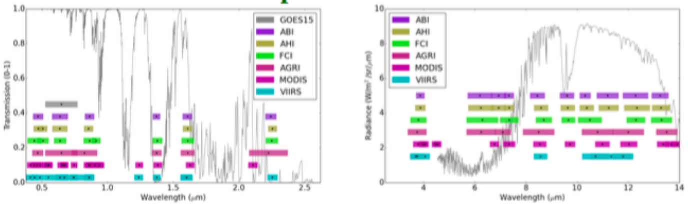
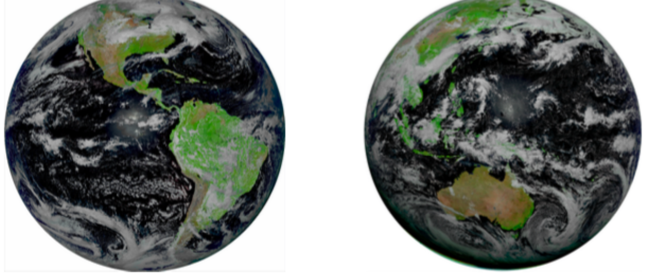
GOES-16 NRT Fire Detection on OpenNEX

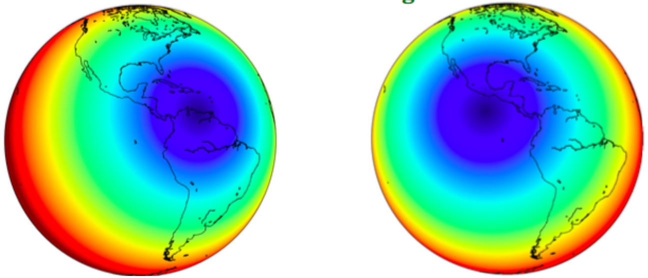
Spectral Bands

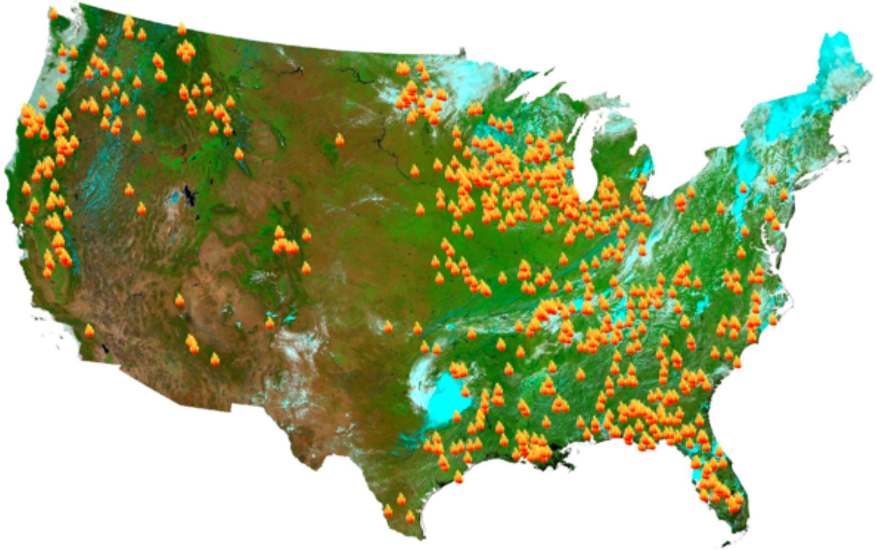


Full-Disk Views



Solar Zenith Angles





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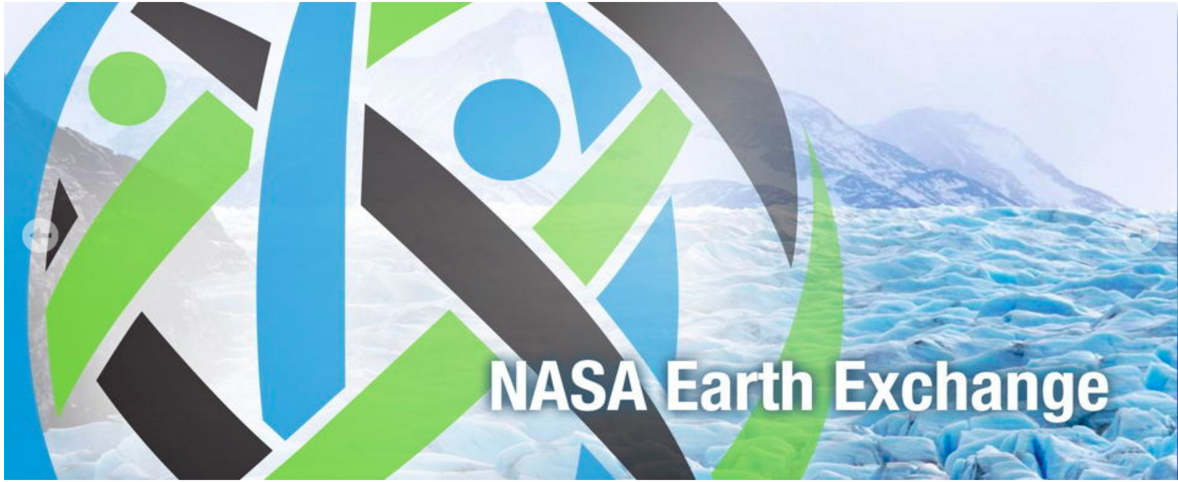
May 9th, 2018

