Remote Sensing of Environment 184 (2016) 436–453

Contents lists available at ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

The development and first validation of the GOES Early Fire Detection (GOES-EFD) algorithm

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ARTICLE INFO

Article history:
Received 17 July 2015
Received in revised form 4 July 2016
Accepted 15 July 2016
Available online 30 July 2016

Keywords:
Geostationary
Satellite
Fire detection
Wildfire detection
Early wildfire detection
Wildfire
Detection timeliness
Fire monitoring
Remote sensing
GOES Early Fire Detection
GOES-EFD

ABSTRACT

Decades of successful active fire mapping from space, have led to global informational products of growing importance to scientific community and operational agencies. In contrast, detecting fires from space faster than current conventional capabilities in the continental U.S. has not been considered attainable, except in remote, sparsely populated areas. We present a research prototype version of the GOES Early Fire Detection (GOES-EFD) algorithm focused on minimizing the time to first detection of a wildfire incident. The algorithm is designed for regional-scale surveillance and combines multitemporal anomaly tests developed in our previous work, contextual hot-spot tests, and dynamic event classification and tracking. The GOES-EFD version 0.4 was initially tested with 40-day summer 2006 data over central California. The algorithm identified most of large (final size > 2 ha) wildfires within 30 min and 31% of the wildfires were detected before they were reported by the public. Under identical operation conditions, GOES-EFD 0.4 provided quicker initial detection than the temporally filtered operational WF-ABBA algorithm (version 6.1) and committed fewer false alarms. There is a substantial potential for further reducing detection latency and increasing reliability. Following the ongoing optimizations, tests, and integration in collaboration with the fire management agencies and first responders, GOES-EFD could be deployed for regional scale real-time surveillance to complement existing fire identification methods.

1. Introduction and background

Wildland fire response and management represent issues of growing global importance. In the last 15 years, the number of large wildfires (or simply fires, hereafter) and annual area burned, particularly in the western U.S., has increased markedly, resulting in significant threat to public safety and the environment. Incident response and management have caused critical budget impacts due to overwhelming costs of suppression. For example, in an average year during 2005–2014, wildfires consumed 2.7M hectares at a cost of $1.6B (suppression only) to federal agencies (NIFC, 2014). Only ~1% of ignitions in the U.S. become large escaped fires, i.e. fires that have exceeded initial attack capabilities and expanded beyond 40 ha of forest or 120 ha of shrub/grass (QFR, 2014). However, these fires have highest risk potential to firefighter safety and are responsible for most of the total burned area and suppression costs (e.g. NICC, 2013). The suppression costs form only a small fraction of the total societal losses from large wildfires that include loss of life and property and impacts on public health, economic activity, and environment (QFR, 2014). Consequently, rapid and prioritized response to fire ignitions that have a great risk to become large incidents could lead to high benefits to society.

Timely and informed management decision making critically depends on how quickly ignitions are identified and confirmed. Earlier detection often leads to a smaller fire size at initial attack, thus increasing the probability of containment (Hirsch et al., 1998). How rapidly the value of wildfire detection information decreases with time depends on various factors, including a human component. The authors are not aware of studies providing a quantitative account of this issue. Fire managers and first responders are convinced that to contain potentially damaging wildfires, ignitions should be identified within the first hour, but preferably within minutes.

New ignitions over the continental U.S. are identified primarily by human observations, i.e. the general public, commercial airline flights,

Abbreviations: ABI, [GOES-R] Advanced Baseline Imager; BT, brightness temperature; BT_4, brightness temperature in GOES band 2 (~4 μm); BT_{11}, brightness temperature in GOES band 4 (~11 μm); c.c., connected component; DDM, Dynamic Detection Model; EFD, early fire detection; GOES, Geostationary Operational Environmental Satellites; GOES-EFD, GOES Early Fire Detection; GVAR, GOES VARiable [format]; IADC, Iterative Anomaly Detection and Classification; INR, [GOES] Image Navigation and Registration; MODIS, Moderate Resolution Imaging Spectroradiometer; OCM, Operational Cloud Masking; RCD, Retrospective Cloud Detection; SCD, Single-Frame Cloud Detection; TIR, thermal infrared; WF-ABBA, Wildfire Automated Biomass Burning Algorithm; VIIRS, Visible Infrared Imager and Radiometer Suite.

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http://dx.doi.org/10.1016/j.rse.2016.07.021
0034-4257/

fire lookout stations, aerial reconnaissance during periods of high fire danger or ignition potential. Most of the ignitions are rapidly seen and reported. However, as the conventional discovery methods are non-systematic, infrequent, and/or geographically localized, there are routinely situations where a fire went undetected for hours or days, both in remote and populated areas (e.g. downed power lines in the overnight hours, smoldering ignitions after lightning events, and incompletely extinguished or illegal campfires). Furthermore, after an initial report, significant confusion and uncertainty often remain about the incident location, magnitude, or its very existence, making it more difficult for first responders and managers to develop and execute an appropriate response strategy.

Under these circumstances, the thermal infrared (TIR) observations from currently operational environmental and weather satellite programs, such as NASA's Earth Observing System, NOAA's Polar-orbiting Operational Environmental Satellites (POES), its successor JPSS (Joint Polar Satellite System), and Geostationary Operational Environmental Satellites (GOES), have been considered as potential means to rapidly detect wildfire starts over large areas and be used for initially alarming or as a necessary confirmation of recent alarms received from conventional sources. Indeed, as these programs were launched to support a broad range of civilian applications, they offer a range of valuable practical advantages, including low per-application cost, global systematic coverage, operational stability, and long-term continuity.

