HOTMAP: Global hot target detection at moderate spatial resolution

Sam W. Murphy, Carlos Roberto de Souza Filho, Rob Wright, Giovanni Sabatino, Rosa Correa Pabon

1. Introduction

Fires and volcanoes are examples of hot targets that can be monitored from space. These phenomena have significant impact on human health, can cause large-scale damage to property, and release a magnitude of aerosols into the atmosphere that is large enough to affect the climate. To better understand how these phenomena behave at any given point in time, including how they are likely to behave in the future, it is necessary to monitor them.

Target detection is the foundation of any monitoring system. Hot targets are typically dynamic, and often ephemeral, surface features. Intuitively this calls for the use of a high temporal resolution data set (i.e. at least daily observations). On the other hand, a consistent global perspective requires the use of polar orbiting satellites (i.e. geostationary satellites inevitably suffer from severe distortion towards the edges of their observable discs). As such, existing global hot target monitoring systems utilize data from low spatial resolution (i.e. 1 km) polar orbiting sensors (e.g. Giglio, Desclötres, Justice, & Kaufman, 2003; Wright, Flynn, Garbeil, Harris, & Pilger, 2004). Additionally, the meteorological heritage of these satellites insured that they have a distribution architecture for getting the data from the spacecraft to the end-user in near-real time, which is crucial for rapid response to dynamic phenomena.

However, the large instantaneous field of view (IFOV) of low spatial resolution detector elements hinders target detection. This is because of a propensity for background radiance to dominate the signal from a relatively small and/or subtle hot target. A large IFOV also impedes the ability to retrieve spatial information (e.g. location, size, shape) from active hot targets, as they will typically be subpixel in size.

Higher spatial resolution imagery has been available from the Landsat series of satellites since 1972. Landsat-class sensors have been used to study active volcanism (e.g. Francis and Rothery, 1987; Oppenheimer, 1991; Flynn, Mouginsmark, and Horton, 1994; Harris and Stevenson, 1997; Wooster, Kaneko, Nakada, and Shimizu, 2000; Murphy, de Souza Filho, and Oppenheimer, 2011; Murphy, Wright, Oppenheimer, and Filho, 2013; Blackett, 2014) and to a lesser extent fires (e.g. Flynn and Mougins-Mark, 1995; Morisette, Giglio, Csiszar, and Justice, 2005; Giglio et al., 2008; Böhme, Bouwer, and Prinsloo, 2015) for decades. However, a global monitoring system has not yet been created, principally because of i) limited temporal resolution, ii) latency between data acquisition and data availability, iii) the cost of buying the data, and iv) limited duty cycles. These restrictions are either no longer present or are in the process of being eliminated (see following section). The aim of...
this work is to therefore develop algorithms for the detection of hot targets within Landsat-class imagery.

1.1. Hot target monitoring using Landsat-class sensors: an idea whose time has come

A single moderate spatial resolution (i.e. 20–200 m) polar orbiting imager will typically have a temporal resolution of 10 to 16 days. This revisit period will improve (i.e. decrease) away from the equator due to convergence of satellite tracks. Fig. 1 displays global revisit periods as a function of latitude for a) Landsat 8, b) Sentinel 2a and c) Landsat 8 and the complete Sentinel 2 mission (i.e. 2a and 2b). The combined revisit period of the Landsat 8 and Sentinel 2 missions ranges from 2 to 4 days between ±60° latitude. This would provide a temporal resolution that is high enough for useful time sequences over a significant number of larger wildfires, and most subaqueous volcanoes. Data streams from additional satellite missions could further improve temporal resolution (e.g. 1.5–3 days if also including Landsat 7 data).

Historically, the latency between data acquisition and availability would often exceed 24 h for Landsat-class data. Advances in satellite data downloading, processing and distribution have reduced this lag to near-real time (i.e. within 3 h). Recent innovations in satellite data transfer and processing have paved the way for real-time (i.e. seconds to minutes) monitoring of the Earth’s surface by processing image segments as they are being received by the demodulator (Böhme et al., 2015). This technology solution has already been demonstrated using Landsat 8 imagery. It is currently running at Geoscience Australia’s Alice Springs ground receiving station and is being installed at the European Space Agency (ESA) Matera ground station for use with Sentinel 2 data. There are also, of course, a significant number of hot target detection applications that are less time sensitive (e.g. studies of long-term time series, analysis of contemporaneous satellite and field measurements, creation of hazard maps, etc.).

The cost of an individual Landsat scene has ranged in the past from hundreds to thousands of US dollars. The entire Landsat archive (i.e. including Landsat 8) is now available at no cost to the end-user for this service. The G-POD catalog is fully synchronized with the USGS Landsat 8 archive and shall be fully synchronized with the Sentinel 2 archive once the commissioning phase is completed. Data are available within 3 to 24 h of satellite overpass. This lag time could be reduced to 30 min after overpass and, as mentioned previously, potentially just a few minutes when processing image segments as they are downloaded; this capability should be fully operational at Matera ground station by early 2016 (Böhme, personal communication). A beta version of the Hotmap software is aimed for release to the public for 2016.

