GOES EARLY FIRE DETECTION (GOES-EFD) SYSTEM PROTOTYPE

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ABSTRACT

Timely identification of wildfires by operational agencies maximizes their situational awareness and facilitates strategic and tactical planning and response activities. Traditional wildfire identification methods leave considerable uncertainties in complex decision making, thus highlighting the necessity to better leverage remote sensing technologies. To address the urgent need for timely and cost-effective information about new fire ignitions, and the limitations of existing satellite fire detection algorithms to provide consistent and reliable early detection capabilities, University of California, Davis in collaboration with the USDA Forest Service Remote Sensing Applications Center (RSAC) have been developing and initially testing a new GOES Early Fire Detection (GOES-EFD) system that focuses on the timeliness of the first detection of wildfire incidents. During initial tests on 40-day summer 2006 GOES-11 data over densely populated parts of California, the pre-alpha version of GOES-EFD detected ~75% of large California wildfires within the first hour of activity, and more than 25% before they were reported. There is a substantial potential for further reducing detection latency, pending GOES-EFD optimization and integration with end user operational procedures.

KEYWORDS: early fire detection; GOES; geostationary; change detection; wildfire; Dynamic Detection Model; multitemporal; satellite remote sensing

INTRODUCTION AND BACKGROUND

Response and management of wildfire (or simply fire, hereafter) represent issues of growing global importance. In recent years, the number of large fires and annual area burned, particularly in the western U.S., has increased markedly, resulting in significant impacts on public safety and the environment (NICC, 2007). Fire incident response and management have caused critical budget impacts due to overwhelming costs of suppression. In 2006 and 2007 a total of 7.8M hectares burned at a cost $3.7B to USA federal agencies (ILWDP 2008). Large escaped fires (i.e. fires that have exceeded initial attack capabilities) form only ~1% of ignitions in the U.S. However, these fires have highest risk potential to fire fighter safety and incur as much as 95% of the total burned area and account for 85% of total suppression costs (CPPE, 2005). Consequently, rapid and prioritized response to fire ignitions that have a great risk to become out of control could lead to high benefits to society.

A critical factor enabling timely and informed management decision making is the timeliness of identification of ignitions. Earlier detection often leads to a smaller fire size at initial attack, which in turn, is inversely related to probability of containment (Hirsch et al. 1998). Presently, identification of new ignitions over the continental U.S. are done primarily by passive and active human observations, i.e. general public, commercial airline flights, fire lookout stations, aerial reconnaissance during periods of high fire danger or ignition potential. The non-systematic, infrequent, and/or geographically localized nature of these ignition identification methods may lead to substantial latency before detection of ignitions and thus to considerable uncertainties in the resource deployment decision making process. Although most of the ignitions are rapidly seen and reported by the public, there are routinely situations where a fire went undetected for several hours, both in remote and populated areas (e.g. a downed power line ignited a fire in the overnight hours, smoldering ignitions after the passage of a dry lightning front, etc.). How
rapidly the value of wildfire detection information decreases with time depends on various factors. Practitioners are convinced that to contain and suppress potentially damaging wildfires new ignitions should be regularly identified within the first one-two hours, but preferably minutes.

Under these circumstances, satellite surveillance in thermal infrared (TIR) could potentially provide a complementary low-cost systematic means to rapidly detect wildfires over large areas and be used for initially alarming or as a necessary confirmation of recent alarms received from conventional sources. Nevertheless, while large active (and known) fires have been successfully mapped from space for decades from polar-orbiting and geostationary platforms, the corresponding fire detection products have not significantly reduced the time to first detection of new ignitions. Measurements by polar-orbiting sensors are spaced by a few hours, and therefore are only suitable for early detection in the most scarcely populated areas. Images from geostationary platforms like Geostationary Operational Environmental Satellites (GOES), although available at 15-min time steps, have coarse spatial resolutions, leading to small-magnitude thermal anomalies at the pixel level, thus creating significant challenges to developing an effective fire detection algorithm.

