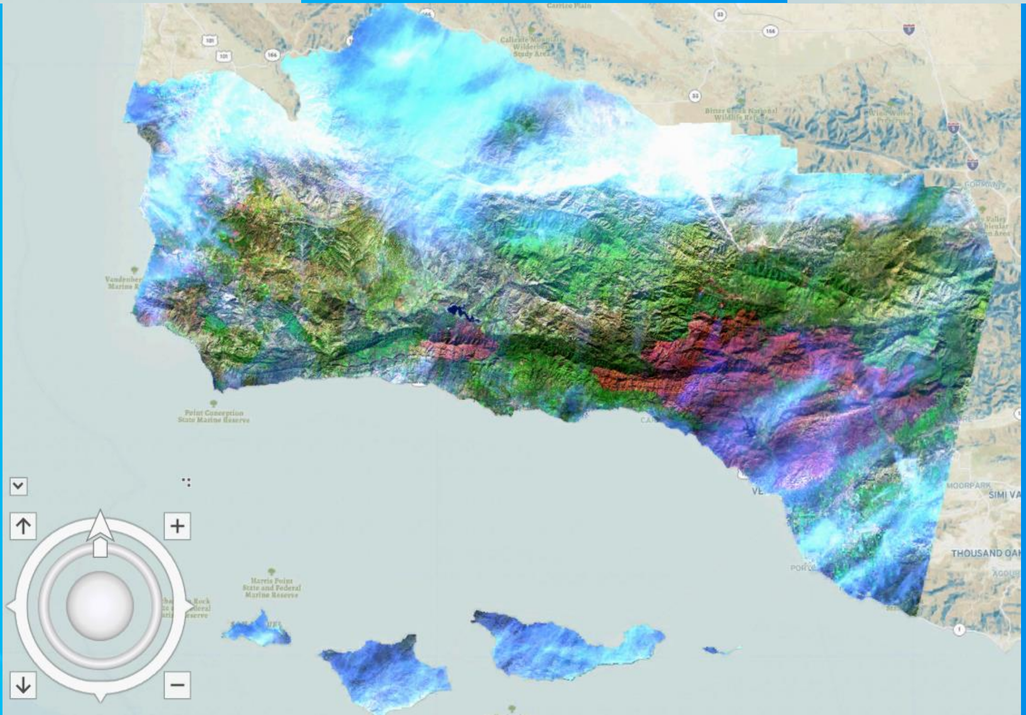
Post Fire

During Fire

9th Dec, 2017



10th Jan 2018



25th Dec 2017

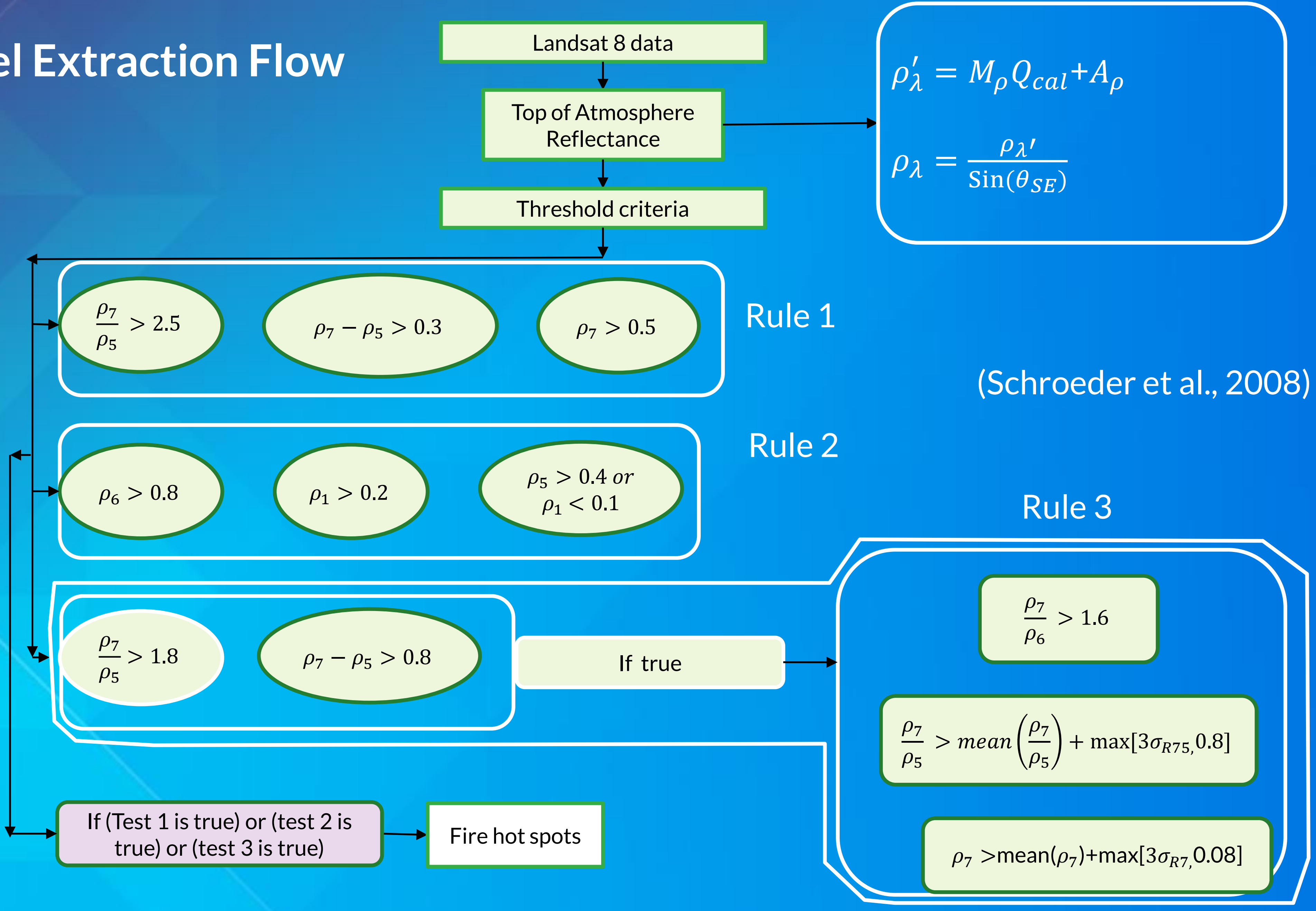
Methodology :

- Top of Atmospheric reflectance conversions are performed in order to remove haze and atmospheric disturbances while satellite images are acquired.
- The main goal is to obtain imagery which represents solar radiation incident on the instrument independent of position of sun w.r.t earth.
- Main advantage of doing this is two TOA images can be compared which are acquired at a different dates.