The NASA Earth eXchange (NEX)

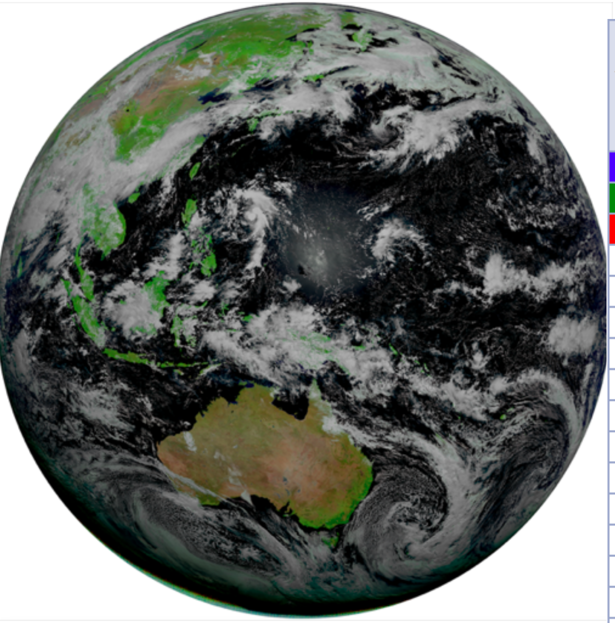
The NASA Earth eXchange (NEX, https://nex.nasa.gov) provides a collaboration and knowledge-sharing platform for the Earth science community housed at Ames Research Center.



OpenNEX is part of NEX as its public cloud infrastructure portal, hosted on the Amazon Web Services (AWS) cloud for public accessibility.

Over the past five years, NEX team supported over 100 NASA-funded researchers.

Himawari 8 AHI and GOES-16 ABI



Wave length [μm]	Himawari-8/9			
	Band number	Spatial resolution at SSP [km]	Central wave length [μm]	
			AHI-8 (Himawari-8)	AHI-9 (Himawari-9)
0.47	1	1	0.47063	0.47059
0.51	2	1	0.51000	0.50993
0.64	3	0.5	0.63914	0.63972
0.86	4	1	0.85670	0.85668
1.6	5	2	1.6101	1.6065
2.3	6	2	2.2568	2.2570
3.9	7	2	3.8853	3.8289
6.2	8	2	6.2429	6.2479
6.9	9	2	6.9410	6.9555
7.3	10	2	7.3467	7.3437
8.6	11	2	8.5926	8.5936
9.6	12	2	9.6372	9.6274
10.4	13	2	10.4073	10.4074
11.2	14	2	11.2395	11.2080
12.4	15	2	12.3806	12.3648
13.3	16	2	13.2807	13.3107