**Sub-Pixel Fire Detection in Thermal Infrared**

The physical basis for TIR fire detection at sub-pixel scale (Dozier, 1981) stems from the Planck’s law and underlies today's state-of-the-art operational algorithms for satellite-based fire monitoring: the GOES Wildfire Automated Biomass Burning Algorithm (WF-ABBA, Prins and Menzel, 1994) and the fire monitoring algorithm by Giglio et al. (2003) used in MODIS Active Fire (MOD14) product (Giglio 2010). Potential fires are found by detecting anomalously large 4\(\mu\)m band brightness temperatures (BT4), and further assessment of the difference between the brightness temperatures in the 4\(\mu\)m band and the 11\(\mu\)m band (\(\Delta BT = BT4 - BT11\)). These methods are implemented as several contextual and fixed-threshold TIR tests that are logically merged and coupled with auxiliary techniques and data along with visible channel(s) to filter out false positives. Both WF-ABBA and MOD14 utilize information from only the *inspection* (detection) image (frame). Combining fixed-threshold and contextual tests by MOD14 and WF-ABBA proved effective for the objective of global monitoring of large active fires, and their detections are used by the operational agencies to support management of known wildfires and a range of environmental and climate applications including fire meteorology; global change and carbon cycle research; emissions, aerosol, trace gas, and air quality modeling; and policy decision making.

Consistently with their intended applications, these algorithms were designed to optimize the performance measures based on counting correctly classified pixels — i.e. pixel-wise false positive and false negative rates Schroeder et al (2008). In contrast, an early detection system, such as GOES-EFD, needs to inspect images for a very different type of targets: previously undetected ignition events that may span multiple pixels in GOES images. Furthermore, the primary objective of an early detection system is to detect new events as early as possible, which is obviously not an objective of an active fire monitoring algorithm. Indeed, for a typical seven-day incident, a two-hour delay in initial detection in GOES data increases the pixel-wise false-negative rate by as little as ~1\%, or less. However, this is likely to greatly reduce the value of the detection information for initiating a timely tactical response. Today, as a result of the successful multi-year algorithm research and optimization effort, contextual techniques are at a very advanced stage, while the temporal dimension of the satellite image sequences, has been underutilized on the operational level.

When using the data temporal dimension for fire detection, fires are sought as a class of temporal changes in the scene. The GOES-EFD utilizes temporal dimension of the data based on the Dynamic Detection Model (DDM, Koltunov et al. 2009) approach for anomaly detection. The DDM method separates anomalous changes in the scene (e.g. fires, clouds) from changes in the image due to regular environment and normal background evolution. At a detection time \(t\) and pixel location \(s\), the DDM first represents the background (*“no anomaly”*) intensity \(W(s,t)\) as a function \(H\) of intensities that were observed at \(s\) previously, at \(P\) past time moments termed *basis* times and denoted \(t_1, \ldots, t_P\). When function \(H\) is chosen to be a linear function, the background prediction model becomes:

\[
W(s,t) = \beta_1(t)W(s,t_1) + \ldots + \beta_p(t)W(s,t_p),
\]

(1)

where \(\beta(t)\) stands for the observation conditions at time \(t\) and does not depend on the spatial location. Hence, the predictor in Eq. (1) transforms past images into a current image jointly, following the same rule for all pixels. These past images are called *basis* images and form an *Image Database* (IDB). Pixels that are outliers with respect to the prediction model (1) are considered anomalies. Basis times \(t_1, \ldots, t_P\) are found in advance, during the Training stage. At the Detection stage the unknown vector \(\beta(t)\) are estimated using a randomized set of pixel locations forming an over-determined system of equations to be solved in the least-squares sense. The DDM requires image registration across time and that anomalously changed pixels be rare, compared to

ASPRS 2012 Annual Conference
Sacramento, California ♦ March 19-23, 2012
the total number of pixels used to estimate $\beta(t)$. Koltunov and Ustin (2007) have applied the DDM method to MODIS images and demonstrated that temporal dimension of satellite data can be significantly more informative than the spatial dimension for detecting thermal anomalies. However, the use of temporal dimension also introduces problems leading to new types of false alarms. Indeed, some of the dynamic events in the scene can be misinterpreted as fire ignitions. These include apparent changes in the pixel intensities due to image misregistration, disappearance of certain types of clouds, appearance of sun glints, and other events. As a result, development of a complete and effective multitemporal fire detection algorithm requires detailed analysis of the apparent anomalies.

**Paper Objective and Outline**

This paper demonstrates that applying recently developed multi-temporal and state-of-the-art contextual anomaly detection methodologies to images from currently operational geostationary platforms could lead to earlier identification of fire ignitions, and in some cases, provide the earliest detection in areas of dense population or where other traditional methods of fire detection are utilized. In the next section we describe an initial, not yet optimized version of the GOES-EFD algorithm that is being developed at the Center for Spatial Technologies and Remote Sensing (CSTARS) at University of California, Davis in collaboration with USDA Forest Service Remote Sensing Applications Center (RSAC). The algorithm is described in section 2. Its first experimental validation on California 2006 fire season data is presented in section 3, followed by discussion and conclusion.