$$\rho_\lambda' = M_\rho Q_{cal} + A_\rho \qquad \text{....Eq 1}$$

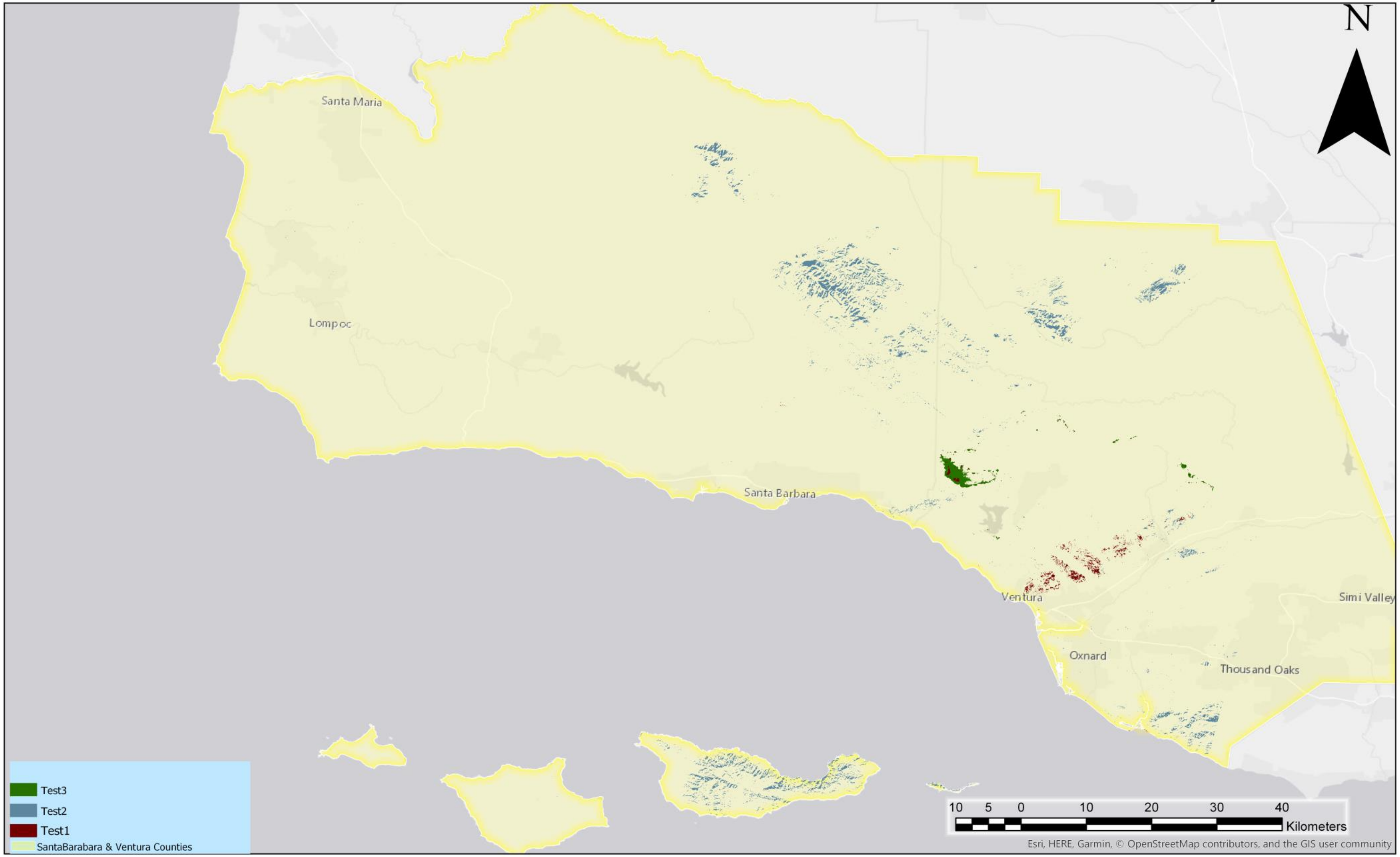
$$\rho_\lambda = \frac{\rho_\lambda'}{\mathrm{Sin}(\theta_{SE})} \qquad \text{....Eq 2}$$

Fire Pixel Extraction Flow



(Schroeder et al., 2008)

Active Fire Pixel detection from Landsat 8 data - 9th Dec, 2017



Active Fire Pixel detection from Landsat 8 data - 25th Dec, 2017

Normalized Burn Ratio:

An Overview:

- Similar to NDVI except that it uses NIR and SWIR wavelengths
- Useful for highlighting the burned areas and estimate the fire intensity.
- Calculated as NBR = (NIR – SWIR)/(NIR + SWIR)