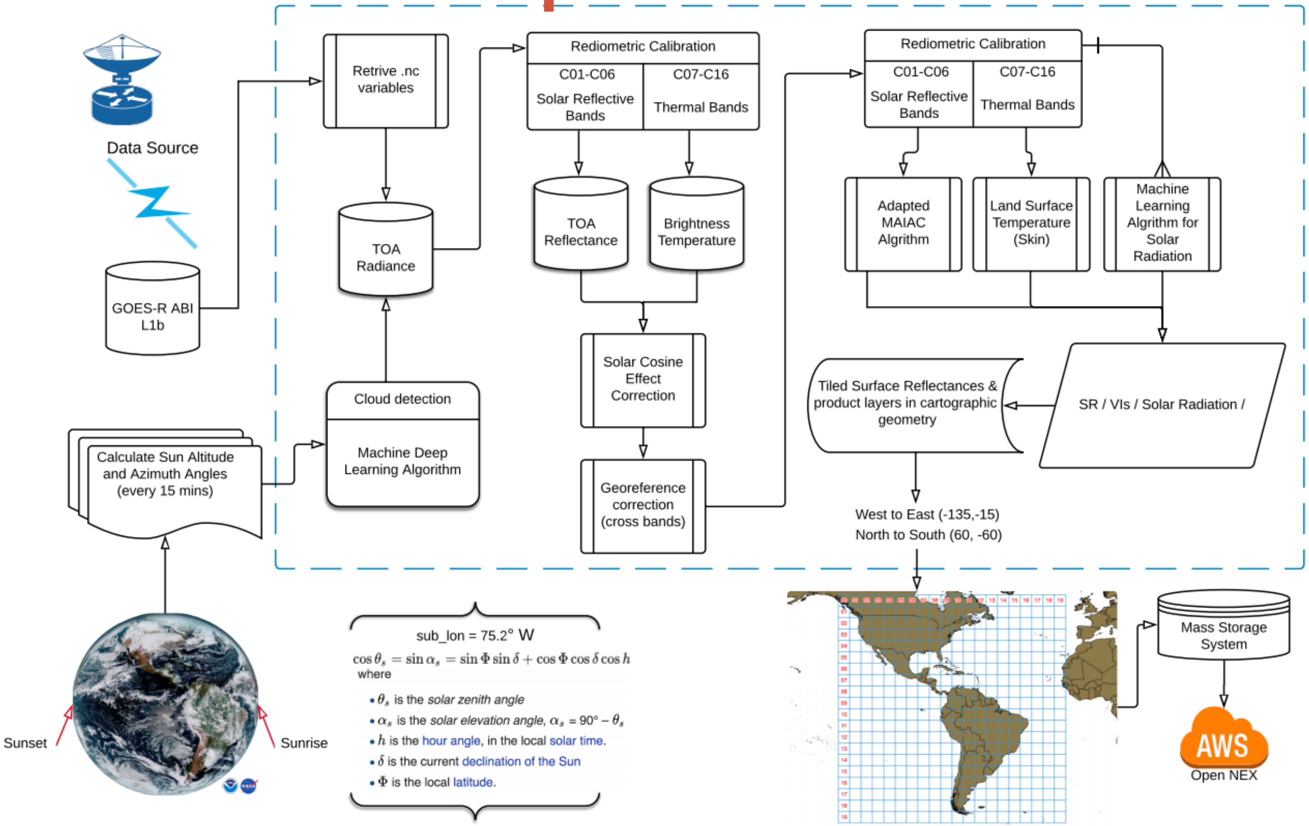
Himawari 8 AHI fullDisk
launched October 7, 2014
Himawari 9: November 2, 2016

GOES-16 ABI fullDisk
launched November 19, 2016
GOES-17 March 1, 2018

Table 1. Summary of the wavelengths, resolution, and sample use and heritage ins
bands. The minimum and maximum wavelength range represent the full width at
or 50%) points. [The Instantaneous Geometric Field Of View (IGFOV).]

Future GOES imager (ABI) band	Wavelength range (μm)	Central wavelength (μm)	Nominal subsatellite IGFOV (km)	Sample use
1	0.45–0.49	0.47	1	Daytime aerosol over land, coastal water mapping
2	0.59–0.69	0.64	0.5	Daytime clouds fog, insolation, winds
3	0.846–0.885	0.865	1	Daytime vegetation/burn scar and aerosol over water, winds
4	1.371–1.386	1.378	2	Daytime cirrus cloud
5	1.58–1.64	1.61	1	Daytime cloud-top phase and particle size, snow
6	2.225–2.275	2.25	2	Daytime land/cloud properties, particle size, vegetation, snow
7	3.80–4.00	3.90	2	Surface and cloud, fog at night, fire, winds
8	5.77–6.6	6.19	2	High-level atmospheric water vapor, winds, rainfall
9	6.75–7.15	6.95	2	Midlevel atmospheric water vapor, winds, rainfall
10	7.24–7.44	7.34	2	Lower-level water vapor, winds, and SO_2
11	8.3–8.7	8.5	2	Total water for stability, cloud phase, dust, SO_2 rainfall
12	9.42–9.8	9.61	2	Total ozone, turbulence, and winds
13	10.1–10.6	10.35	2	Surface and cloud
14	10.8–11.6	11.2	2	Imagery, SST, clouds, rainfall
15	11.8–12.8	12.3	2	Total water, ash, and SST
16	13.0–13.6	13.3	2	Air temperature, cloud heights and amounts

