Fire Detection and Characterization with GOES-R ABI

Fire Detection and Characterization Application Team

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What is it?

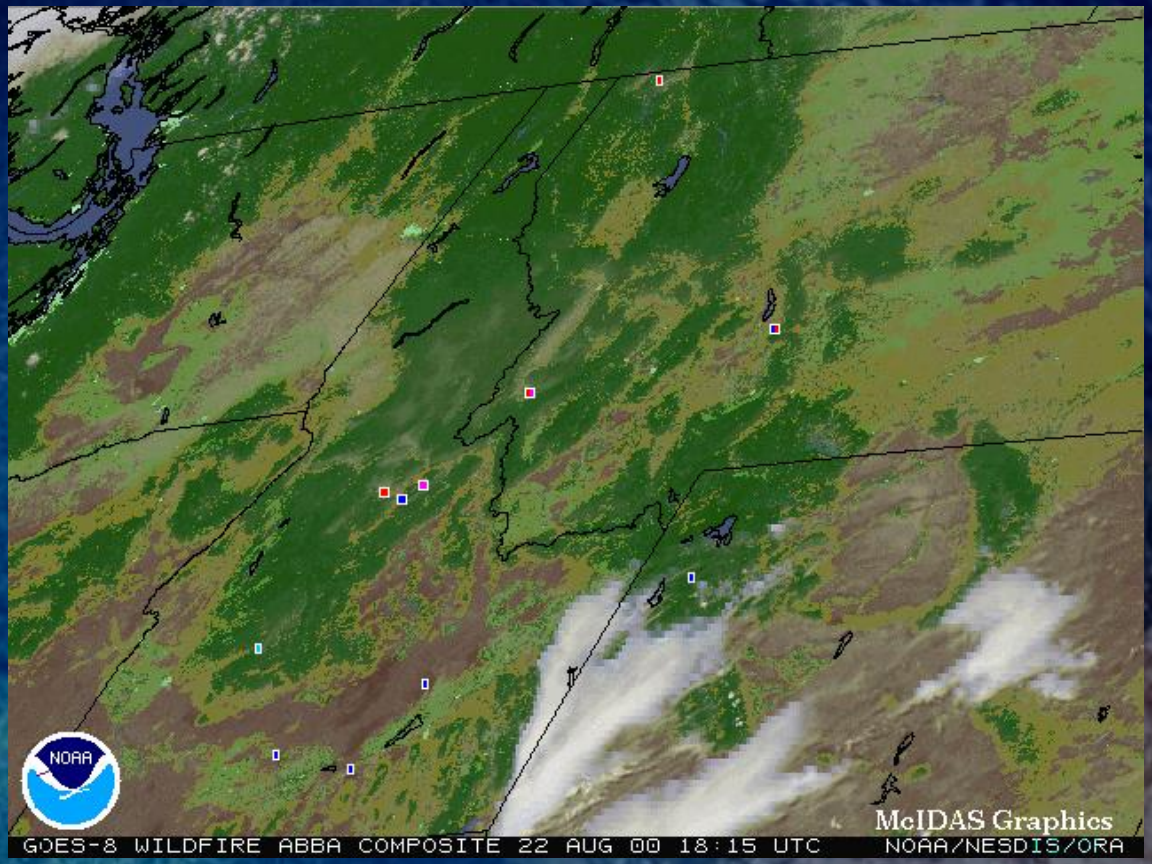
What is the ABI Fire Detection and Characterization Algorithm?:

- The FDCA is a dynamic, multi-spectral, thresholding contextual algorithm that uses the visible (when available) and the 3.9 and 11.2 µm bands to locate fires and characterize sub-pixel fire characteristics. The 12 µm band is used along with the other bands to help identify opaque clouds.
- 5 minute CONUS, 15 minute full disk refresh; 2 km resolution
- ABI version of the current GOES Wildfire Automated Biomass Burning Algorithm (WF_ABBA), an Operational product since 2002
- Product outputs:
  - Fire location
  - Fire instantaneous size, temperature, and radiative power
  - Metadata mask including information about opaque clouds, solar reflection block-out zones, unusable ecosystem types.

What is it?

WF_ABBA Example:

- 22 August 2000, 18:15 to 23:45 UTC
- Fire complex had started on 14 August
- Loop shows intensification in the afternoon as the winds pick up
- Valley smoke can be seen, as well as a fire induced cloud with a glaciated top



Why?

Why do we care about geostationary fire detection and characterization?

- 24/7 monitoring of a hemisphere allows for tracking trends and detecting fires earlier than allowed by polar platforms
- The fire's radiative power (FRP), size, and temperature can be used to estimate emissions and intensity
  - FRP is related to the mass consumed
  - FRP is proportional to temperature to the fourth power times size
- Knowing what we cannot see is as important and knowing what we do see – the metadata mask is invaluable information
- The large footprint makes early detection of wildfires difficult, but is still useful where human observers are few and far between

How?

How do we detect and characterize fires? (aka "Is it more than a difference image?"):

- The FDCA uses the visible, 3.9, 11.2, and 12 µm bands.
- It identifies and records block-out zones due to sunglint and ecosystem type and does an initial pass at identifying and characterizing all remotely possible fire pixels.
- It then proceeds through a multi-layer decision tree to determine if a pixel is a possible fire pixel by comparing the pixel to thresholds.
- Once a hot pixel is located the algorithm incorporates ancillary data to screen for false alarms, correct for water vapor attenuation, surface emissivity, solar reflectivity, and semi-transparent clouds. Pixels that fail certain tests are given a second chance later in the decision tree to become a possible fire pixel.

How?