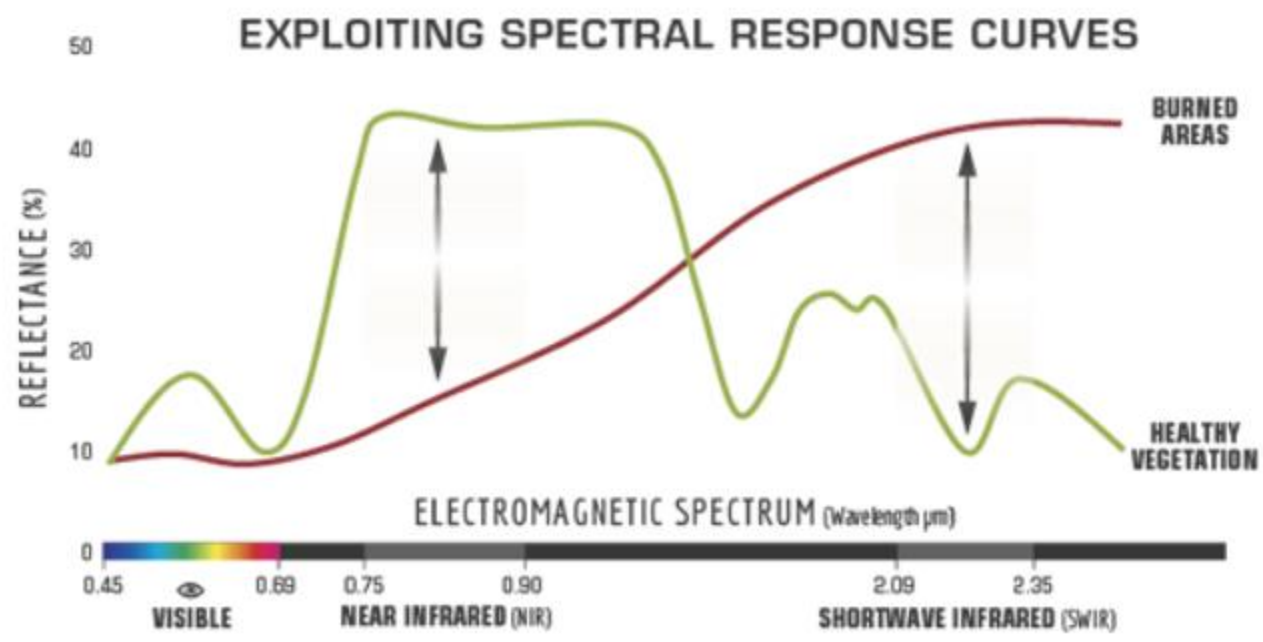


Image Credit: US Forest Service

Burn Severity:

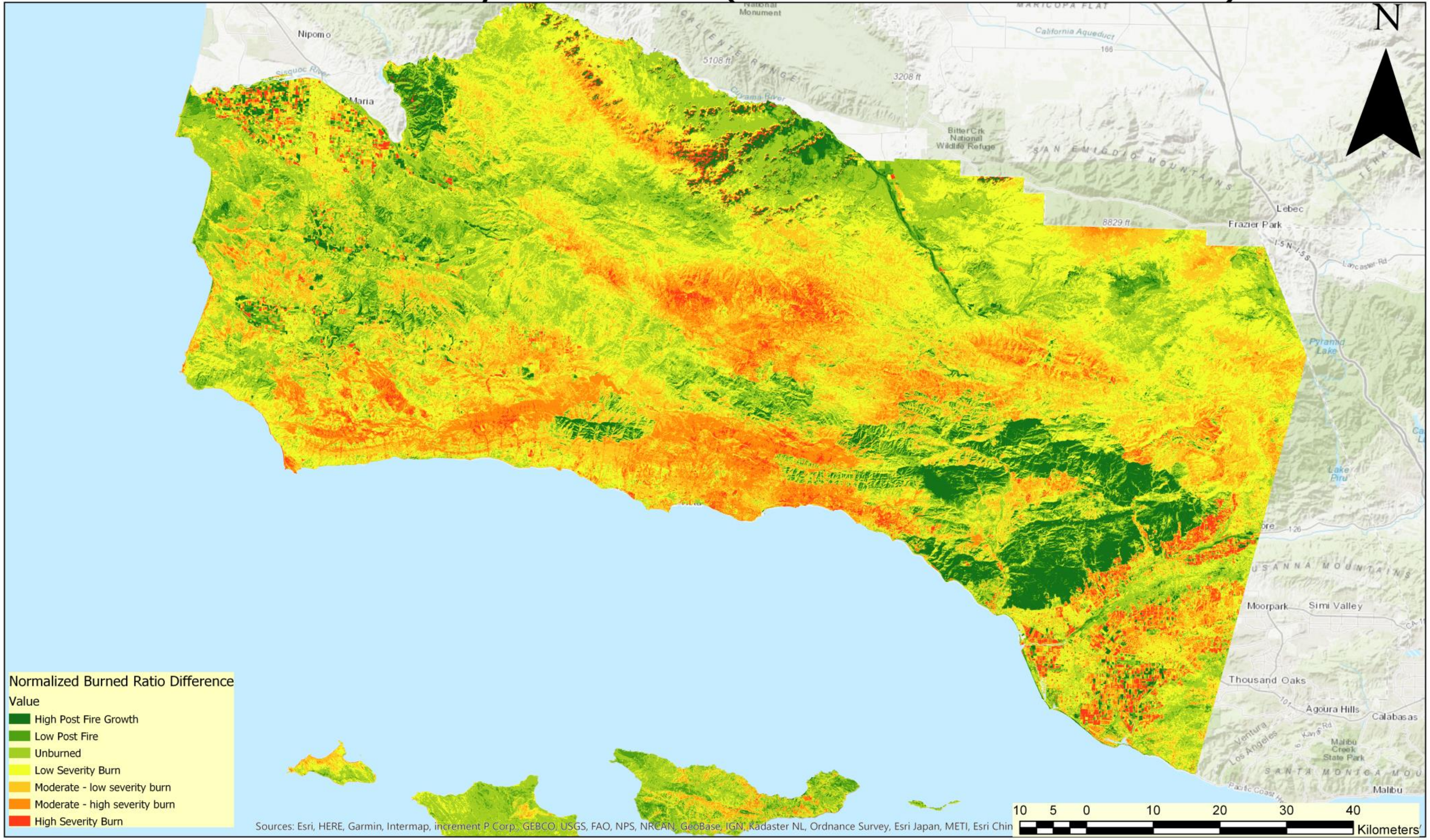
- Imagery collected before a fire will have a very high infrared values and low mid infrared values, which is exactly inverse for the imagery collected after a fire.
- Normalized Burn Difference is given by