2. Hotmap

Hotmap is an application of satellite data to detect hot targets globally. Its scope at present is the identification of thermally anomalous pixels in Landsat 8 and Sentinel 2 imagery. The software, which is currently in the alpha phase of its release cycle, is installed on the Grid Processing on Demand (G-POD) environment made available by ESA Research and Service Support (RSS) (Marchetti et al., 2012). It allows end-users to search for thermal activity on the Earth’s surface using an interface made accessible via a web browser. There is no charge to the end-user for this service. The G-POD catalog is fully synchronized with the USGS Landsat 8 archive and shall be fully synchronized with the Sentinel 2 archive once the commissioning phase is completed. Data are available within 3 to 24 h of satellite overpass. This lag time could be reduced to 30 min after overpass and, as mentioned previously, potentially just a few minutes when processing image segments as they are downloaded; this capability should be fully operational at Matera ground station by early 2016 (Böhme, personal communication). A beta version of the hotmap software is aimed for release to the public for 2016.

3. Satellite sensors

Landsat 8 was launched in February 2013. It is an 11-channel imaging radiometer with two optical subsystems, one in the visible through short-wave infrared (VSWIR) spectral range and another in the thermal infrared (TIR). The VSWIR subsystem, i.e. the Optical Land Imager (OLI), has nine channels and a spatial resolution of 30 m. The TIR subsystem, i.e. the Thermal Infrared Sensor (TIRS), has two channels and a spatial resolution of 100 m. Band numbers and spectral locations are given in Table 1. The imaging swath for all bands is 185 km cross-track. The
acquisition plan for Landsat 8 is systematic coverage of land and coastal surfaces between −57 and 57 degrees latitude.

ESA successfully launched the first of the two satellites of the Sentinel 2 mission in June 2015. The second satellite will be launched in mid-2016. Each will carry an integrated 12-channel VSWIR imager (Table 1). The mission will provide systematic global coverage of all land and coastal surfaces (between −56° and +84° latitude). The relatively wide swath (i.e., 290 km) and twin satellite configuration will provide a temporal resolution of just 5 days at the equator. As with the Landsat series, ESA have made a commitment to long-term data collection for all Sentinel missions (i.e., including Sentinel 2). This is important because decadal time series are crucial for understanding change at the global level.

4. Data

This study uses 45 Landsat 8 OLI scenes. They are processed to Level 1 T, i.e. Standard Terrain Correction, which includes radiometric and geometric correction using a Digital Elevation Model (DEM) for topographic accuracy. The scenes are delivered in a 16-bit Digital Number (DN) format and subsequently converted to either i) at-sensor radiance or ii) Top of Atmosphere (TOA) reflectance – as required – using the scaling factors provided in the product metadata. We selected five scenes from each of the nine geographical regions defined in Giglio et al. (2008), i.e. Africa, Australia, Europe, India, Mexico, Russia, South East Asia, South America and USA-Canada. In total, the scenes cover an area of $2.5 \times 10^6$ km$^2$. Scene location and acquisition dates were selected based on output from the MODIS fire detection product available through NASA’s Fire Information for Resource Management System (FIRMS). The locations of the selected Landsat 8 scenes are displayed in Fig. 3.

5. Hot target detection

To detect thermal activity from fires or volcanoes within satellite imagery it is necessary to use at least one waveband that is sensitive to the radiation emitted by hot targets. To create a global monitoring system at moderate spatial resolution it is essential to combine data streams from multiple satellite missions in order to attain a sufficiently high temporal resolution. Observations from different sensors within a constellation must therefore be self-consistent. This necessitates the use of wavebands with similar spectral characteristics and images with comparable spatial resolutions. For the platforms outlined in Table 1 the relevant sensitive wavebands are centered at around 1.6 and 2.2 μm.

5.1. Previous detection algorithms

The identification of hot targets in satellite imagery has typically been executed on an ad hoc basis (e.g. by eye or using a simple scene-specific threshold algorithm). This is, in large part, due to the lack of a historical necessity for a globally applicable solution. Consequently, there have only been two published attempts at creating hot target detection algorithms for global moderate spatial resolution data sets (Davies et al., 2006; Giglio et al., 2008) with another currently in press (Schroeder et al., 2015).

5.1.1. Autonomous Sciencecraft Experiment (ASE)

The Autonomous Sciencecraft Experiment (ASE) is a software application that runs on the Earth Observing-1 (EO-1) satellite. It is designed to autonomously detect and monitor dynamic processes on Earth (Chien, 2004). Its design includes the detection of volcanic thermal emissions using imagery from the Hyperion imaging spectrometer (Davies et al., 2006). The relevant algorithm uses four channels, two for hot target detection and two to account for idiosyncratic sensor noise. Performance was reported as satisfactory for both diurnal and nocturnal imagery. The wavebands used for hot target detection in this algorithm are centered at 1.65 and 2.28 μm, which is a spectral region that suffers little impedance on transmission through the atmosphere. There are similar wavebands, i.e. around 1.6 and 2.2 μm, available on both Landsat 8 and Sentinel 2 (Table 1). It is therefore possible to adapt this algorithm to these sensors as outlined below.