**GOES EFD SYSTEM PROTOTYPE**

Multi-temporal background reconstruction by DDM plays an essential role in all major components of the algorithm operation: image preprocessing, cloud detection, and fire detection. The current version of GOES-EFD utilizes only linear DDM with a background model (1) and only two thermal bands of GOES Imager: band 2 and 4, centered at about 4 μm and 11 μm, respectively. Thus, a generic variable $W$ in eq. (1) may stand for either $BT_2$, or $BT_4$, or $\Delta BT$. Three anomaly detection algorithms (called *detectors*, hereafter) are constructed for each BT band image:

- **DDM$_1$**: a multitemporal detector using the same static IDB for analyzing all inspection images.
- **DDM$_2$**: a multitemporal detector using the basis images of DDM$_1$ and an image taken at $t-30$ min.
- **CTX**: a contextual hot spot detector used in the MOD14 product, as described in Giglio et al. 2003.

As seen from the above description, the DDM-based detectors differ by the sets of basis images (i.e. the IDB). Therefore, they respond to different dynamics and temporal scale of changes in the scene. Each detector is applied to three brightness temperature bands $BT_4$, $BT_{11}$, and $\Delta BT$, resulting in prediction residual images denoted by $R_4$, $R_{11}$, and $R_\Delta$. These residuals of the detectors normalized by their respective r.m.s.e. generically denoted by $\sigma$, are used to detect and classify anomalies, as described in the following sections.

**Overview of Algorithm Operation**

The GOES-EFD algorithm proceeds in two modes: the Training Mode and Detection Mode. Training is normally performed once a year before the surveillance season. The Detection Mode refers to a regular mode of operation, in which GOES multispectral frames are inspected to detect fires.

**Training Mode.** In the Training stage (Figure 1), past frames of the scene are first preprocessed to BT values, the cloud cover is spectrally estimated by thresholding BT values, and automatically registered across bands and across time toward a selected reference coordinate system which can be a coordinate system of one of the frames. Next, the least cloudy and well-aligned frames are used to choose the basis images to form an image database (IDB). The basis images are chosen at half-hourly steps. Training is finalized after interactive preview, possible refinement, and approval of the automatically pre-selected basis images.

**Detection Mode.** In the Detection stage (Figure 2), the current, inspection image acquired at the inspection time $t$ is first preprocessed, pre-screened for clouds, and its registration transform toward the reference coordinate system is iteratively computed (see sect. 2.2.1 and 2.2.2 below). All basis images are warped toward the inspection image. Next, the Anomaly Classifier assigns pixels into one of 12 classes by iteratively running anomaly detectors and combining their outputs with auxiliary information. These classes include "no-anomaly", 7 fire confidence classes related to the anomaly magnitude, and other classes (details are given in sect 2.2.3 and 2.2.4 below). The current version of the Anomaly Classifier represents a non-optimized knowledge-based decision tree and consists of a series of sequential tests applied in two passes: a Preliminary pass and the Main pass (Figure 2). The objective of the Preliminary pass is to identify pixels (e.g. clouds, higher intensity fires, and miscellaneous anomalies) that will not

ASPRS 2012 Annual Conference
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participate in constructing background band images for the subsequent Main pass. The Preliminary pass proceeds in
three iterations or until the class membership does not change for more than 99.95% of land pixels, whichever
comes first. During the Main pass all three detectors (sect. 2) are applied. The multitemporal detectors are run as
follows. First, the IDB of a detector is warped toward the inspection image coordinate system. Next, the IDB is
partitioned into a number of groups. For each group that is suitable for predicting BT values of a part of the scene, a
DDM-based predictor is constructed using (1). The coefficient vector \( \beta(t) \) in (1) is computed for each predictor by
robust stepwise regression (as proposed by Koltunov and Ustin, 2007). In this way, a plurality of DDM-
based predictors are constructed per detector. Each predictor corresponds to a subset of pixels of the scene. Among
the predictors that are applicable to a given pixel, the predictor with the smallest adjusted determination coefficient
is chosen. The partition is built to minimize or limit the number of pixels whose background values cannot be
predicted due to clouds or missing values in the basis images. These pixels are not processed by the current version
of GOES-EFD. Also, frames with more than 90% cloud cover or those for which preprocessing has failed for any
reason are excluded from further processing.

Pixels assigned to fire classes by the Anomaly Classifier are further processed by a temporal filter rejecting
detections not found in the previous frame, and the result at the user-chosen level of fire confidence becomes the
input to the event tracking algorithm (sect. 2.2.5) that morphologically analyzes recent detection history to decide
whether a fire pixel represents:
- a new event, i.e. a group of pixels to be considered a previously undetected ignition, or
- an existing event, i.e. an event that was already detected in recent previous frames.