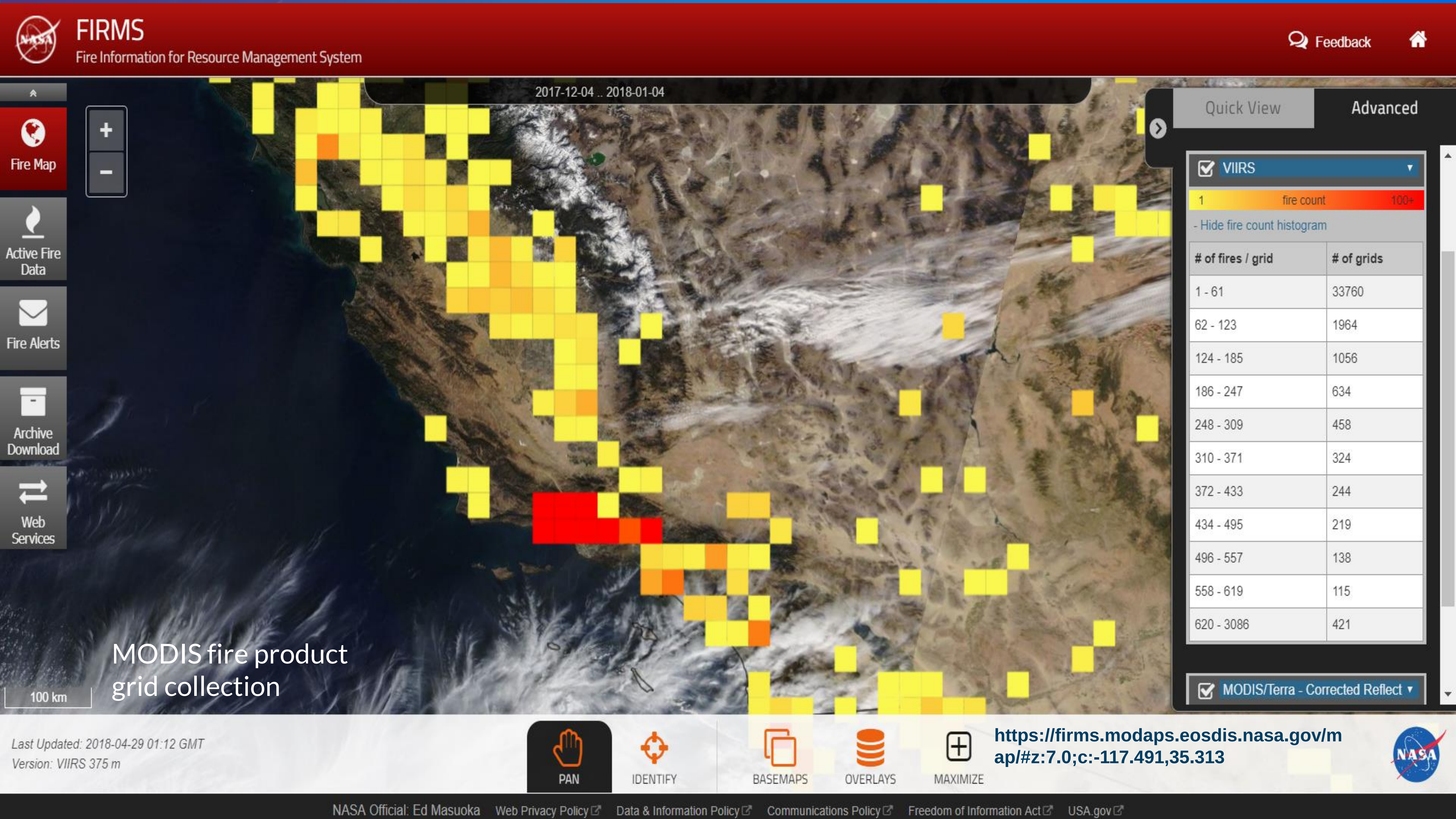
$$dNBR \text{ or } \Delta NBR = PrefireNBR - PostfireNBR$$

- Higher dNBR indicates more severe damage.
- But if we have areas with any negative dNBR values, it means there is an increased vegetation productivity after a fire.

Source: http://gsp.humboldt.edu

Burn Severity Difference (Pre and Post Thomas Fire)