The ASE algorithm classifies thermally anomalous pixels as either HOT or EXTREME. The first step in this process is to identify pixels in a 2.2 μm radiance image with a sufficiently high pixel value. For a pixel to be considered HOT it must exceed at least $1 \text{ W m}^{-2} \text{ sr}^{-1} \mu \text{m}^{-1}$. This reduces false alarms by avoiding pixels that are clearly not thermal-anomalously radiant (e.g. water bodies). For a pixel to be considered EXTREME it must exceed 10 W m$^{-2}$ sr$^{-1}$ μm$^{-1}$, i.e. to ensure that the corresponding ground sampling area is significantly radiant. Algorithm performance is not strongly dependent on the exact value of these minimum thresholds. Davies et al. (2006) originally used 0.625 and 12.5 W m$^{-2}$ sr$^{-1}$ μm$^{-1}$, respectively. The spectral gradient, G, between the 1.6 and 2.2 μm wavebands is calculated for each candidate HOT pixels using the formula:

$$G = \frac{L_{1.2} - L_{1.6}}{2.2 - 1.6} \quad (1)$$

where $L$ is spectral radiance and the subscripts 1.6 and 2.2 denote central wavelengths. A pixel is considered to be HOT if this gradient exceeds zero. This threshold was derived by analyzing the background $G$ distribution of non-radiant surfaces globally. It is similar to the value

---

**Table 1**

<table>
<thead>
<tr>
<th>Band #</th>
<th>$\lambda_{\text{central}}$ (nm)</th>
<th>Pixel size (m)</th>
<th>Band #</th>
<th>$\lambda_{\text{central}}$ (nm)</th>
<th>Pixel size (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>440</td>
<td>30</td>
<td>2</td>
<td>480</td>
<td>30</td>
</tr>
<tr>
<td>3</td>
<td>560</td>
<td>30</td>
<td>4</td>
<td>655</td>
<td>30</td>
</tr>
<tr>
<td>5</td>
<td>865</td>
<td>30</td>
<td>6</td>
<td>1610</td>
<td>30</td>
</tr>
<tr>
<td>7</td>
<td>2200</td>
<td>30</td>
<td>8</td>
<td>590</td>
<td>30</td>
</tr>
<tr>
<td>9</td>
<td>1370</td>
<td>30</td>
<td>10</td>
<td>10,895</td>
<td>100</td>
</tr>
<tr>
<td>11</td>
<td>12,005</td>
<td>100</td>
<td>11</td>
<td>12,005</td>
<td>100</td>
</tr>
<tr>
<td>12</td>
<td>2190</td>
<td>20</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
5.1.2. Contextual Analysis (CA)

Giglio et al. (2008) developed a nighttime detection algorithm and a daytime detection algorithm for the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER). The sensitive waveband that they used for both algorithms was centered at 2.33 μm (i.e. ASTER band 8). Hot targets were detected at night by converting the 2.33 μm waveband into spectral radiance and applying a fixed threshold (i.e. 1 W m⁻² sr⁻¹ μm⁻¹); we put forward an enhancement to this approach – improving subtle anomaly detection – in Section 5.2.

The daytime detection algorithm of Giglio et al. (2008) utilized a second waveband at 0.82 μm (i.e. ASTER band 3); both wavebands are converted to top-of-atmosphere reflectances in the daytime hot target detection algorithm. The reason given is that reflectances at 0.82 and 2.33 μm are linearly correlated over most terrestrial surfaces (e.g. soil, vegetation, clouds and urban areas). Consequently, the ratio of these reflectances will tend to be constant, with an exception over low reflectivity surfaces and hot targets. Thus, by discounting low reflectivity surfaces (i.e. by using reflectance differences) they identify hot targets by searching for anomalously high reflectance ratios (i.e. with the 2.33 μm reflectance value as the numerator). The detection process involves searching for obviously hot pixels and candidate pixels (i.e. pixels that are not obviously hot but might be thermally anomalous). Contextual analysis (i.e. statistical comparison of pixel values to those of proximal neighbors) is used to promote or reject candidate hot pixels.

They report high positive detection rates for the daytime algorithm, which we confirm (Section 7). However, during in-house testing we found that commission errors (i.e. false alarms) are prevalent in urban areas (i.e. rooftops). This is a significant issue because it is at or around human populations that the accuracy and reliability of hot target detection is most critical. False alarms were also observed at other targets with high contextual contrast (e.g. sand banks, open mine pits, etc.).