The new events extracted by the event tracker are the primary output of the GOES-EFD algorithm.

Technical Details

Preprocessing. The Preprocessing procedure (Figure 1) is applied to all GOES images during both the
Training stage and the Detection stage, and consists of several steps. Because GOES images may not be perfectly
aligned, especially across time but also across bands, preprocessing begins with automatic band-to-band
registration. Our algorithm uses a statistical intensity-based approach to registration. For a given frame, the band
images are aligned by fitting the following simple model in the least squares sense, using all pixels:

\[
BT_{11}(x, y) = a_1 BT_4(x + u, y + v) + a_0, \quad \text{where } u, v < 3 \text{ pixels.} \tag{2}
\]

The unknown variables in this model are the radiometric normalization coefficients \( a_0, a_1 \) and the registration
transform \((u, v)\). Initiated with \((u, v) = 0\), the registration algorithm loops through two steps until convergence:
1) robust estimation of \( a_0 \) and \( a_1 \) followed by radiometric adjustment of the reference band \( BT_4 \) by (2); the
resulting band image is radiometrically similar to \( BT_{11} \), which is required by step 2) below;
2) iterative estimation of the registration transform using a method by Irani (2002) that is based on the gradient-
based approximation of the optical flow (Lucas and Kanade, 1981) and Gaussian pyramids.

GOES image registration across time uses the same step 2) but modifies step 1) as follows: First, cloud pixels are
tentatively detected in the inspection frame (see sect 2.2.2 below) and masked out. The remaining pixels are used to
construct a reference image (i.e. image in the reference coordinate system) that is radiometrically normalized to the
inspection image. This is done by a DDM (1) with the basis images that have been selected and during the Training
stage and warped toward the reference coordinate system according to their respective registration transforms.

Cloud Pre-screening. Clouds markedly affect fire detection, rendering cloud delineation indispensable for a
fire detection system. Requirements from cloud detection quality and therefore the corresponding algorithms, vary
among different blocks of the EFD system. For image registration across time, clouds are pre-screened and filtered
out conservatively (\( BT_{11} < 270\text{K} \)). Although, a large number of “warm” cloud pixels may remain undetected,
the distribution of spatial gradients of intensity at these pixels is expected to center around zero, in which case the least
squares solution for the optimal registration transform is not affected. Subsequent more accurate cloud detection
tests are incorporated into the scene classification block and utilize both spectral and multitemporal information
(sect 2.2.3).

Anomaly Classifier – Preliminary Pass. In the Preliminary Pass, the following tests are applied to determine
pixels whose thermo-physical properties have significantly changed and, therefore, cannot be used for determining
the coefficients \( \beta(t) \) in the background model (1).

<table>
<thead>
<tr>
<th>Test 1</th>
<th>Test 2</th>
</tr>
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<tbody>
<tr>
<td>( R_s &gt; \gamma \sigma ) \text{ AND } ( R_s &gt; \gamma \sigma ), for ( \gamma &gt; 2.0 )</td>
<td>holds for multitemporal detectors DDM(_1) or DDM(_2).</td>
</tr>
</tbody>
</table>

Test 2 detects cold high-altitude clouds or snow as anomalous drop in BT\(_{11}\):
\[ R_{11}^{\text{DDM1}} < -3\sigma \quad \text{OR} \quad R_{11}^{\text{DDM1}} < -2\sigma \quad \text{AND} \quad R_{11}^{\text{DDM1}} < 3\sigma. \] (4)

**Test 3** identifies night time clouds and fog by the condition:
\[ R_{11}^{\text{DDM1}} < -1.5\sigma \quad \text{AND} \quad R_{A}^{\text{DDM1}} < -1.5\sigma. \] (5)

**Test 4** flags pixels off land that were inaccurately predicted by multitemporal detectors, including pixels that may appear similar to fires or clouds:
\[
\begin{align*}
|R_4| > 2.0\sigma \quad \text{OR} \quad |R_4^{\text{DDM1}}| > 2.0\sigma \quad \text{OR} \\
|R_{A}^{\text{DDM1}}| > 2.0\sigma \quad \text{AND} \quad |R_{A}^{\text{DDM1}}| > 1.0\sigma \quad \text{AND} \quad R_{A}^{\text{DDM1}} > 1.0\sigma.
\end{align*}
\] (6)

These pixels are excluded from the subsequent iterations of anomaly detection, as they contaminate temporal and contextual background estimation models.