Nevertheless, while active fires have been successfully mapped by these programs for decades (Justice et al., 2011; Csiszar et al., 2014; Prins et al., 2001; Schmidt and Prins, 2003; Prins et al., 2010), the corresponding fire detection products have not significantly reduced the time to first detection of new ignitions (Martell, 2015). Measurements by polar-orbiting sensors are a few hours apart, often have significant data dissemination lags, and therefore they currently have a marginal value as early warning tools. Images from GOES do have sufficiently frequent temporal coverage of the Western hemisphere: normally, at 15-min time steps, and every 5–7 min under GOES Rapid Scan operations. However, they also have a coarse spatial resolution (e.g. ~25 km^2 over California). Consequently, small-magnitude thermal anomalies at the pixel level during early phases of burning can be difficult to automatically discern from naturally dynamic background. Despite this and other factors complicating geostationary detection (Schmidt et al., 2012), previous individual case studies (e.g. Feltz et al., 2003; Weaver et al., 2004; Koltunov et al., 2012a) indicated that the high temporal coverage of GOES imagery could often be sufficient to provide early alarms about new ignitions. Thus, it is natural to ask a question: is the early warning potential of the GOES satellites already fully utilized by the current operational wildfire algorithm?

1.1. Early detection of new ignitions is a new type of satellite wildfire remote sensing

Wildfire remote sensing from GOES is operationally realized by the Wildfire Automated Biomass Burning Algorithm (WF-ABBA, Prins and Menzel, 1992, 1994; Prins et al., 1998, 2001, 2003) that in the early 1990s pioneered geostationary wildfire remote sensing and recently expanded to other geostationary satellites across the globe (Prins et al., 2010). The WF-ABBA algorithm was not specifically designed as an early warning tool; and its primary applications include fire weather analysis and forecasting; climate, land-use, and land-cover change research; emissions, aerosol, and trace gas modeling, and other environmental applications. Consistently with these applications, WF-ABBA was developed and optimized for the performance measures based on counting correctly classified pixels (i.e. pixelwise false positive and false negative rates) and maximizing the number of *eventually* detected incidents (Koltunov et al., 2012a). In contrast, early fire detection (EFD) systems need to inspect images for a very different type of targets: previously undetected ignition events that may span multiple pixels in GOES images (see Table 1). Furthermore, the primary objective of an EFD system is to detect new events as rapidly as possible, which is a low priority for most WF-ABBA users. Indeed, for a typical seven-day wildfire incident, a two-hour delay in initial detection in GOES data increases the pixelwise false-negative rate by about 1% (roughly, the ratio of delay time to burning time), with a similar expected effect on products like estimates of total gas emissions from this incident. However, such a delay is likely to greatly reduce the value of the detection information for initiating a timely tactical response.

Table 1
Primary objectives and features for two distinct types of geostationary wildfire remote sensing: Active Fire Monitoring and Early Fire Detection.

Active fire monitoring e.g. WF-ABBA	Early fire detection e.g. GOES-EFD
Maximize detected fire pixels	Maximize detected fire ignitions (incidents)
Minimize false detection fire pixels	Minimize false alarms
Estimate fire characteristics (radiative power, area, temperature)	Minimize time to initial detection
Globally, not regionally calibrated	Regionally and seasonally calibrated
Global coverage is essential	Deployment in selected regions, as needed
Operational system available	In research and development

Target objects of an EFD algorithm are by orders of magnitude more rare than fire pixels. Although the incident in our example is present in as many as 672 GOES images (95 images per day, with routine scanning), there is only one true target *object* for an EFD system for this incident, whereas there can be nearly 2000 true wildfire *pixels* to detect (assuming without loss of generality 3 fire pixels per image on average). Thus development and real-data validation experiments may not have many true-positive examples to work with, unless the image sequence is very large. This situation is further complicated, as higher-resolution imagery that is effective at validating expected pixelwise performance (Schroeder et al., 2008a, 2008b) is too infrequent to resolve ignition times, making the EFD developer rely on an often incomplete and occasionally inaccurate wildfire report data to evaluate detection timeliness for incidents (Koltunov et al., 2012a).

Furthermore, hot spot pixels from the same wildfire incidents do not occur at random locations or random times: they have very strong temporal and spatial autocorrelations. Hence, to achieve the same relative detection accuracy (i.e. # true positives/# positives) for incidents as for pixels the false positive pixels would have to show a similar strength of spatio-temporal autocorrelation as true wildfires, which would make it possible to report one false incident per hundreds or thousands of these pixels. Unfortunately, spatio-temporal autocorrelation between non-fire hot spot pixels is not strong, i.e. they appear more randomly in the image sequence. As a result, an algorithm that is reliable when target objects are *pixels* inevitably becomes far less reliable when the target objects are wildfire *incidents*. A practical illustration of this phenomenon was provided by Koltunov et al. (2012a), who evaluated WF-ABBA over California fire season 2006 and found that >75% of detected fire pixels were true wildfire pixels, but only between 17 and 40% of apparent new fire starts were true wildfire incidents. The challenge in keeping false positives under control is magnified, as the EFD goals discussed above necessitate detection of significantly subtler anomalies to prevent delays. Indeed, under Gaussian noise assumption the false positive probability grows exponentially with detection sensitivity; so, for example, detection with a Z-score (standardized residual) threshold of 1.75 instead of 3.5 entails a nearly 170-fold increase in the number of potential false positives.

Thus, monitoring/characterization of active fires and early detection of fire starts represent two clearly distinct types of wildfire remote sensing, although the same general term "fire detection" has been