Adaptation from ASTER to Landsat 8 (or Sentinel 2) is straightforward because each of these sensors have similar wavebands around 0.82 and 2.33 μm (e.g. Schroeder et al., 2015). For convenience, we will refer to the daytime detection algorithm of Giglio et al. (2008) as the Contextual Analysis (CA) algorithm.

5.1.3. Temporal CA (TCA)

Schroeder et al. (2015), article in press, are putting forward a fire detection algorithm for Landsat 8 that builds on CA and previous work by Schroeder et al. (2008). The nighttime algorithm is the same as in CA. The daytime detection procedure also includes the concept of searching for obvious and candidate hot pixels, and carries out contextual analysis on candidate pixels. However, there are three significant additions: i) they explicitly account for potential oversaturation in the 2.2 μm waveband by using reflectance values in bands 1 (0.44 μm) and 6 (1.61 μm), ii) they developed a relatively advanced water pixel mask to ensure validity of background pixels and to reduce false alarms, iii) they take advantage of the improved geolocation of Landsat 8 to map hot pixel detections through time. The latter contribution is the most significant. It allowed them to differentiate between temporary and persistent hot sources (e.g. vegetation fires and gas flares, respectively), as well as to potentially flag false alarms from stationary reflective surfaces (e.g. factory rooftops and solar farms, etc.). Reported performance is exceptionally high (e.g. 0% commission errors in over half of validation scenes), indicating that this method could be invaluable for studies that have very low tolerance to false alarms (e.g. precision air quality assessments and hazard mapping, etc.). We leave a comparative analysis of algorithm performance for future studies given the concurrent nature of these publications.

5.2. Enhanced nighttime detection algorithm

The SWIR response in nighttime imagery is essentially limited to sensor noise over areas that exhibit normal terrestrial temperatures (i.e. <60 °C). It is therefore possible to detect most hot targets at night using a fixed threshold of 1 W m⁻² sr⁻¹ μm⁻¹ (Giglio et al., 2008). Pixels that surpass this threshold are considered ‘obviously hot’. Relatively subtle thermal anomalies below this threshold will be missed. Our enhancement focuses on detecting these subtle anomalies. This is achieved by searching for statistically significant deviations from sensor noise. In particular, we define pixels that are at least five standard deviations, 5σ, above sensor noise as ‘candidate pixels’. Candidate pixels are promoted to ‘hot pixels’ if they are juxtaposed to at least one other candidate or obviously hot pixel. The reason for filtering out isolated candidate pixels is to avoid extreme noise events.

In more detail, background noise at night in the 2.2 μm waveband of Landsat 8 is around 4 × 10⁻⁴ W m⁻² sr⁻¹ μm⁻¹ (mean apparent radiance) with a standard deviation of 3 × 10⁻³. Therefore, a pixel that is 5σ above mean noise can have an apparent radiance as low as 0.015 W m⁻² sr⁻¹ μm⁻¹. This is significantly lower than the
fixed threshold of $1 \text{ W m}^{-2} \text{ sr}^{-1} \mu \text{m}^{-1}$. If we can assume – as a first order estimate – that the factors that collectively contribute towards sensor noise manifest themselves in a normal statistical distribution, then the likelihood that a pixel will be falsely flagged as a candidate due to extreme noise is $1$ in $3.5$ million. Given that a Landsat 8 SWIR image typically contains around $60$ million pixels, then the number of expected extreme noise events per scene in the $2.2 \mu \text{m}$ waveband would be $17$ pixels. We consider $17$ pixels per scene to be a non-negligible systematic error. This was resolved by rejecting isolated candidate pixels because, assuming that noise is independent, the chance that two noise derived candidate pixels are juxtaposed is just $0.003\%$. Thus, the use of straight-forward background noise statistics can increase the detection rate for subtle thermal anomalies without significantly increasing the commission error. Dynamically accounting for sensor noise in this way means that it is possible to detect isothermal targets as low as $74$ °C degrees in nighttime SWIR imagery if the target fully occupies at least two IFOV of juxtaposed detector elements (i.e. a target that is at least $1800 \text{ m}^2$ in size).

5.3. Novel daytime detection algorithm

Daytime detection of targets in VSWIR imagery must account for reflected solar radiation. This quantity is highly variable, both spatially and temporally, due to its dependence on atmospheric constituents and Earth–sun–satellite geometry. It is possible to detect hot targets without atmospheric correction when using wavelengths in atmospheric windows (e.g. Davies et al., 2006; Giglio et al., 2008), however, Earth–sun–satellite geometry must be explicitly accounted for. One approach is to normalize at-sensor radiance by the hypothetical radiance that the Earth would reflect if it were an airless, non-radiant white body. This quantity is known as reflectance. Giglio et al. (2008) pioneered the use of reflectance for the detection of hot targets in moderate spatial resolution daytime imagery. Our algorithm also uses TOA reflectance as input.