**Test 5** attempts to map thin or apparently warmer clouds or haze:
\[
\begin{align*}
R_{11}^{\text{DDM1}} < -2.0\sigma \quad \text{AND} \quad R_{A}^{\text{DDM1}} > 2.0\sigma \quad \text{OR} \\
R_{4}^{\text{DDM1}} < -1.0\sigma \quad \text{AND} \quad R_{11}^{\text{DDM1}} < -1.5\sigma \quad \text{AND} \quad R_{A}^{\text{DDM1}} > 1.5\sigma.
\end{align*}
\] (7)

**Anomaly Classifier – Main Pass.** In the Main Pass, the Tests 1 through 5 of the Preliminary pass are reapplied. Pixels classified as fires based on temporal information as described above in this section are subject to several false alarm elimination tests. These tests use the contextual detector, CTXT, to detect weak hot spots by the following condition:
\[ R_{4}^{\text{CTXT}} > 1.5\sigma \quad \text{AND} \quad R_{A}^{\text{CTXT}} > 1.5\sigma. \] (8)

Contextual test condition (8) is applied only in the Main pass of the classifier, with the neighboring pixels that were assigned to a fire or cloud class in the Preliminary pass being excluded from contextual estimation of the background signal. A fire pixel candidate that is not a weak hot spot is eliminated, if any of the following conditions return true:
- the fire is detected by DDM2 and was an anomaly (with \( R_{4}^{\text{DDM1}} < -2.0\sigma \)) in the image at \( t-30 \) min;
- the fire pixel is detected by DDM2, not detected by DDM1, and was not assigned to any of the fire or cloud classes in the image at \( t-30 \) min;
- the fire pixel is adjacent to a detected cloud pixel in any of the frames time-stamped \( t \), \( t-30 \) min, or \( t-15 \) min.

Areas surrounding detected clouds often represent thin clouds, which if undetected, may result in a biased representation of normal background conditions;
- the fire pixel is not adjacent to a hot spot defined by (8).

The first three tests are aimed at eliminating false positives sometimes committed by multi-temporal detector DDM2 due to undetected clouds in the basis images or possible residual misregistration. Furthermore, a fire pixel is rejected if: \( R_{11}^{\text{DDM1}} < -2.0\sigma \), or \( BT_x < 290\text{K} \), or it is a part of a spatially connected region of fire pixels with more than 5 pixels.

The Main pass of the Anomaly Classifier results in a frame-wise product. To reduce the number of false positives, a temporal filter is applied to the frame-wise fire detection product. The temporal filter delays acceptance of fire-candidates until they have been detected (i.e. spatially matched within one-pixel buffer) in two consecutive frames at a confidence \( \gamma > 3.5 \).

**Event Tracker.** Events are extracted based on temporal evolution of spatially connected components (c.c.) formed by detected fire pixels in the GOES image coordinate system. For a frame collected at detection time \( t \), the event tracking algorithm groups fire pixels into events as follows:

1. Partition fire pixels into connected components.
2. Initially, when the past detections are not available, each c.c. is considered a new event.
3. When past detections are available, for each fire pixel \((x,t)\), find the nearest location \( \xi \) that was flagged fire at least once during last 24 hrs. If \( \|x-\xi\| < b \), then \((x,t)\) is called a re-detected fire pixel. Otherwise, it is called a new fire pixel. Let \( E(\xi) \) denote the existing event corresponding to \( \xi \).
4. Connected components with no re-detected pixels become new events.
5. For connected components that do include re-detected pixels the analysis is slightly more complex:
   a. Re-detected pixel-members \((x,t)\) are assigned to their respective previously detected events \( E(\xi) \).
   b. New pixel-members are assigned depending on the set of events to which re-detected pixel members of this c.c. are assigned:
      i. if all re-detected pixel-members of this c.c. are assigned to the same event \( E \) (note that \( E \) is an existing event), then so are the new fire pixels.
      ii. otherwise, all new pixels are assigned to new events.
PERFORMANCE EVALUATION USING CALIFORNIA 2006 FIRE SEASON DATA

The study scene includes Central and Southern California and Western Nevada and occupies nearly 700,000 km$^2$ (Figure 3). This scene includes a range of ecosystems: from semiarid shrublands, conifer dominated forests, annual grasslands, intensive agriculture, to wetland ecosystems. This diversity leads to different fire regimes and dynamics. Furthermore, some portions of the study scene within California are densely populated. Consequently, it can be reasonably assumed that wildfires in the vicinity of these areas would have a higher likelihood of been reported soon after they start. This circumstance can make it extremely difficult to detect fires from space earlier than by conventional means.