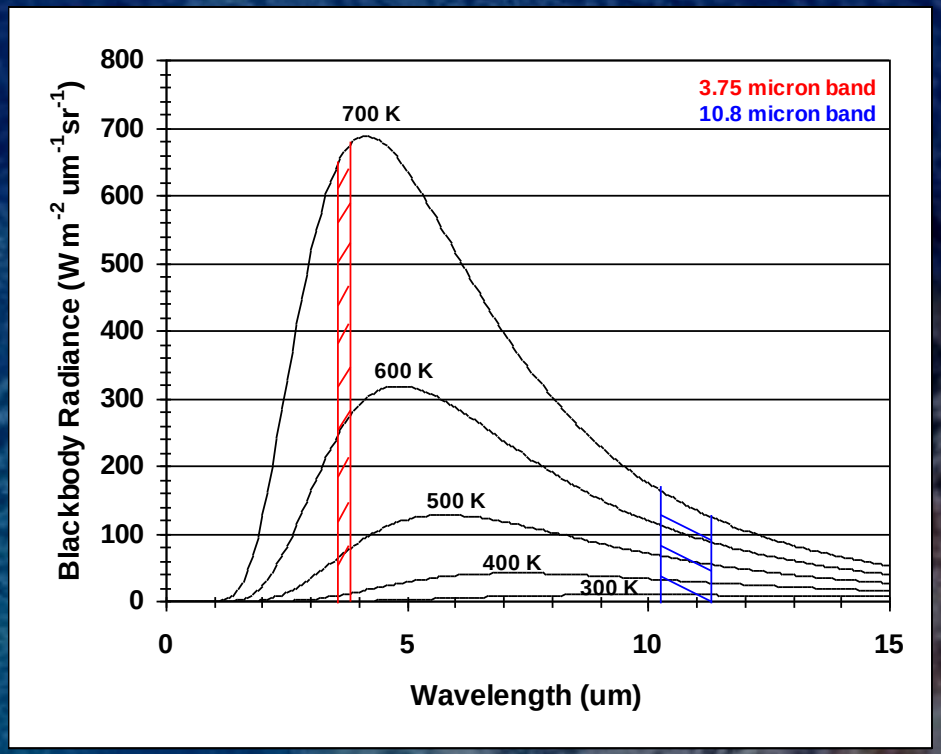
How do we detect and characterize fires? (aka "Is it more than a difference image?"):

- The algorithm utilizes the Dozier technique to calculate sub-pixel estimates of instantaneous fire size and temperature. Fire Radiative Power (FRP) is also calculated.
- At the end of the FDCA, additional thresholds are applied, high temporal resolution data is used to filter out false alarms, and appropriate confidence levels are assigned to the fire product.
- Delivered code is around 5300 lines of Fortran 90, not counting the framework.
- Development started in the 1990s, the archive starts with GOES-8 in 1995. The WF_ABBA works with all current GOES, Meteosat Second Generation, and MTSAT with support for COMS and INSAT-3D in the near future.

The Science

What is the science?:

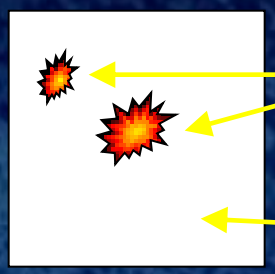
- The change of radiance with respect to temperature is greater at 4 μm than 11 μm, as illustrated below.
- This allows fires to be differentiated from other pixels.
- Knowledge of the background temperature is very important to proper characterization.
- The same initial general approach is used for fire detection from AVHRR, MODIS, and JPSS. Implementation details vary with platform.

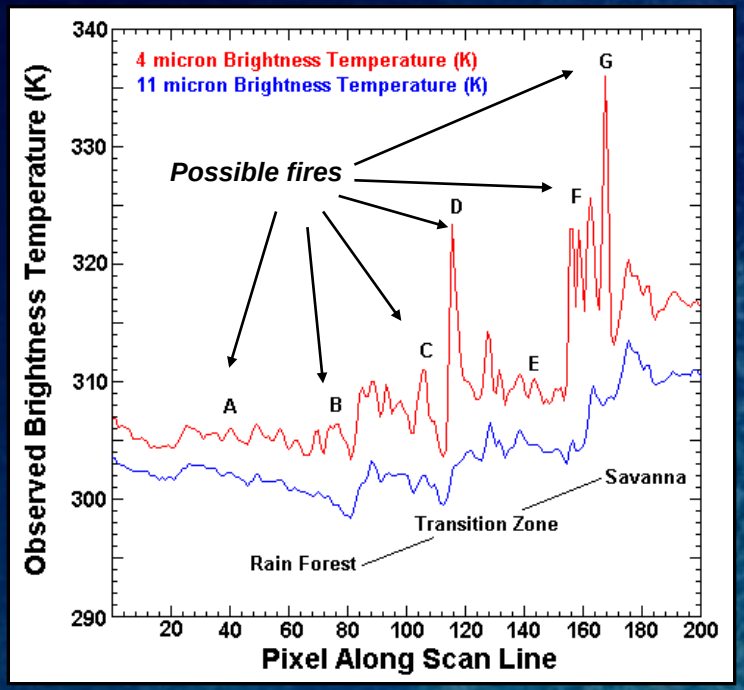


The Science

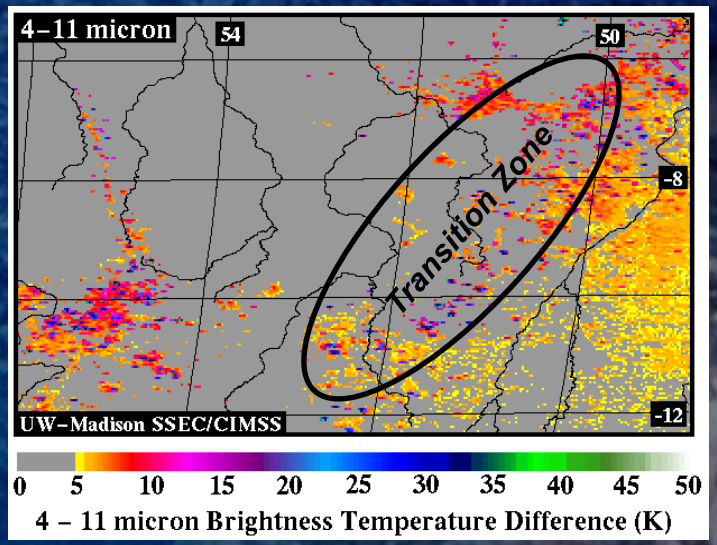
Typically, the difference in brightness temperatures between the two infrared windows at 3.9 µm and 11.2 µm is due to reflected solar radiation, surface emissivity differences, and water vapor attenuation. This normally results in brightness temperature differences of 2-4 K.

Larger differences occur when one part of a pixel (p) is substantially warmer than the rest of the pixel (1-p). The hotter portion will contribute more radiance in shorter wavelengths than in the longer wavelengths.