GEONEX Real Time Pipeline

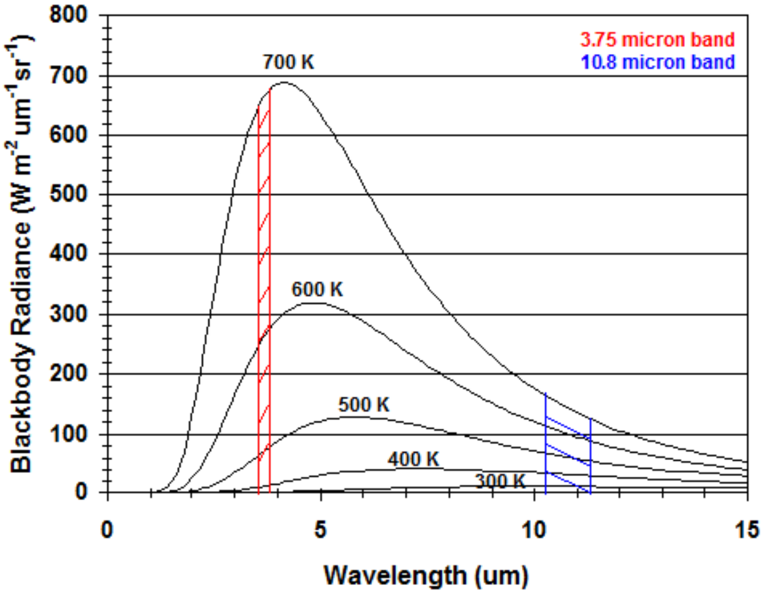


Flowchar for GOES-R Advanced Baseline Imager Processing

How will the GOES ABI characterize fires?

Fire properties can be characterized in three ways: instantaneous fire size, instantaneous fire temperature and fire radiative power (FRP).

Fires produce a stronger signal in the midwave IR bands (around 4 microns) than they do in the longwave IR bands (such as 11 microns). That differential response forms the basis for most Fire Detection and Characterization (FDC) algorithms, including the algorithm used for GOES. FDC was taken into account when creating the specifications of the 3.9 micron band on ABI, allowing GOES-16 to exceed the FDC performance seen with previous GOES satellite sensors.



Wildfire Detection Algorithm (AHI-FSA)

remote sensing

MDPI

Article

Development of a Multi-Spatial Resolution Approach to the Surveillance of Active Fire Lines Using Himawari-8