The use of reflectances also increases compatibility between sensor systems, which is a critical factor for satellite constellations. This is because solar irradiance [$\text{W m}^{-2}$] is more sensitivity to changes in wavelength than the spectral reflectance [$\rho \mu \text{m}^{-1}$] of typical terrestrial materials (Fig. 4). Fig. 4A represents spectral regions (i.e. horizontal bars) of equivalent wavebands in the i) NIR and ii) SWIR for three different satellite sensors (i.e. Landsat 7, Landsat 8 and Sentinel 2). The number within each bar represents the solar irradiance at TOA for the spectral region of that waveband. Solar irradiance is sensitive to both spectral location and width. Fig. 4B shows examples of common reflectance spectra (i.e. man-made materials, rock forming minerals and vegetation). They typically exhibit graybody behavior (i.e. have flat reflectance spectra) over these wavelengths.

The proposed daytime detection algorithm consolidates spectral information from three separate wavebands into the following two binary parameters, $\alpha$ and $\beta$.

$$\alpha = \left( \frac{\rho_6}{\rho_5} \geq 1.4 \right) \land \left( \frac{\rho_6}{\rho_7} \geq 1.4 \right) \land \rho_7 \geq 0.15$$

$$\beta = \left( \frac{\rho_6}{\rho_5} \geq 2 \right) \lor \rho_7 \geq 0.5$$

where $\rho_5$, $\rho_6$ and $\rho_7$ are TOA reflectances in bands 5, 6 and 7 of the OLI sensor on Landsat 8, they have corresponding central wavelengths of $0.87$, $1.61$ and $2.2 \mu \text{m}$. The parameter $\alpha$ has a value of one if bands 6 or 7 are saturated; otherwise it has a value of zero. The binary output of both functions is controlled by the logical predicate greater than or equal to (i.e. $\geq$) as well as the Boolean operators ‘AND’ and ‘OR’. Thus, a pixel has an $\alpha$ of one if reflectance in band 7 is at least 40% greater than reflectance in both bands 5 and 6 (i.e. because the $2.2 \mu \text{m}$ waveband is expected to be relatively sensitive to hot targets), and if reflectance in band 7 is not too low (i.e. Eq. (2)). This latter condition is imposed to avoid creating false alarms over low reflectivity surfaces such as water bodies. A pixel will have a $\beta$ of one if reflectance in band 6 is at least twice as high as in band 5, and if reflectance in band 6 is at least 0.5. The latter fixed threshold is to ensure that the pixel is sufficiently radiant; algorithm performance is not sensitive to this threshold. Alternatively, a pixel could also be assigned a $\beta$ of one if either bands 6 or 7 are saturated.

The $\alpha$ parameter was designed to exhibit very few false alarms and to be able to identify at least one pixel in the majority of fire pixel clusters. However, it can miss particularly hot targets due to saturation in band 7 (i.e. $2.2 \mu \text{m}$). The $\beta$ parameter was designed to avoid saturation and identify very hot pixels. However, in isolation the $\beta$ parameter can flag a significant number of false alarms. The complementary strengths of the two parameters are combined synergistically through their respective spatial relationships to determine which pixels are considered hot or not. This is achieved by clustering the $\alpha$ and $\beta$ pixels using a Moore neighborhood search space (i.e. the 8-pixel ring around a given pixel). Hot pixel clusters that do not contain at least one $\alpha$ pixel are discarded (i.e. to mitigate false alarms). All of the pixels in the remaining pixels clusters are classified as thermally anomalous. In effect, this mimics the spatial association that is intuitive to a human analyst. The outline of the algorithm is depicted in Fig. 5.

![Fig. 4. A) The spectral position and width of equivalent wavebands in i) NIR and ii) SWIR from Landsat 7, Landsat 8 and Sentinel 2 sensors, numbers represent irradiance on TOA in corresponding spectral regions; B) reflectance spectra of common terrestrial materials approximate graybodies over these wavelengths.](image-url)
6. Algorithm evaluation

Detection algorithms attempt to optimally minimize omission errors (i.e. missed pixels) and commission errors (i.e. false alarms). The concept of minimizing omission error is equivalent to maximizing the positive detection rate, D:

\[ D = \frac{h}{t} \times 100 \]  

where \( h \) is the number of successful pixel hits, and \( t \) is the total number of true hot pixels. The location of true hot pixels was determined manually via expert human analysis for each of the 45 Landsat 8 scenes. This included visual and spectral analysis of Landsat 8 imagery and inspection of co-located high-resolution Google Earth imagery. A total of 78,000 true fire pixels were identified throughout the nine geographical regions (Table 2). Note region labels are used in subsequent figures.

It is not always possible to conclusively define where the hot target ends and the background begins in moderate spatial resolution imagery (i.e. along the edges of hot pixel clusters). This introduces a degree of subjectivity in any true hot pixel map (Giglio et al., 2008). It is possible, however, to at least determine how well a given algorithm performs relative to an expert human analyst. The crucial difference, of course, is that an algorithm is able to perform operationally on a global scale.