Brightness temperatures along a scan line in NE Brazil



NE Brazil along the transition zone between forest and savanna

The Dozier Method

For a given suspected fire pixel the following simultaneous equations are solved for p and T_t. The solution is exact with respect to the input data, however the input data is not itself perfect, and the solution is sensitive to the bias and error of the input data.

$$L_4(T_4) = p\, L_4(T_t) + (1-p)\, L_4(T_b) + (1-\varepsilon_4)\, \tau_{4s}\, L_{4\ solar}$$

$$L_{11}(T_{11}) = p\, L_{11}(T_t) + (1-p)\, L_{11}(T_b)$$

$L_x(T_x)$ is the radiance calculated by integrating the product of the Planck function and the response function for each spectral band x

L_4	4 µm observed radiance
L_{11}	11 µm observed radiance
L_{4s}	4 µm reflected solar radiance term
p	proportion of pixel on fire
1-p	proportion of pixel not on fire
T_4	4 µm observed brightness temperature
T_{11}	11 µm observed brightness temperature
T_b	Background/non-fire brightness temperature
T_t	Average instantaneous target temperature of sub-pixel fire
τ_{4s}	Transmittance of the 4 µm solar term
ε_4	4 µm emissivity

FRP

- Relies on the same 4 and 11 µm data as the Dozier method
- FRP_{DEF} is the definition of FRP
- Can be estimated by applying Dozier solution to FRP_{DEF} or from radiances using FRP_{MIR}. In the range of temperatures and sizes that the Dozier is known to perform well in, the two methods agree well.

$$FRP_{DEF} = A_{sample} \varepsilon \sigma \sum_{k=1}^{n} p_k T_k^4$$

$$FRP_{MIR} = \left(\frac{A_{sample} \sigma}{a} \right) \left(L_{MIR} - L_{B,MIR} \right)$$

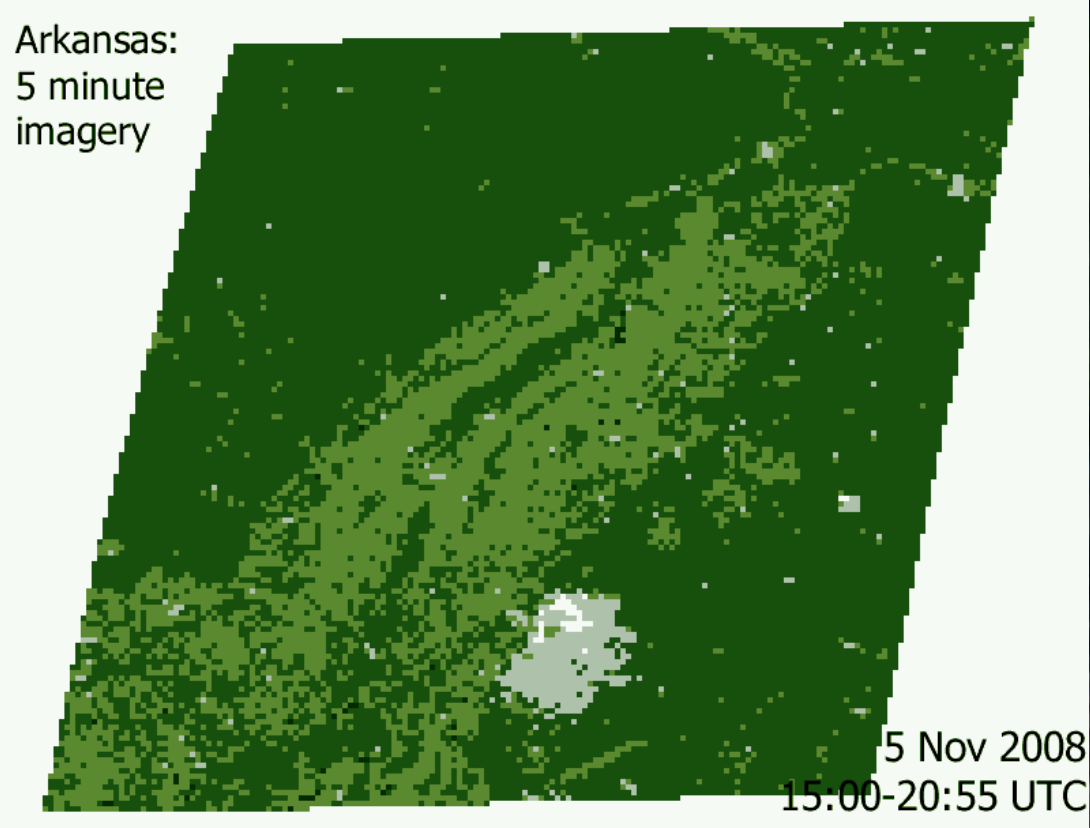
L_{MIR}	4 µm observed radiance
$L_{B,MIR}$	4 µm calculated background radiance
A_{sample}	Area of pixel
a	A constant (function of instrument SRF)
p_k	Instantaneous proportion of pixel on fire
T_k	Instantaneous target temperature of sub-pixel fire
ε	Emissivity of fire (typ. assumed to be 1)
σ	Stefan-Boltzmann constant

Why do we care about FRP? The FRP is the time derivative of the fire radiative energy, which is proportional to the biomass consumed by the fire. This value can be directly applied when calculating emissions.

ABI Proxy Examples

Example case:

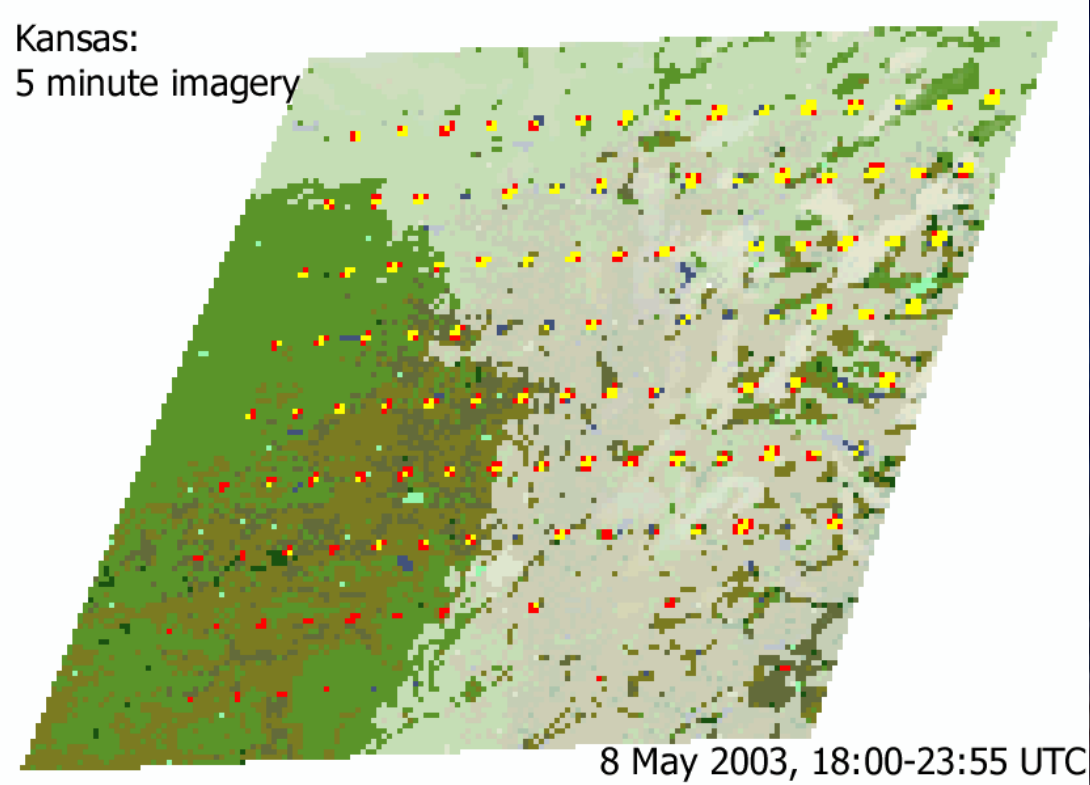
- Model-derived courtesy CIRA
- 5 minute, 2 km imagery
- Fires initialized from GOES-12 WF_ABBA fire product
- “Alphablended” imagery – ecosystem map used to represent surface, clouds appear in shades of white, fires are predominantly red (processed) in this case



ABI Proxy Examples

Example case:

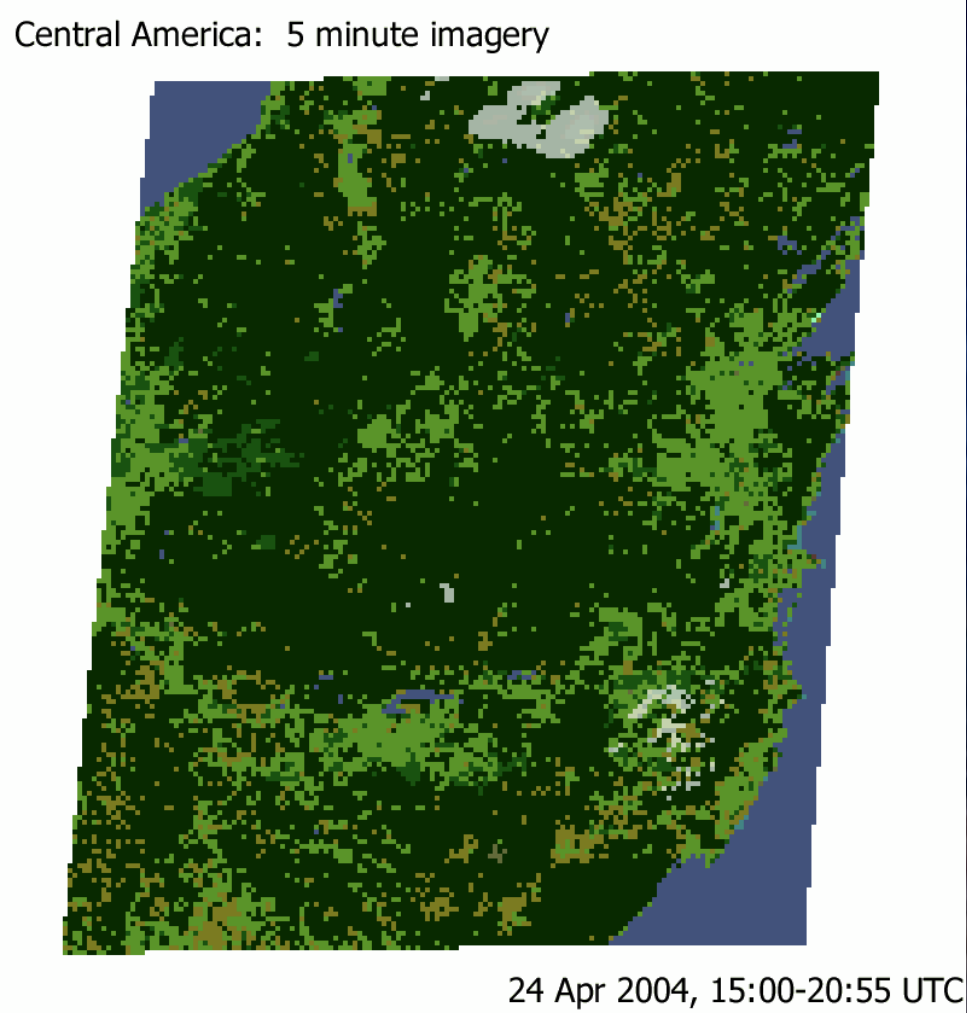
- Model-derived courtesy CIRA
- 5 minute, 2 km imagery
- Fires arranged in a grid: coolest & smallest in bottom left, hottest & largest in upper right
- Yellow fires are saturated pixels; in this case, unrealistically hot and large fires burn through cumulonimbus clouds; this has not been observed in the real world.



ABI Proxy Examples

Example case:

- Model-derived courtesy CIRA
- 5 minute, 2 km imagery
- Fires initialized from GOES-12 WF_ABBA fire product
- Fires are red (processed) and yellow (saturated)
- Gray region is the solar blockout zone, consisting of two regions of high solar reflection



Validation Strategies

FDCA Routine Validation

Current practice for GOES WF_ABBA:

No automated realtime method is available. Ground-based fire reports are incomplete and typically not available in realtime. At the Hazard Mapping System Human operators look at fire detections from various satellites and at satellite imagery to remove potential false alarms. This method is labor intensive and actual fire pixels are often removed.

FDCA Validation

ABI near realtime "validation":

- Co-locate ABI fire pixels with other satellite data
  - Ground-based datasets tend to be incomplete and not available in realtime
  - Fire detections from other satellites (polar orbiting) can be used in near realtime
  - Perfect agreement is not expected. Due to resolution, viewing angle, and sensor property differences a substantial number of valid fires will be seen by only one platform
  - Satellite to satellite comparison in this case is not truly "validation", it is more like a sanity check
- Other fire properties (instantaneous fire size, temperature, and radiative power) have no available near realtime validation source (see Deep-Dive tools)

What we can say about algorithm accuracy:

- The table on the following slide shows example of statistics from model-generated proxy data cases. 75 MW of fire radiative power is the estimated threshold for fire detectability for ABI based on proxy data studies.

