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1.1 Sentinel-3 Optical Products and Algorithm Definition

Sentinel-3 SLSTR Level 2 Active Fire Detection and FRP Product Algorithm

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Acronyms and Abbreviations

AVHRR Advanced Very High Resolution Radiometer

ATBD Algorithm Theoretical Basis Document

(A)ATSR (Advanced) Along track Scanning Radiometer

BT Brightness Temperature

CLM CLoud Mask

EO Earth Observation

ECV Essential Climate Variable

FRP Fire Radiative Power

FRE Fire Radiative Energy

GTOS Global Terrestrial Observing System

LUT Look-Up Table

LWIR LongWave InfraRed

MAD Mean Absolute Deviation

MIR Middle InfraRed

MWIR Mid-Wave InfraRed

MODIS Moderate-Resolution Imaging Spectroradiometer

NIR Near Infrared spectral region

PSF Point Spread Function

ROI Region of Interest

SLSTR Sea and Land Surface Temperature Radiometer

SWIR shortwave InfraRed

TIR Thermal InfraRed

VIS Visible spectral region

The Sentinel-3 SLSTR channel naming convention and the matching scientific notation used throughout this document is detailed in Table 1.



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2 INTRODUCTION

2.1 Landscape Fire Background

The burning of vegetation, together with surface organic matter such as carbon-rich peatland soils, occurs annually across many millions of square kilometres of the Earth surface and perturbs a greater area over a wider variety of biomes than any other natural disturbance agent (Lavorel et al., 2006). The widespread nature, and sporadic, unpredictable character of fire, means that frequent data from Earth Observation (EO) satellites are key for providing information necessary for the large-scale investigation and quantification of biomass burning and its consequences, such as the resulting emissions into the atmosphere of carbon, trace gases and aerosol. The SLSTR Active Fire detection and FRP retrieval algorithm is designed to produce two Essential Climate Variables (ECV) related to 'Fire Disturbance' datasets highlighted by The United Nations Framework Convention on Climate Change (UNFCC, namely Active Fire [detection] and Fire Radiative Power [fire characterisation] (Sessa and Dolman, 2008; Csizar at al., 2008). Active Fire records the time and location of fires that were burning as the sensor imaged the Earth surface, expressed either in spatial and temporal coordinates or by an indicator of fire presence or absence in a raster map. Active fire detections are used, for example, to identify fire emissions source locations and timings, to determine fire-related parameters within ecosystem models having a representation of fire (such as fire rate of spread), and to identify fire seasonal cycles and spatiotemporal trends, potentially in relation to environmental variations such as climate change (e.g. Levine et al., 1996a, 1996b; Kaufman et al., 1998; Wooster and Strub, 2002; Sukhinin et al., 2004; Csiszar et al., 2005; Giglio et al., 2006a, Giglio et al., 2006b; Lodoba and Csiszar, 2007). Fire Radiative Power (FRP) is the rate at which the actively burning fire is emitting radiative energy [at the time of observation] expressed in units of power (Js-1 or Watts). This radiative emission is primarily in the infrared, though fires emit visible light as well (seen for example as their luminous "flames"). Through a series of airborne, ground-based and satellite data intercomparisons, FRP has been shown to be well related to the rate of fuel consumption, smoke aerosol production, and trace gas release, and thus offers a direct route for quantifying the magnitude of these processes (Kaufman et al., 1998; Wooster et al., 2005; Ichoku and Kaufman, 2005; Jordan et al., 2007: Freeborn et al., 2008; Kaiser et al., 2012; Nguyen and Wooster, 2020).



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2.2 SLSTR Active Fire Algorithm Evolution

This document describes the theory for the active fire detection and fire radiative power algorithm, designed to operate on Level 1 data from the Sea and Land Surface Temperature Radiometer (SLSTR) sensor. SLSTR is one of the key instruments onboard the Copernicus Sentinel-3 satellites, two of which are operational concurrently. The ATBD provides a detailed description of the algorithm used in the production of the Level 2 SLSTR Active Fire Detection and Fire Radiative Power (FRP) Product.