For a successful detection to take place, an algorithm hit must overlap with a true hot pixel. When they do not overlap, there has been either a false alarm (i.e. algorithm hit only) or a missed pixel (i.e. true hot pixel only). To account for subjectivity in the manual selection of true hot pixels it is convenient to define two types of false alarm i) those that are associated with true hot pixels and ii) those that are not. The concept of ‘association’ is defined by grouping together true hot pixels and algorithm hits together into clusters. If a cluster has at least one true hit then any false alarms in that cluster are defined as ‘associated false alarms’ (Fig. 6). If a pixel cluster has no true hits then each pixel in that particular cluster is defined as a ‘non-associated’ false alarm. The rate of associated false alarms, \( F_a \), is defined as:

\[ F_a = \frac{f_a}{t} \times 100 \]  

where \( f_a \) is the number of associated false alarms and \( t \) is the total number of true hot pixels. Non-associated false alarms are simply quantified by the total number of such pixels in a given scene.

7. Results

Each of the algorithms was able to detect fires in a range of environments using Landsat 8 imagery (Fig. 7). Examples are shown for a) a savannah grassland fire, b) small agricultural fires and c) a boreal forest fire. The first image for each example (i.e. ai, bi, ci) is of an infrared false color composite (R: 2.2 μm, G: 1.61 μm, B: 0.87 μm). This depicts hot targets in ‘warm’ colors (e.g. reds, oranges and yellows) and non-active background areas in ‘cool’ colors (e.g. blues and greens for health vegetation, and gray for exposed rock). We note that smoke plumes are largely transparent at these wavelengths (e.g. Fig. 7cii is a true-color composite of the same area shown in Fig. 7cii). The performance of each algorithm is compared visually for each scene (Fig. 7a, bii, civ) by assigning the binary output (i.e. hot or not) of each algorithm to a separate color band (i.e. R: ASE, G: CA, B: new). If all three algorithms hit a given pixel then it will appear white in this RGB color composition. The black background therefore depicts where none of the algorithms hit a pixel. The presence of colors between black and white indicates that algorithm performance varies. For example, about a third of the savannah grassland fire is depicted as cyan in the performance evaluation image (Fig. 7aii) along the edges of the fire. This indicates that they were detected by the CA and the new approach (i.e. green and blue) but not by the ASE method (i.e. red). Some pixels on the very edge of the fire are blue (i.e. only seen by the new algorithm).

Scenes acquired over India frequently exhibit small, low intensity fires such as those shown in Fig. 7b. The fires appear as clusters of just a few pixels in size and have a pinkish to purple hue in this infrared composite due to their low radiant intensity and the relatively strong NIR reflectance in agricultural areas (i.e. from healthy vegetation). Most of the fire pixel clusters are detected by at least one of the

<table>
<thead>
<tr>
<th>Geographic region</th>
<th>Region label</th>
<th># True fire pixels</th>
<th># Total pixels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Africa</td>
<td>Afr</td>
<td>7.1 × 10⁴</td>
<td>3.0 × 10⁴</td>
</tr>
<tr>
<td>Australia</td>
<td>Aus</td>
<td>2.1 × 10⁴</td>
<td>3.0 × 10⁴</td>
</tr>
<tr>
<td>Europe</td>
<td>Eur</td>
<td>5.3 × 10³</td>
<td>3.1 × 10⁸</td>
</tr>
<tr>
<td>India</td>
<td>Ind</td>
<td>1.8 × 10³</td>
<td>3.0 × 10⁸</td>
</tr>
<tr>
<td>Mexico</td>
<td>Mex</td>
<td>8.3 × 10²</td>
<td>2.9 × 10⁸</td>
</tr>
<tr>
<td>Russia</td>
<td>Rus</td>
<td>1.0 × 10⁴</td>
<td>3.3 × 10⁸</td>
</tr>
<tr>
<td>South East Asia</td>
<td>SEA</td>
<td>1.1 × 10⁴</td>
<td>3.0 × 10⁸</td>
</tr>
<tr>
<td>South America</td>
<td>Sou</td>
<td>4.1 × 10³</td>
<td>2.9 × 10⁸</td>
</tr>
<tr>
<td>USA-Canada</td>
<td>USA</td>
<td>3.6 × 10³</td>
<td>3.1 × 10⁸</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td></td>
<td>7.8 × 10⁴</td>
<td>2.7 × 10⁹</td>
</tr>
</tbody>
</table>
algorithms; although certain possible fires are missed by all three (i.e. yellow outlines).

Boreal forests are able to sustain large, high intensity wildfires (Fig. 7c). The conflagration shown here is over 10 km in length. The white dashed box in Fig. 7ci outlines the area depicted in Fig. 7ciii and civ. The thick smoke in this area results in algorithm hits that extend beyond the likely limit of the fire. The magenta pixels in the performance evaluation (Fig. 7civ) image depict where the ASE (red) and new (blue) algorithms detect fires. Red pixels depict where only the ASE algorithm hit. Although algorithm performance is adversely affected by thick smoke, it is possible to detect fires through smoke plumes with relatively low loss in accuracy compared to the gain.