The validation experiments and analysis described below in this section were aimed at the following objectives:
1. to assess detection timeliness by the current version of GOES-EFD, with respect to conventional reporting mechanisms and determine baseline false positive rates;
2. to estimate the maximal detection timeliness by the current version of GOES-EFD, and the associated baseline false positive rates; and
3. to compare detection timeliness performance of GOES-EFD and operational WF-ABBA under similar conditions of application.

The GOES image time series available for this test spans the period from June to October 2006. For training the GOES-EFD algorithm we used frames acquired in June-July (640 frames). The Detection stage of operation was applied to 2852 images acquired during August 3 – October 1 at variable time step (~20 min on average). The available Detection stage GOES image data had three significant temporal gaps for technical reasons: 8/23 11:30 PDT through 8/28 14:00 PDT; and 9/08 21:30 PDT through 9/25 15:00 PDT. This period (August 3 – October 1), excluding the data gaps, will be referred to as the detection period. To accomplish our objectives, we respectively ran GOES-EFD in the following three modes:
- EFD-regular: All available GOES frames are processed (2852 frames, in our experiment).
- EFD-rapid: All available GOES frames are processed without the temporal filter (section 2.3.4), so that new events are reported without delay.
- EFD@30min: Available GOES frames are processed at half-hourly step (1494 frames, in our experiment), to facilitate a comparison with WF-ABBA.

Validation Methodology

The timeliness and accuracy of fire detection were validated against interagency fire reporting records. These data, provided in geospatial format, are independent of the fire detection or satellite observation processes. The validation methodology is discussed in detailed by Koltunov et al. (2011) and is briefly summarized below in this section.

Two wildfire databases for year 2006 have been merged: a fire perimeter polygon database compiled by the California Department of Forestry and Fire Protection (CAL FIRE) and point and polygon databases created by the Geospatial Multi-Agency Coordination (GeoMAC) group. Both databases are based on the incident report data from multiple U.S. agencies, including CAL FIRE, USDA Forest Service, Bureau of Land Management, National Park Service, and other federal and local agencies and departments. The fire incident records in the databases included, in particular, fire final size, initial report and final containment dates, and for some incidents – the initial report hour. After excluding 18 co-occurring (i.e., overlapping in space and time) incidents to avoid optimistic bias in detection timeliness assessment (see Koltunov et al. (2011) for discussion of this aspect), the test sample included 25 fires that burned more than 3 ha and which started during the detection period. The initial report hour was recorded for 13 of these 25 incidents. The information about the fires is summarized in first four columns of Table 1.

The timeliness of detection was evaluated as detection latency Δτ that is offset by the time of initial report from conventional sources. The relative latency is defined as difference between the times of the first alarm by GOES-EFD and the recorded time of initial reports. The latency did not account for GOES data delivery and processing time. All 25 fires were used to estimate the fraction of incidents detected within 12 hours of the initial report (or on the same day, for fires with unavailable report hour information). Fractions of incidents detected within the first hour and before the initial report were estimated using 13 wildfires with recorded report hour. Other fires that were active during the detection period were used to avoid mislabeling pixels as false positives. A fire was considered active at time t, if it was reported earlier than t + 3 hours and was contained later than t - 48 hours. In this way, we attempted to account for possible delays in fire initial reporting and also for the possibility of residual burning after the fire was deemed contained.
Denoting \( p_k \), the bounding box of the perimeter polygon for a fire incident \( f_k \), the fire pixel-to-incident matching rules is formulated as follows:

- A fire pixel \((x, t)\) centered at a spatial location \( x \) detected in a frame acquired at detection time \( t \) matches incident \( f_k \) if and only if \( f_k \) is active at time \( t \), and either \( \text{dist}(x, p_k) < b_1 \), or \( \text{dist}(x, p_k) < b_2 \) and fire \( f_k \) is the closest active fire to pixel \((x, t)\).

where \( b_1 = 5.6 \text{ km} \) is the linear size of a GOES imager pixel in north-south direction; and \( b_2 = 11.2 \text{ km} \). This two-buffer rule responds to the uncertainty or limited accuracy of the information about fire actual start and end times. Because of this uncertainty, when a detected fire pixel coincides in time and is spatially close to more than one actual incident, it is difficult to determine which one has been detected. In this case, using the above two-buffer matching rule, in addition to excluding co-occurring incidents from the sample, puts a barrier against mistaking detection of an older active fire for early detection of a newer ignition.