The algorithm was initially designed pre-launch to detect and characterise vegetation fires burning on the land surface, and tested using data from MODIS (Wooster et al, 2012). Post-launch the algorithm was updated to deal with the characteristics of real SLSTR observations, and initially was focused on land surface areas at night and when the middle infrared (MIR) (S7) channel was not saturated over significant areas of the land surface ('classical case' situations normally addressed by active fire detection algorithms such as that applied to MODIS Level 1b data e.g. Giglio et al., 2003). The detail of this version of the algorithm was published in Xu et al. (2020). Whilst the focus was primarily on night-time scenes and landscape fires, the algorithm also included aspects dealing with elevated temperature sites of active volcanism and industrial sources such as gas flares. The version of the algorithm described in this ATBD has now been extended to work on all daytime SLSTR Level 1 data (that collected during the Sentinel-3 ascending node), as well as on night-time (descending node) data and over the ocean (for gas flares at night-time) as well as on land.

The reason that a full daytime algorithm poses challenges is that by day, significant saturation is experienced in the standard 'S7' middle infrared (MIR) channel of SLSTR – even over ambient land surfaces in warmer regions and seasons. The MIR waveband is the most important for active fire detection and FRP retrieval, and during these types of saturated daytime cases wider use of the F1 'low-gain' MIR band is required. However, the fact that F1 channel measurements are not perfectly co-located with those from the standard gain (S1 to S9) channels introduces some complexity. Thus, full daytime processing in cases where the S7 channel is saturated over the ambient background is more intricate even than that required for night-time and 'classical case' daytime analyses (when F1 data is typically only required to be used over the fires themselves). See Xu et al. (2020) for further details and for the solutions required in the latter two cases. This ATBD presents the full solution for joint use of S7 and F1 in all cases.



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The Level 2 Active Fire Detection and FRP Product is generated from Level 1 granules. Initially pixels containing active fires are detected using primarily MIR (S7 and/or F1) observations and co-current observations made in the long-wave thermal infrared (TIR) region (S8). One the set of active fire (AF) pixels have been detected in a granule, their characterisation proceeds via calculation of their fire radiative power (FRP). FRP represents a measure of a fires total radiative power output integrated over all wavelengths and over the viewing hemisphere encompassing the fire (i.e. the azimuthal and zenith angles). The AF detection procedure actually identifies pixels containing many different types of sub-pixel high temperature sources – such as gas flares and volcanoes with elevated temperatures – as well as landscape fires. FRP is also calculated for these other types of detected hotspots, and whilst the FRP derived via the MIR radiance method is most appropriate for pixels containing landscape fires (Wooster et al. 2003; 2005), that derived via the analysis of the SWIR radiances is most relevant for hotter targets such as gas flares (Fisher and Wooster, 2018; 2019). Both measures are thus included in the algorithm output, and a geographic mask is used to classify each detected AF pixel as a likely landscape fire, volcano or gas flare. At night, the ratio of the spectral radiances recorded in the two SLSTR shortwave infrared (SWIR) channels (S5 and S6) is also reported, since this provides additional information as to the temperature of the sub-pixel high temperature heat source and can thus be useful in confirming the likely type of hotspot contained within the pixel (Fisher and Wooster, 2018; 2019). In this ATBD however, for simplicity the different classes of hotspot are here referred to primarily as "Land Hotspots" and "Ocean hotspots", and in the detailed description, the word "fire" is generally used to refer to all types of hotspot potentially encountered, including vegetation fires, volcanoes and gas flares. Occasionally the word 'hotspot' is used to provide clarity when talking specifically about a specific hotspot type.

2.3 Sentinel-3 AF Detection and FRP Product Purpose

Open vegetation fires are critical elements in the Earth System, acting as a widespread agent of change by altering land cover properties, consuming very significant quantities of terrestrial vegetation, and releasing copious amounts of trace gases and aerosols (Lavorel *et al.*, 1996). Such fire activity acts across all vegetated continents but is often highly variable in its magnitude and specific location, making satellite EO data key in its quantification (Bond and van Wilgen, 1996). Data on fire activity is used within many areas of terrestrial environmental research, such as for prescribing the source terms for regional or global atmospheric emissions of carbon, trace gases and aerosols, and for developing periodic assessments of land cover changes such as tropical deforestation. The information is also used in fire and ecosystem management planning and



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operation (such as fire use, preparedness and wildfire suppression) and for informed policy development (Csiszar *et al.*, 2008).