Fig. 7. Examples of fires types a) savannah, b) agricultural and c) boreal forest, as seen in Landsat 8 imagery, displayed as false color composites (red outline; items ai, bi, ci, ciii), anomaly maps (green outline; items aii, bii, civ) and a true color composite (blue outline, item cii).

Fig. 8. Lava flow at Tolbachik volcano (Russia) imaged by Landsat 8. It is displayed as i) an infrared color composite and ii) an anomaly map (see text).
acquired when using Landsat-class sensors instead of MODIS-class sensors.

Hot target detection algorithms can also be used to identify thermal activity at volcanoes (Fig. 8). Displayed are i) a Landsat 8 infrared false color composite and ii) an algorithm performance RGB, as before. They depict a lava flow field at Tolbachik volcano (Russia). Flow direction is roughly SE. There is a large channelized flow towards the top of the field and a number of smaller flows, with relatively hot termini, further south. The algorithms are able to detect most of the hot pixels. The width of the main channelized flow is over-estimated slightly by all of the algorithms. This could be due to reflection and/or scattering close to the target, or due to sensor related issues, or a combination of these factors. Only the new method is able to correctly flag hot regions in the center of the large hot channelized flow (i.e. blue pixels in Fig. 8ii).

Performance statistics for each of the three approaches are displayed in Fig. 9. The positive detection rate (Fig. 9a) is displayed atop of the associated false alarm rate (Fig. 9b). Together they illustrate how well each algorithm is able to a) detect hot pixels and b) avoid false alarms around the edges of hot pixel clusters. The height of the bars represents the mean value for a given algorithm in a specific geographic region, the color depicts the algorithm used i) red (ASE), ii) green (CA), iii) blue (this article).

The positive detection rate for both the CA algorithm and the approach proposed here are typically around 80 to 90% of pixels on average (Fig. 9a). Output from the ASE algorithm, on the other hand, typically only detects around 50% of hot pixels on average. Each of the algorithms has a low associated false alarm rate, i.e. typically <10% (Fig. 9b). India is an exception with associated false alarm rates as high as around 30% on average. This number is strongly dependent on the incidental concentration of urbanized areas within the field of view of the sensor at the time of image acquisition. Fig. 11, for example, depicts part of the city of Adelaide (Australia) using an infrared color composite of a Landsat 8 scene acquired on 4th January 2015. To the NE of the city is a large burn scar with active fire pixels highlighted in yellow. The insert is a zoom of the area enclosed by the dashed white rectangle. It shows part of the urban environment in more detail. The non-associated false alarms from the CA method are highlighted in red.

Computational efficiency is a key constraint for a global detection system given the magnitude of the search area. We quantified the processing time for each algorithm after conversion of DNs to at-sensor radiance or TOA reflectance. The ASE algorithm and the proposed algorithm are typically one or two orders of magnitude faster than the CA approach. The proposed algorithm is sufficiently fast for real-time operation.

7.1. Hotmap application

The new daytime and nighttime algorithms for hot target detection proposed here have been successfully integrated onto ESA
GPOD servers. Output will be available in a variety of formats to facilitate end-user application once the beta version is released. These include ASCII files (.txt), vector files (.shp, .kml) and quick look imagery (.png). The Google Earth format (.kml) is one of the most popular GIS file formats in terms of usage, in part because the Google Earth software is free, easy to use and useful to millions of people worldwide. We envisage that by providing hotmap output in this format will allow non-specialists to easily explore, and then use, the results. This, in turn, should increase the effectiveness of the service. Fig. 12 shows examples of Google Earth visualizations of hotmap output for a) an Australian wildfire, and b) a lava flow at Kizimen volcano (Russia). The red lines outline the

![Figure 10](image10.png)

**Fig. 10.** False alarms not associated with true hot targets in each of the nine geographic regions (see Table 2 for non-abbreviated names).

![Figure 11](image11.png)

**Fig. 11.** Urban environments can cause false alarms in the CA method. Shown is a Landsat 8 image (R: 2.2, G: 1.61, B: 0.87 μm) of Adelaide (Australia). Overlain are false alarm pixels in red and true fire pixels in yellow.
The algorithm put forward here has i) positive detection rates and ii) associated false alarm rates that are on par with the CA approach. Crucially, however, it manages to also maintain a low non-associated false alarm rate. Furthermore, it executes almost as quickly as the ASE method. These characteristics, in our opinion, make it the optimal choice for a global monitoring system.