Validation Strategies

CIRA Model Simulated Case Studies^								
	CIRA Truth			ABI WF_ABBA				
	Total # of fire clusters*	Total # of ABI fire pixels*	Total # of ABI fire pixels > FRP of 75 MW*	Total # of detected clusters	% Fire clusters detected*	Total # of fire pixels detected > FRP of 75 MW*	% Fire pixels detected > FRP of 75 MW*	% False postives (compared to model truth, will not be available for routine validation)
Kansas CFNOCLD	9720	63288	52234	9648	99.3%	47482	90.9%	<1%
Kansas VFNOCLD	5723	36919	26600	5695	99.5%	551	80.6%	<1%
Kansas CFCLD	9140	56553	46446	8768	95.9%	39380	84.8%	<1%
Cent. Amer. VFCLD	849	2859	1669	808	95.2%	1424	85.3%	<1%
Oct 23, 2007 California VFCLD	990	4710	2388	989	99.9%	2090	87.5%	<1%
Oct, 26 2007 California VFCLD	120	522	252	120	100%	211	83.7%	<1%

CFNOCLD	Constant Fire No Cloud
VFNOCLD	Variable Fire No Cloud
CFCLD	Constant Fire with Cloud
VFCLD	Variable Fire with Cloud

^ Limit to ~ 400K minimum fire temperature

* In clear sky regions, eliminating block-out zones

Deep-Dive Validation Tools

- Deep-dive fire detection and characterization validation tool builds on methods originally developed for MODIS and GOES Imager
  - Use of near-coincident (<15min) Landsat-class and airborne data to generate sub-pixel summary statistics of fire activity
    - Landsat-class data are used to assess fire detection performance
      - History of successful applications using ASTER, Landsat TM and ETM+ to estimate MODIS and GOES fire detection probabilities and commission error rates (false alarms). Methods published in seven peer reviewed journal articles
      - Limited fire characterization assessment (approximate fire size only). Frequent pixel saturation and lack of middle infrared band prevent assessment of ABI's fire characterization parameters
    - Airborne sensors are used to assess fire characterization accuracy
      - High quality middle-infrared bands provide fine resolution data (<10m) with minimum saturation allowing full assessment of ABI's fire characterization parameters (size, temperature, Fire Radiative Power)
      - Sampling is limited compared to Landsat-class data
        - » Regional × hemispheric/global coverage
        - » Targeting case-study analyses

- **These same techniques can be used with fires detected by any platform, such as VIIRS on JPSS**

Deep-Dive Validation Tools

- Several national and international assets will be used to support ABI fire validation
  - USGS Landsat Data Continuity Mission (2013)
  - ESA Sentinel-2 (2013)
  - DLR BIROS (2013)
  - NASA HysPIRI (TBD ~2020)
  - Airborne platforms as available
- Will perform continuous assimilation, processing and archival of reference fire data sets
  - Daily alerts targeting false alarms, omission of large fires
    - Main output: Quick looks (PNG) for visual inspection of problem areas showing ABI pixels overlaid on high resolution reference imagery
  - Probability of detection curves and commission error rates derived from several weeks/months of accumulated validation data
    - Main output: Tabular (ASCII) data containing pixel-based validation summary (graphic output optional)

Deep-Dive Validation Tools

Using Landsat-class imagery to validate ABI fire detection data

Sample visual output of simulated ABI fire product (grid → 2km ABI pixel footprints) overlaid on ASTER 30m resolution RGB (bands 8-3-1). Red grid cells indicate ABI fire detection pixels; green on background image corresponds to vegetation; bright red is indicative of surface fire

ASTER binary (fire – no fire) active fire mask indicating 494 (30m resolution) active fire pixels coincident with GOES-R ABI simulated fire product

Summary

- Fire detection and characterization is a baseline product derived from a current Operational fire algorithm, the WF_ABBA

- Routine validation consists of co-locating ABI detected fires with those from polar orbiting platforms (JPSS, for example).

- Deep-dive tools utilize high resolution data from satellite instruments similar to ASTER and could conceivably be automated if a reliable source of high resolution data is secured