Polar-orbiting sensors with suitable spectral channels, such as SLSTR, can provide data on each of the 'Fire Disturbance' Essential Climate Variables (ECVs) identified by the Global Terrestrial Observing System (GTOS) as being necessary for determining transient change, adaptation, impact and mitigation possibilities in relation to climate and associated environmental changes, namely Burned Area, Active Fire Detections and Fire Radiative Power (Sessa and Dolman, 2008). The latter two types of 'active fire' information have been produced from data acquired by the MODIS sensor operating onboard the Terra and Aqua satellites since the early 2000's (Giglio et al., 2016). With the Terra satellite expected to change operations and/or reach its end of life in the 2020's, the Sentinel-3 Active Fire Detection and FRP Product derived from SLSTR observations is expected to ultimately take over morning and evening supply of active fire information, based on observations from its 10:00 hrs and 22:00 hrs equatorial crossing time overpasses (similar to the 10:30 hrs and 22:30 hrs equatorial crossing time overpasses made currently by Terra). The algorithm presented herein is used to derive Level 2 Sentinel-3 SLSTR Active Fire Detection and FRP Products. These products are aimed at delivering information relevant to the 'Fire Disturbance' ECVs using a consistent, standardised set of tests operating over the entire Earth, frequently and repetitively. An example of Level 2 data produced by the algorithm is shown in Figure 1 alongside that from MODIS Terra.



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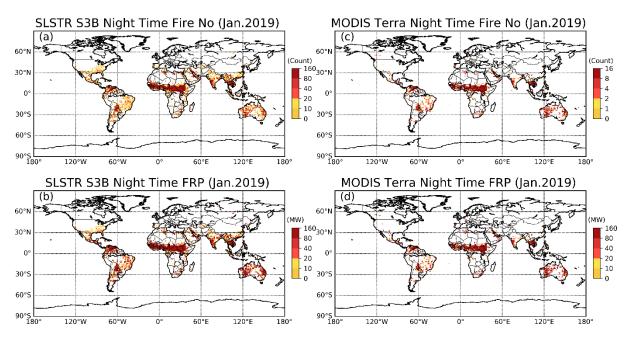


Figure 1. Global total active fire pixel count and total FRP of actively burning fires detected within 1° grid cells across the Earth during January 2019. (a) Sentinel-3B SLSTR AF pixel count; (b) Sentinel-3B SLSTR total FRP; (c) Terra MODIS AF pixel count; (b) Terra MODIS total FRP. All data are from night-time overpasses only and those from the SLSTR (onboard Sentinel-3B) were generated from the night-time part of the algorithm detailed herein, whilst those from Terra MODIS were taken from the MODIS MOD14 Active Fire and Thermal Anomaly Product (Giglio et al., 2016). Similar data can be produced from the SLSTR operating onboard Senteinl-3A, and both Sentinel-3A and -3B systems together provide global daily coverage both day and night. See Xu et al., (2020) for a detailed discussion of the similarities and differences in the SLSTR- and MODIS-derived information shown.

Whilst earlier versions of the Sentinel-3 Active Fire Detection and FRP Product algorithm focused on the night-time and 'classical daytime' case (when the land surface was not subject to significant areas of saturation in the SLSTR S7 MIR band), the current version reported herein is designed to process data from all night-time and daytime S3 overpasses. Individual SLSTR pixels containing actively burning fires are first identified based on signal increases above the ambient background, in particular in the middle infrared (MIR) channels (primarily S7 in the earliest stages, but using also F1 as necessary). These MIR channels are extremely sensitive to even highly-sub pixel high temperature objects (Robinson, 1991). Signals assessed in the sensors solar reflective and longwave infrared channels are used to decrease the probability of false alarms, for example caused by sunglints from small water bodies or from solar heated warm ground. As detailed above, the primary estimates of the FRP being emitted by the high-temperature object(s) within the identified



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active fire pixel are made via an assessment of the MIR channel signal increase over the surrounding ambient background pixels. The approach used is the Middle infrared (MIR) radiance method of FRP retrieval, developed by Wooster *et al.* (2003; 2005) and first applied operationally in the SEVIRI FRP-PIXEL product (Roberts and Wooster, 2008; Wooster et al., 2015). The same MIR radiance FRP approach is now used in many operational fire products, including the Collection 6 MODIS Active Fire products (Giglio et al, 2016). Due to their higher temperatures, FRP retrievals over gas flares are best made using an adaptation of an approach based on SWIR (rather than MIR)-measured signals (Fisher and Wooster, 2018; 2019), though SWIR signals by day are significantly contaminated by solar reflected radiation. Therefore, for night-time passes a secondary FRP estimate is provided via a SWIR-radiance approach, and for gas flare targets this value is preferrable for use.