A factor that contributed to the success of the new algorithm is that it uses spectral information from three wavebands. The previously published methods both use just two wavebands (i.e. one in a relatively sensitive waveband and another in a less sensitive waveband). An issue with using just two wavebands is that the single sensitive waveband is unlikely to have a sufficient dynamic range and radiometric resolution to account for all the different sizes and intensities of hot targets that it will encounter. Typically, a single waveband that is sensitive enough to detect a significant proportion of hot targets will also saturate frequently at ~30 m spatial resolution. This is the primary reason that the ASE method encountered so many omission errors (i.e. because saturation rendered the EXTREME pixel detection ineffective). Additionally, algorithms that use just two wavebands are more vulnerable to anomalous behavior in either channel. The majority of non-associated false alarms in the CA method are due to features with anomalously high reflectance ratios (i.e. \( \rho > 0.87 \)) and sharp (i.e. not diffuse) spatial boundaries (e.g. anthropogenic structures). This can result from absorption features around 0.87 \( \mu \text{m} \) and/or high reflectivity around 2.2 \( \mu \text{m} \). The new approach uses information at 0.87, 1.6 and 2.2 \( \mu \text{m} \). This allows for saturation free detection of hot targets with low false alarm rates.

**8. Discussion**

The optimal choice of algorithm depends on the application that it will be used for and the resources available (e.g. random access memory, downloading capabilities, time, etc.). The ASE method is extremely fast and results in the least number of false alarms. Thus, even though it misses around half of hot pixels, it is well suited to its purpose, which is to run on-board a satellite system and automatically detect regions of potential scientific interest for further exploration by an integrated network of sensors (i.e. a sensor web). The fact that the algorithm is used to trigger additional observations – which themselves have an associated cost – exacts the extremely low false alarm rate that this algorithm delivers. Furthermore, hot targets that were missed by the ASE algorithm could potentially be observed by the sensor web that it activates.

The CA method offers high positive detection rates whilst maintaining a low associated false alarm rate. However, it encounters the highest rate of non-associated false alarms and is the slowest to execute (i.e. typically by one or two orders of magnitude). The CA method is therefore well suited to highlighting hot targets in a small numbers of scenes for subsequent manual inspection, thus satisfying its primary purpose, which was to use ASTER data to validate contemporary MODIS fire products.

Additional temporal information (e.g. TCA) could help to identify false alarms in urban environments, although care must be taken to avoid classifying them as persistent hot sources. This could be achieved – at some point in the future – through the use of urban maps. Execution of a temporal CA would presumably be the most computationally expensive approach to date, especially if incorporating additional data sets. However, it also has the potential to provide superlative performance statistics in terms of minimal omission and commission errors.

The algorithm put forward here has i) positive detection rates and ii) associated false alarm rates that are on par with the CA approach. Crucially, however, it manages to also maintain a low non-associated false alarm rate. Furthermore, it executes almost as quickly as the ASE method. These characteristics, in our opinion, make it the optimal choice for a global monitoring system.

A factor that contributed to the success of the new algorithm is that it uses spectral information from three wavebands. The previously published methods both use just two wavebands (i.e. one in a relatively sensitive waveband and another in a less sensitive waveband). An issue with using just two wavebands is that the single sensitive waveband is unlikely to have a sufficient dynamic range and radiometric resolution to account for all the different sizes and intensities of hot targets that it will encounter. Typically, a single waveband that is sensitive enough to detect a significant proportion of hot targets will also saturate frequently at ~30 m spatial resolution. This is the primary reason that the ASE method encountered so many omission errors (i.e. because saturation rendered the EXTREME pixel detection ineffective). Additionally, algorithms that use just two wavebands are more vulnerable to anomalous behavior in either channel. The majority of non-associated false alarms in the CA method are due to features with anomalously high reflectance ratios (i.e. \( \rho > 0.87 \)) and sharp (i.e. not diffuse) spatial boundaries (e.g. anthropogenic structures). This can result from absorption features around 0.87 \( \mu \text{m} \) and/or high reflectivity around 2.2 \( \mu \text{m} \). The new approach uses information at 0.87, 1.6 and 2.2 \( \mu \text{m} \). This allows for saturation free detection of hot targets with low false alarm rates.

**9. Conclusion**

Two new methods are put forward for the detection of hot targets in Landsat-class imagery. One is an enhanced nighttime detection algorithm. The other, which is the focus of this paper, is a daytime detection algorithm. Together these algorithms could form the basis of the first global hot target detection system at moderate spatial resolution. The new methods were tested using a global data set of Landsat 8 imagery and found to be optimal in comparison to the existing state-of-the-art methods published to date. The proposed methods have already been incorporated into the Hotmap software, an alpha version of which is installed on ESA Grid Processing on Demand environment (G-POD). This system has full access to imagery acquired by Landsat 8 and Sentinel 2. Free, online access to a beta version of the software is planned to be made available to the public in 2016.

**Acknowledgments**

Funding for this work was provided by the São Paulo Research Foundation, FAPESP (Fundação de Amparo à Pesquisa do Estado de São Paulo), postdoctoral research grant 2013/03711-5. We thank two anonymous reviewers for their input, they helped to improve the article.