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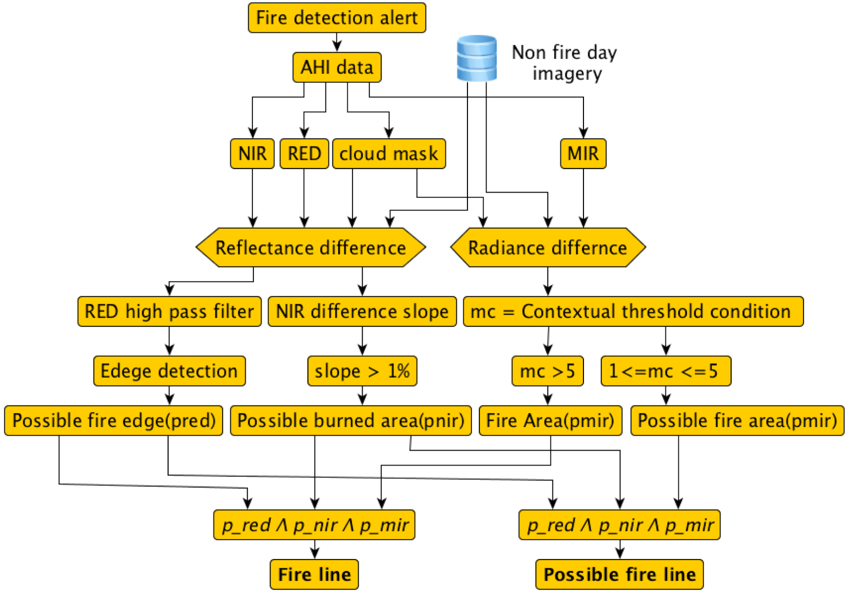
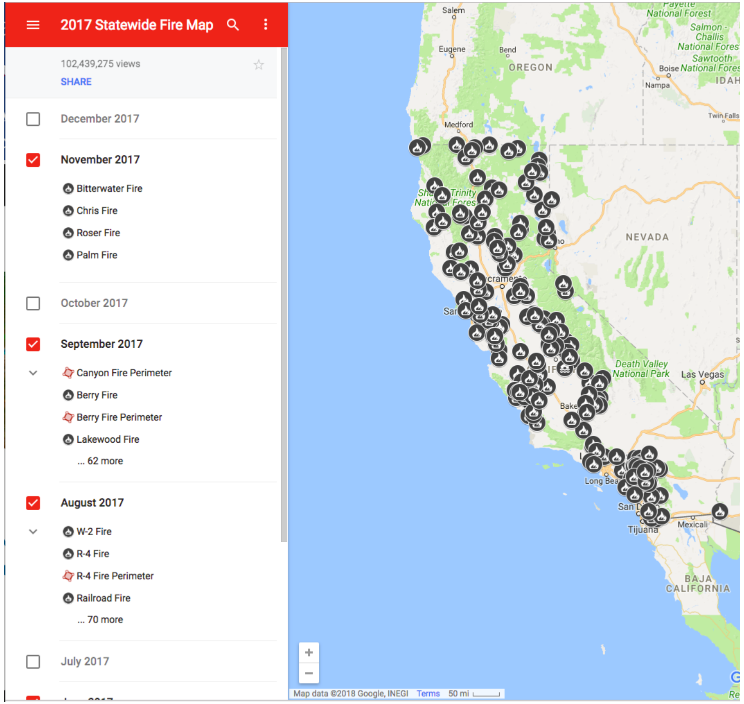
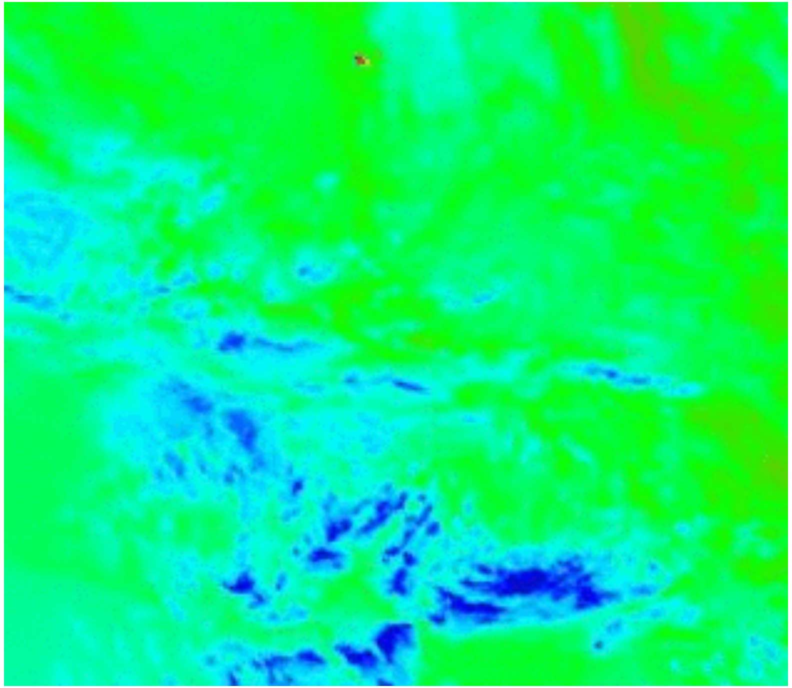