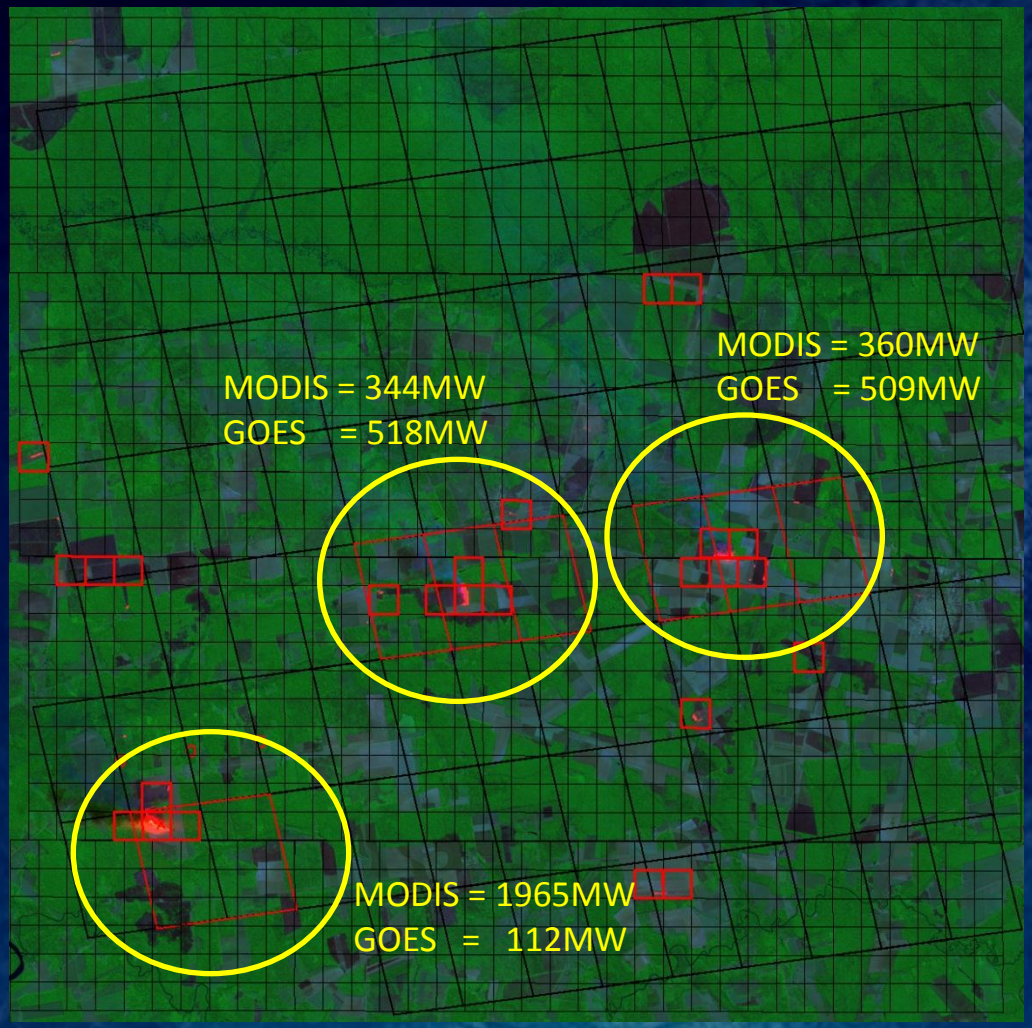
Bonus Slides

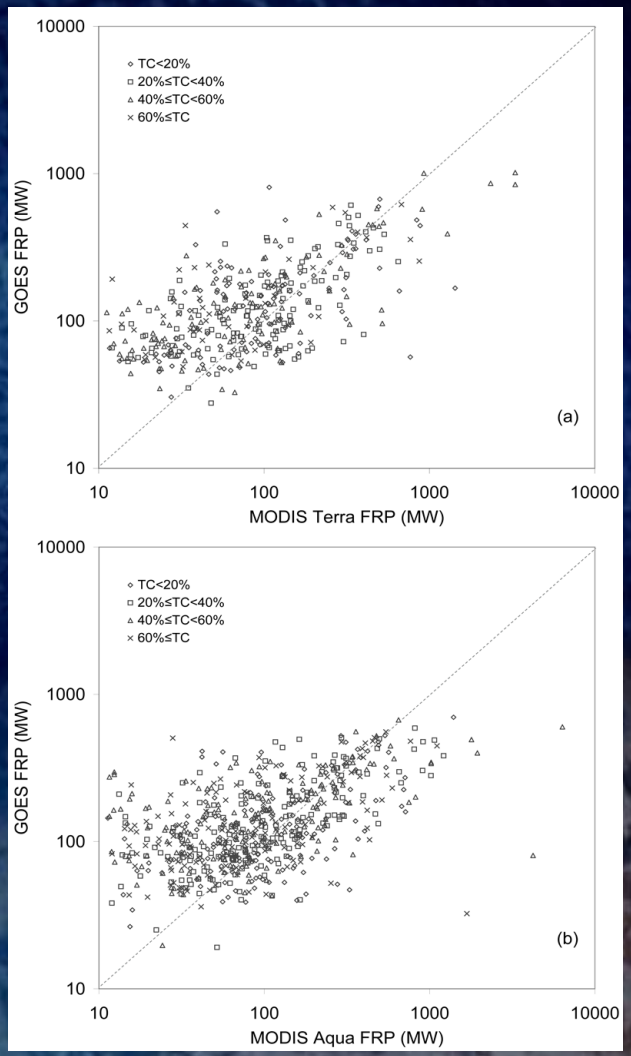
Deep-Dive Validation Tools

- Landsat-class data are **NOT** suited for the validation of ABI fire characterization parameters (Fire Radiative Power (FRP), size and temperature)
  - Frequent fire pixel saturation
  - Lack of middle-infrared band
- **Cross-validation** of pixel-level fire characterization data using other similar satellite products proven **impractical** [Schroeder *et al*., 2010]
  - No single product has been sufficiently validated to date therefore cross-validation analyses provide little useful information
  - Differences in resolution and observation geometry are problematic