An important aspect of validation is the performance measures to use. As was argued by Koltunov et al. (2011), pixel-wise false positive rates do not adequately represent algorithm performance with respect to detection timeliness because of different costs of commission for different pixels. Therefore, a validation analysis should determine true and false new events (not merely pixels) reported by an algorithm as candidates for new ignitions. GOES-EFD extracts new events (section 2.3.5) from the time series of pixel-wise detections, which simplifies validation. Whether an event is a true positive or a false positive is decided by the matching rule:

- An event \( E \) matches fire \( f_k \) if at least one pixel assigned to \( E \) matches \( f_k \).

Comparison with Temporally Filtered GOES WF-ABBA Algorithm. A meaningful comparison of an optimized operational algorithm WF-ABBA with an initial prototype version of GOES-EFD is not an entirely trivial task not only due to different stages of their development, but also due to essential mismatch between the conditions under which these methods are applied. Particularly, WF-ABBA is applied only every 30 min, while GOES-EFD is designed to process all available frames. Therefore, in this paper WF-ABBA is compared to the third variant of GOES-EFD referred above to as EFD@30min.

Furthermore, as an active fire monitoring algorithm, WF-ABBA outputs geographic coordinates of fire pixels (after correction for oversampling in GOES imagery) and not the coordinates of multi-pixel regions (events) forming separate potential incidents. In turn, the objective of GOES-EFD is identifying new ignitions, and therefore, it includes an event tracking module extracting multi-pixel events and separating new events from past ones. Thus, to facilitate a comparison of incident detection quality, WF-ABBA detections were post-processed using the event tracking procedure described in section 2.3.5 and previously used by Koltunov et al. (2011) for validating WF-ABBA. The control parameters that previously resulted in the best estimated performance of WF-ABBA (Koltunov et al., 2011) were also used in our present comparison.

Finally, we ignored low confidence detections of each algorithm. These included WF-ABBA with confidence flag of 5 (low possibility fire) and detections of GOES-EFD with anomaly confidence \( \gamma < 3.5 \) (see sect. 2.3.3), resulting in nearly identical false positive rates, which simplifies comparison.

Results

Figure 4 shows the cumulative distribution functions (c.d.f.) for the relative latency of detection, \( \Delta t \), which is the fraction of fires for which the difference between the time of first satellite detection and the conventional initial report is less than \( x \) minutes. The summary statistics are presented in Table 1, including false positive rates.

As seen from these data, in the regular mode (EFD-regular), in which all available GOES images are processed, GOES-EFD detected 60% of 25 fires within 12 hours of initial report. Nearly 77% of the 13 fires with recorded report hour were detected within the first hour, and 31% of the same 13 fires – before they were reported by the conventional sources, with the total of 142 minute reduction of fire incident latency.

When both GOES-EFD and WF-ABBA are applied at 30-min step, the number of new ignition commission errors (bottom row of Table 1) are nearly identical. However, EFD@30min tends to initially identify wildfires earlier, so that 43% more incidents are detected within the first hour. The fires that were detected by both algorithms were identified by GOES-EFD on average 36 min before WF-ABBA. The total reduction of latency relative to conventional reports improves from 45 min by WFABBA to 105 min by GOES-EFD.

Although GOES-EFD applications in the regular mode and at 30-min step resulted in earlier detection, the algorithm does not yet maximize detection timeliness, or, equivalently, minimize the latency. For example, the algorithm application in the rapid mode leads to a substantially greater reduction of latency: 216 min total (see column “EFD-rapid” in Table 1), but with an order of magnitude increase in false positives relative to the other two modes. Consequently, to benefit from the use of GOES imagery to identify fire detections earlier, the substantially higher false positive rates of the rapid mode must be greatly reduced by further algorithm optimization.
DISCUSSION

Utilizing spatial, spectral, and last but not least, temporal dimension for fire detection requires algorithmically addressing new and difficult problems. The situation is further complicated due to the emphasis on detecting ignitions as early as possible: correctly detected fire pixels that are too late or merely repeat detections of a previously detected incident do not generally count toward the early fire detection algorithm objectives. As a consequence, the GOES-EFD represents a complex system combining several sub-algorithms, thus naturally elevating the level of effort that is necessary for system optimization.

Many of the elements comprising GOES-EFD, such as DDM, the optical flow based image registration, and a contextual hot spot detection, have been proven practically effective by years or decades of research and variety of applications. Nevertheless, presently GOES-EFD is a conceptual research prototype algorithm, which is a starting point for a more systematic and greater-scale development, optimization, and validation work. This work is currently in progress and is aimed at advancing GOES-EFD system to the maturity level that would be acceptable for operational implementation. Specific algorithmic directions to improve GOES-EFD are numerous, including:

1) including visible band of GOES Imager,
2) improving cloud detection algorithm,
3) optimizing the anomaly classifier,
4) incorporating sun angle information to eliminate false positives due to sun glint,
5) optimizing extraction of new events, and
6) improving image registration block.