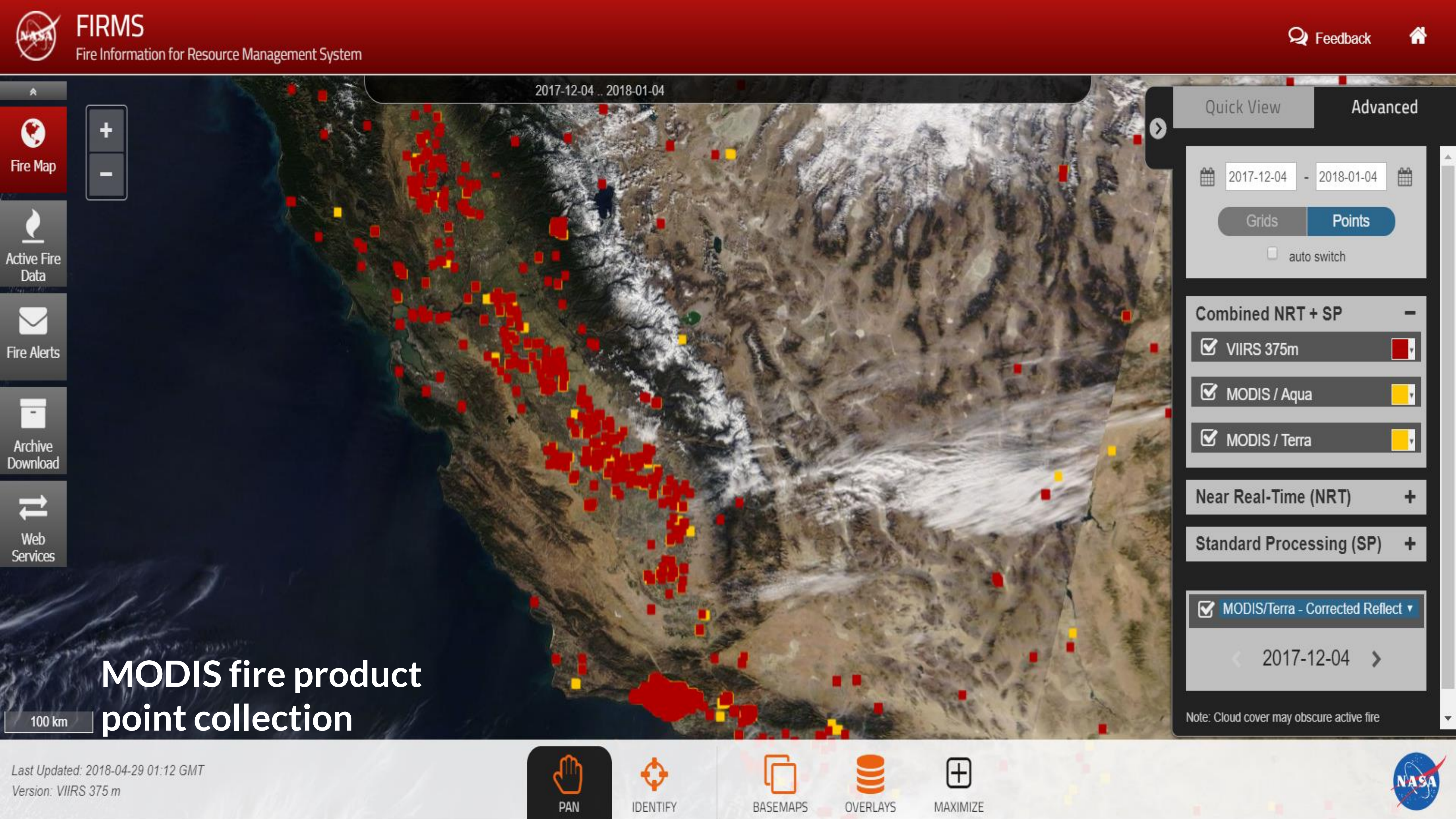




# of fires / grid	# of grids
1 - 61	33760
62 - 123	1964
124 - 185	1056
186 - 247	634
248 - 309	458
310 - 371	324
372 - 433	244
434 - 495	219
496 - 557	138
558 - 619	115
620 - 3086	421

MODIS fire product grid collection

https://firms.modaps.eosdis.nasa.gov/map/#z:7.0;c:-117.491,35.313



MODIS fire product point collection

Conclusions & Possible Future Findings:

- Active fire spots are identified using fire detection algorithm.
- Accuracy Assessment was performed manually using MODIS fire points with an accuracy of 70-80%
- Burn Severity Map is generated showing the Pre-Burn and Post Burn Scenario.
- Steady raise in Landsat class data may create new opportunities in the field of forest fire management activities
- With LandSAT 9 possible launch in 2020, better quality of imagery can obtained and analyzed using image processing techniques.
- With few more satellites launched the increase in temporal resolution can provide us with a better solution in detecting forest fires.

References (Links and Texts)

- Bastarrika. A.; Chuvieco, E. Martín, M.P. Mapping burned areas from Landsat TM/ETM+ data with a two phase algorithm: Balancing omission and commission errors. *Remote Sensing of Environment*. 2011. 105:1003-1012
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- http://www.harrisgeospatial.com/Learn/Blogs/Blog-Details/TabId/2716/ArtMID/10198/ArticleID/15691/The-Many-Band-Combinations-of-Landsat-8.aspx
- https://landsat.usgs.gov/using-usgs-landsat-8-product

Thank you for your time

Queries??