Deep-Dive Validation Tools

MODIS×GOES Imager FRP data intercomparison



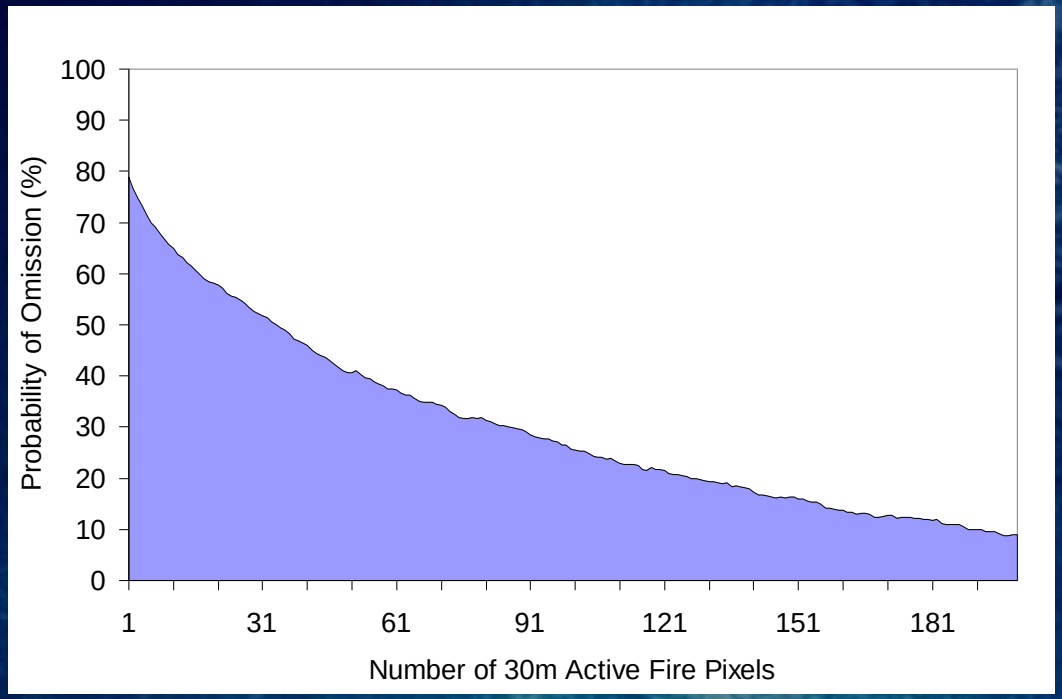


Credit: Schroeder et al, 2010

Deep-Dive Validation Tools

ABI Lon,	ABI Lat,	30m Fires,	30m Clusters,	WF_ABBA,	Sfc_01,	Sfc_02,	Adj_Fires,	Ajd_Cluster,	Distance,	Azimuth
-54.9388123,	-12.3929567,	11,	2,	100,	0.0000000,	0.0000000,	0,	0,	0.0000000,	0.0000000
-54.9003563,	-12.3929567,	3,	2,	100,	0.0000000,	0.0000000,	0,	0,	0.0000000,	0.0000000
-54.9992371,	-12.4121828,	15,	1,	10,	0.0000000,	0.0000000,	0,	0,	0.0000000,	0.0000000
-54.9992371,	-12.4314098,	479,	1,	10,	0.0000000,	0.0000000,	0,	0,	0.0000000,	0.0000000
-55.1969986,	-12.4451427,	19,	1,	100,	0.0000000,	0.0000000,	0,	0,	0.0000000,	0.0000000
-55.1805153,	-12.4478893,	10,	2,	100,	0.0000000,	0.0000000,	0,	0,	0.0000000,	0.0000000

Sample tabular (subset) output depicting ABI pixel-level fire activity derived from one 30m ASTER reference scene



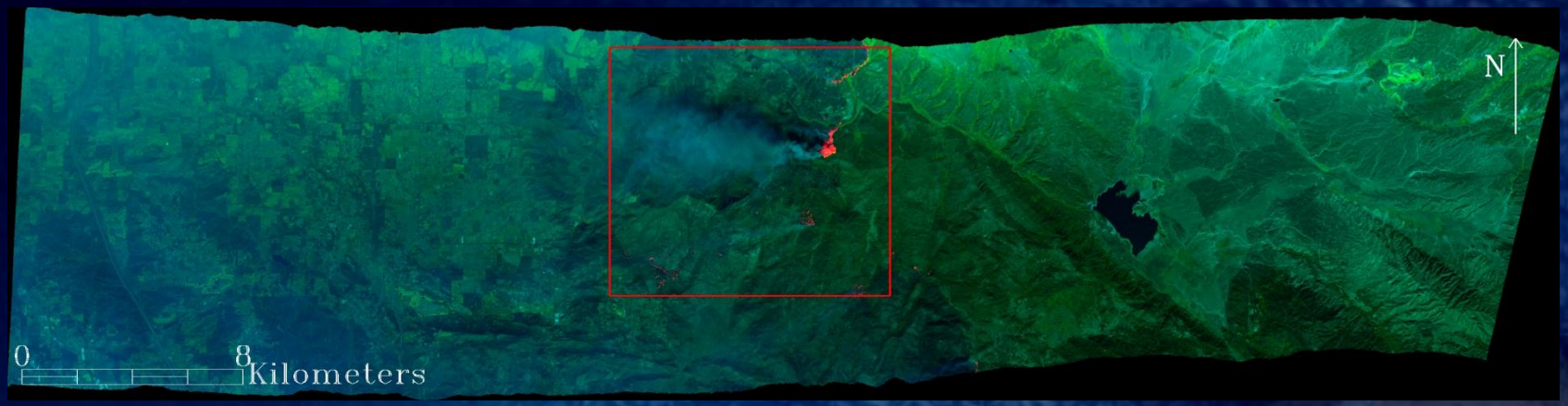
Probability of fire omission calculated for ABI using 161 ASTER scenes acquired over South America

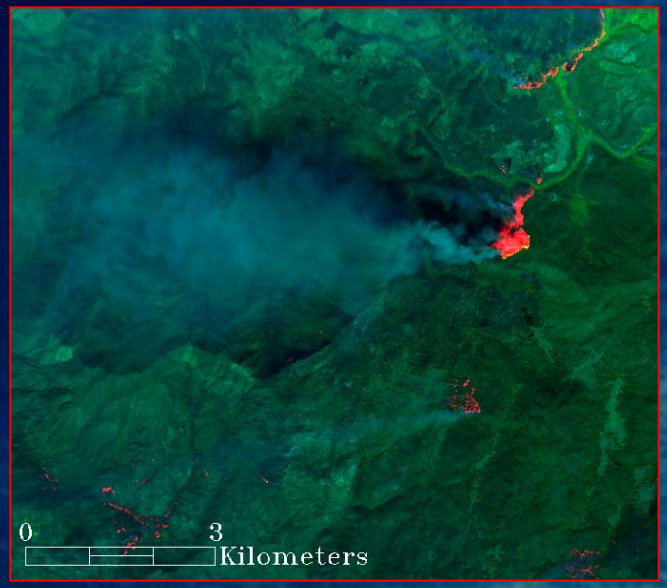
Deep-Dive Validation Tools

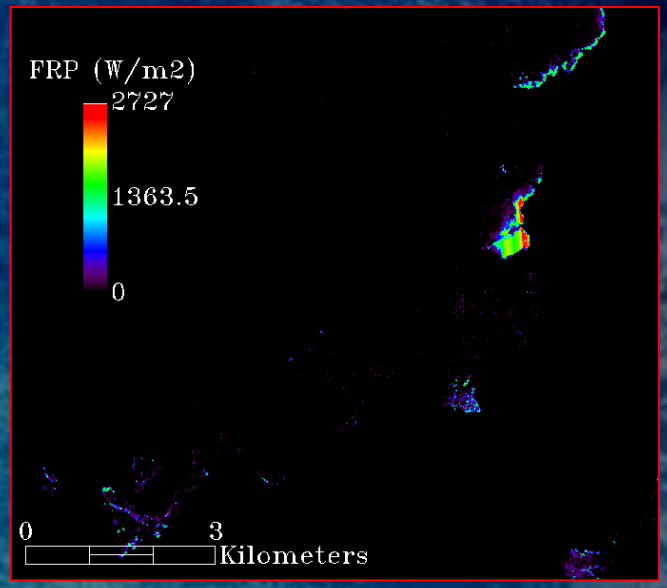
- Data simulation is prone to misrepresent sub-pixel features in fire-affected pixels
  - Lack of quality reference data lead to overly simplistic (**unrealistic**) fire pixel representation
- Airborne sensors provide fine resolution quality fire reference data
  - **Support** detailed analyses of **fire characterization retrievals** (test-case)
  - Airborne data can **help** us better **constrain data simulation**

Deep-Dive Validation Tools

Airborne fire reference data acquisition plan will <u>benefit/leverage</u> MODIS and JPSS/VIIRS fire algorithm development/funding