Archived Fire-event dataset for Machine Learning



California Statewide Fire Map

http://www.fire.ca.gov/general/firemaps

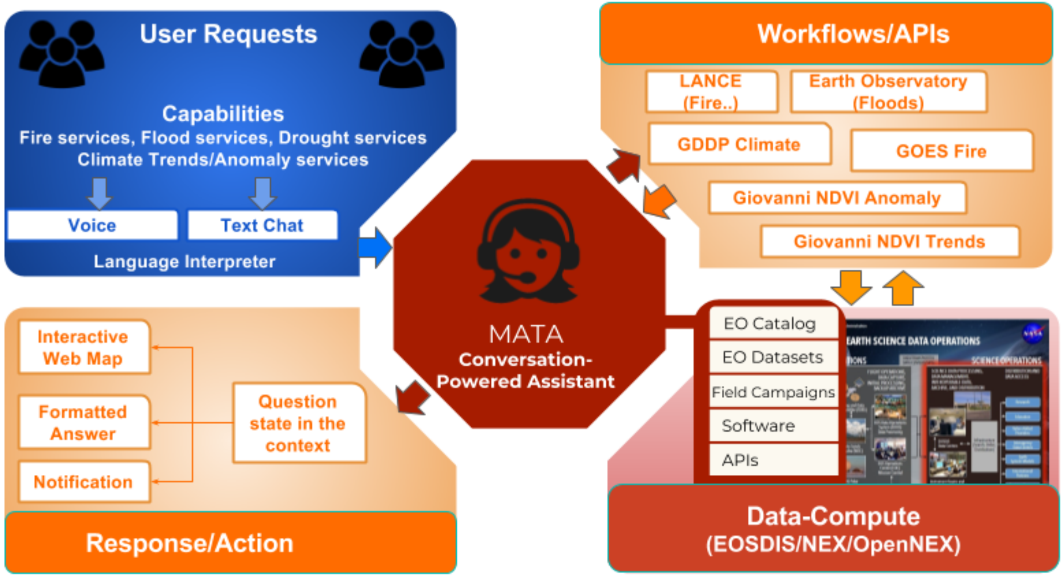


La Tuna Fire, Verdugo Mountains

Los Angeles, CA, Sep 1st - Sep 7th, 2017

NEX-MATA Intelligent assistants

NEX-MATA is an integration of the Speech Recognition (SR), Natural Language Processing (NLP), and Machine Learning (ML) into an intelligent assistant, helping Earth scientists and citizens access the GOES fire database in a conversation-like interface.



Summary

- Real-time GOES-16 data can improve the timeliness of fire behavioral data.
- GEONEX has laid the groundwork for real-time wildfire monitoring on a public cloud.
- Using the denser temporal data available from GOES to track the status of pixels such as non-fire, fire, and burnt area, could reduce false detection rates seen from polar-orbiting data sources.

Thank You!

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GEONEX Real Time Pipeline

1. GEONEX is a real-time pipeline deployed on OpenNEX to process geostationary datasets such as those from GOES-16 and Himawari into higher level products. Planned products include TOA, SR, LAI, NDVI, GPP and Fire.

2. The real-time feed and full historical archive of original resolution Advanced Baseline Imager (ABI) radiance data (Level 1b) and full resolution Cloud and Moisture Imager (CMI) products (Level 2) are added into AWS as soon as they're available (netCDF4 format).

3. GEONEX, a real-time pipeline prototype to convert ABI data from radiance data into top-of-the atmosphere (TOA) reflectance and surface reflectance (SR) outputs for advanced detection. Himawari-8 (AHI) data were processed following similar steps.

4. GEONEX is designed as a real-time processing chain, deployed both on the AWS cloud as well as on the NAS supercomputer at NASA Ames.

WF-ABBA (CIMSS)

Remote Sensing of Environment
Volume 127, December 2012, Pages 194-209

On timeliness and accuracy of wildfire detection by the GOES WF-ABBA algorithm over California during the 2006 fire season

Alexander Koltunov [a], Susan L. Ustin [a], Elaine M. Prins [b]

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Abstract

The Wildfire Automated Biomass Burning Algorithm (WF-ABBA) is a state-of-the-art algorithm for geostationary wildfire detection whose results have been increasingly used in a range of environmental applications. At present, the WF-ABBA validation activities and, in general, fire product validation methodologies are at a markedly less advanced stage than the algorithm itself. Particularly, little is known about detection timeliness, despite the value of such information for assessing the potential of geostationary observations to improve tactical decision making of first responders. This paper contributes to reducing this gap in two ways. Firstly, we describe a new methodology that is suitable for evaluating geostationary satellite wildfire detection in terms of incidents with regard to both timeliness and reliability. This methodology utilizes available official multi-agency wildfire reporting information and multitemporal Landsat imagery. Secondly, we apply the proposed validation method to temporally filtered GOES-West WF-ABBA (ver. 6.1) detections for the 2006 fire season over the State of California and present incident-wise and pixel-wise performance information. The results indicate highly reliable pixel-wise performance of WF-ABBA, with about 75% of fire pixels (or more) corresponding to actual recorded active wildfires. A substantial portion of wildfires were detected during their first hour of activity, and a few incidents—even before the initial reports from conventional sources. Although the WF-ABBA performs best at what it was designed for: consistently re-detecting (monitoring) active fires, we believe there is an additional potential for automated detection from current geostationary data to reduce wildfire ignition latencies in the Western U.S. Our results can serve as a guideline for algorithm developers and users of the WF-ABBA fire product.