Reducing the number of false positive new events (i.e. new ignition candidates) should be the central focus of development. Currently, false positives are mainly caused by undetected clouds, misregistration, shifted or damaged scan lines, and other reasons. Although we anticipate substantial improvements in the future versions, we acknowledge that these rates will never go down to zero. Therefore, it is imperative to develop an appropriate protocol for the future operational use of the detection product, including rapid and efficient mechanisms for verification of GOES-EFD detections. The combination of satellite surveillance and independent verification will offer an active approach to fire identification, which is largely under control of the responsible authorities and agencies, contrasting to passively waiting for a phone call from a human observer.

As comparison with WF-ABBA shows, the GOES-EFD extracts information that is complementary to the outputs of the current operational satellite wildfire detection tools. This is not surprising, because WF-ABBA algorithm was not specifically designed as an early warning tool, but for monitoring and consistently redetecting active fires (Koltunov et al. 2011).

SUMMARY AND CONCLUSION

Capitalizing on previous efforts of different research teams (Prins & Menzel 1994; Giglio et al. 2003; Koltunov and Ustin 2007), the presented prototype of the GOES Early Fire Detection algorithm combines two major approaches to fire detection, multitemporal and contextual, in the framework of an image-understanding algorithm. Currently, an initial pre-alpha version of the GOES-EFD algorithm has been developed. Although the algorithm is not yet optimized and currently uses only two thermal bands, it includes the minimal set of modules that are necessary for regional scale surveillance: installation, semi-interactive training, spectro-temporal cloud detection, band-to-band and frame-to-sequence registration, iterative multi-temporal and contextual anomaly detection, anomaly classification, and false-alarm filters.

First tests of the GOES-EFD have provided experimental evidence that even in the era of mobile communication and in densely populated areas of the US, such as the State of California, geostationary surveillance...
could become a consistent early wildfire detection tool. For the fraction of fires that a satellite fire detection system can provide the earliest detection, the expected minimization of societal and natural resource losses increases the expected value of timely detection information per incident. Furthermore, detecting a fairly large proportion (more than 75% in our test) of incidents during the first hour in California is no less valuable than occasionally providing the earliest alarm for at least three reasons. Firstly, satellite detection information received minutes after the initial report has a significant operational value. Secondly, these result indicate that the earliest alarms by GOES-EFD could become routine in contrast to traditional methods of wildfire identification and reporting. Finally, and the most importantly, with the upcoming launch of the next generation of geostationary satellites, GOES-R/GOES-S, detection capability and timeliness is expected to remarkably increase.

The initial results presented in this paper show the potential of geostationary wildfire detection and argue for a collaborative effort to further develop and comprehensively test the GOES-EFD system within the operational framework of fire management agencies. This will ensure an optimal and appropriate application of current and future early fire detection informational products for fire management, and directly improve the information suite that aids resource allocation decisions in response to potential fire ignitions. Greater societal and natural resource benefits from completing this work are expected when the ready-to-use GOES-EFD system is applied to GOES-R Advanced Baseline Imager to complement the active fire monitoring capabilities of the WF-ABBA algorithm.

ACKNOWLEDGMENTS

We wish to acknowledge NASA support under subcontract on grant #NNG04GK34G, “Studies of biosphere-atmosphere interactions with a GCM with MODIS spectral resolution” and USDA and UC Davis support under Cost Share Agreement 10-IA-11130400-009 “Evaluating operational potential of geostationary early fire detection capabilities at regional level”. We thank Mr. Mark Rosenberg from California Department of Forestry and Fire Protection (CAL FIRE) for providing geospatial wildfire database and useful discussions. We also thank Mr. George Scheer (UC Davis) for systems administration and other computation support that enabled us to analyze these data.

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ASPRS 2012 Annual Conference
Sacramento, California ♦ March 19-23, 2012


**Figure 1.** GOES-EFD: Training Stage and Preprocessing schema

**Figure 2.** Test scene located in C. California

**Figure 3.** GOES-EFD: Detection Stage schema

**Figure 4.** Cumulative distribution function (c.d.f.) of detection timeliness relative to recorded times of initial reports from conventional sources. The c.d.f. curves represent three modes of the GOES-EFD algorithm (section 3) and the temporally filtered WF-ABBA.