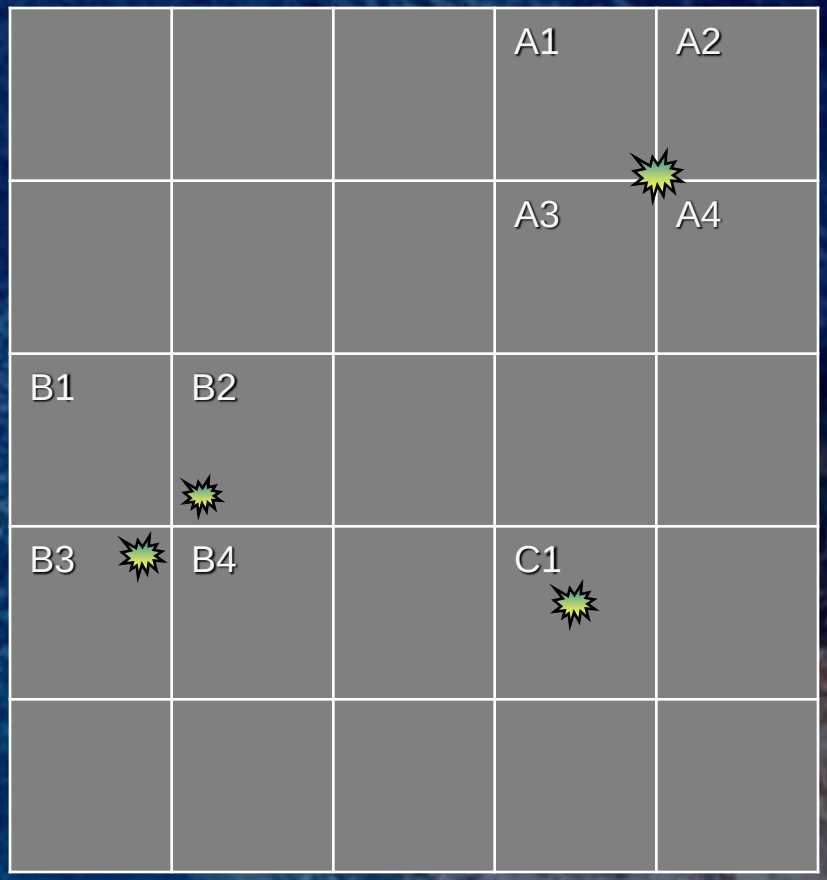
Airborne (AMS) data collected over Southern CA fire in 2007. Fire radiative power (FRP), fire size and temperature are derived for use in the validation of GOES-R ABI fire characterization parameters.

Subpixel Issues

Most fires will only occupy a very small portion of an ABI pixel.

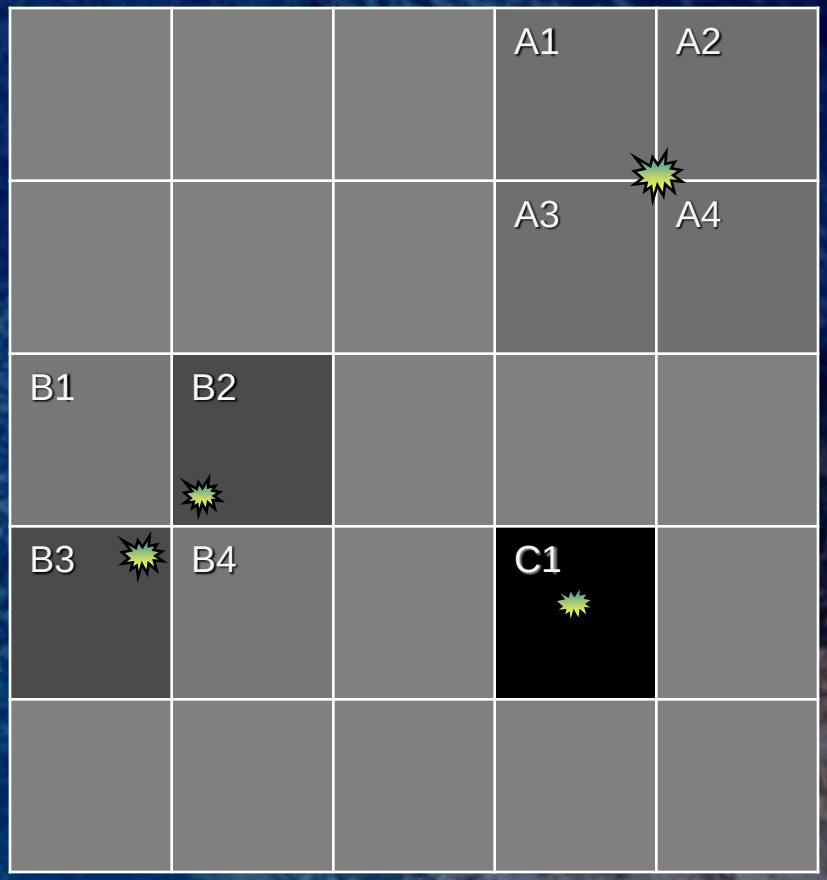
- **A fire cluster is a group of adjacent pixels affected by a single or multi-front fire or complex (e.g. Clusters A, B, and C)**
- **ABI fire pixel refers to each ABI pixel within a cluster that is impacted by any fire activity. (e.g. A1-A4, B1-B4, C1)**
- **In clear sky detectability and characterization of a fire is dependent on size/temperature and location within a pixel.**
- **Fire A is slightly larger than Fire C, but signal is divided among multiple pixels and may not provide a strong enough signal to be accurately characterized, while Fire C is detected and well characterized.**
- **Fires in B2 and B3 may be difficult to distinguish from each other, since they are located on the edge of a pixel impacting surrounding pixels due to diffraction.**

GOES-R ABI 3.9 µm pixels



Subpixel Issues

Note: Brightness temperatures are simulated here. Assume all fires are the same size and temperature, and that the PSF described above has been applied. Darker represents hotter pixels.

- **Fire C1 is a saturated pixel, the fire lines up with the peak of the PSF.**
- **The 2 fires in pixels B2 and B4 impacts 4 pixels.**
- **The one fire between pixels A1-A4 impacts all four pixels, but to a small degree**
- **This sub-pixel behavior of fires must be included in the proxy data in order to accurately estimate algorithm performance.**

GOES-R ABI 3.9 µm pixels