Geostationary EO satellites provide the highest temporal resolution active fire data, whose data can be used to demonstrate the marked fire diurnal cycle seen in many environments (Figure 2). The strong tendency for fire activity to vary over the day is one reason that the Sentinel-3 Active Fire Detection and FRP Product is expected to take over from the Terra MODIS Active Fire and Thermally Anomaly product and ultimately extend the long-term data record started from that sensor, because their similar imaging times mean they measure fires at a similar point on the daily fire diurnal cycle. Though geostationary data having pixel sizes 2 km to 4 km are extremely useful for the active fire application (e.g. Wooster et al., 2015), they are limited in their ability to detect and characterise the smaller and/or less intensely burning (i.e. the lower FRP) component of a regions fire regime due to their relatively coarse spatial resolution (the minimum FRP detection limit essentially scales with pixel area). However, low FRP fires are far more common than high FRP fires (Wooster and Zhang, 2004; Ichoku et al. 2008), so active fire observations from polar orbiting sensors such as SLSTR that are able to detect lower FRP fires remain essential. Furthermore, the view from geostationary orbit offers poor coverage of key higher latitude fireaffected areas, such as the boreal zone. The Sentinel-3 SLSTR Active Fire Detection and FRP Product will provide the information needed to continue to generate long-term, global-scale 'Fire Disturbance' ECV records extending those from e.g. MODIS Terra, supporting further characterisation and change detection across all of Earth's fire regimes - as well as for example the monitoring of quantitative trends in industrial gas flaring (Fisher and Wooster, 2019).



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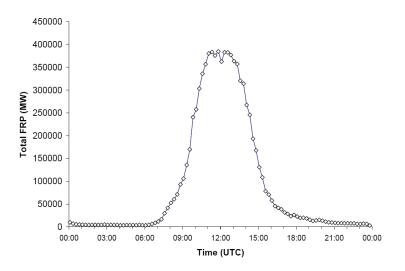


Figure 1. Diurnal cycle of total FRP recorded by the Meteosat SEVIRI FRP-PIXEL product from all active fire pixel detected across southern Africa, as described in Wooster et al. (2015). Data are provided every 15 minutes, and this example is from 14 July 2004. Local time across the region is up to three hours in advance of UTC. A very strong fire diurnal cycle is clearly evident. At the peak, around 5000 Meteosat SEVIRI active fire pixels were detected across southern Africa, producing a combined FRP of 382 GW. This rate of thermal radiative energy release corresponds to many hundreds of tonnes of biomass being burned per second (Wooster et al., 2005).

2.4 Algorithm Identification and Design

When observed from space with moderate spatial resolution instruments (~ km scale pixels such as those of SLSTR), actively burning fires represent sub-pixel features. The fires typically cover only a very small fraction of the individual detector ground pixel footprint, and optimum active fire detection in such circumstances generally requires that the sensor possesses measurement channels in the middle-infrared (MIR; 3-5 µm) and longwave thermal-infrared (TIR; 8-12µm) spectral regions. Data from solar reflective (VIS to NIR) channels are used to assist with false alarm identification, for example by removing pixels affected by sunglint whose strong MIR signals can look very similar to those of fire pixels. Potential active fire pixels can be identified via multi-channel thresholding of the MIR, TIR and VIS band data, but if the algorithm is to remain effective over large areas, as well as through seasonal cycles, the specific thresholds used must be allowed to vary with environmental condition (Flasse and Ceccato, 1996). For this reason, a self-adaptive, contextual fire detection scheme whose thresholds vary in response to the background



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signals recorded at confirmed non-fire pixels has been identified as the most effective approach for use with SLSTR. Such algorithms have been extremely successful in terms of their underlying for example the MODIS (Giglio et al., 2016) and Meteosat SEVIRI (Wooster et al., 2015) active fire products. At night solar radiation is absent, so additional AF detection capabilities can be provided via use of SWIR channel measurements. High temperature objects emit effectively in these wavebands and this signal can be detected relatively easily against a background that is (at night) close to zero (Wooster et al., 2012; Fisher and Wooster, 2018).

Table 1 provides detail on the SLSTR spectral channels. Whilst the active fire (AF) detection and fire radiative power (FRP) retrieval algorithm described herein uses data from many of these channels, it is primarily reliant on those in the MIR (3.7 µm; S7 and F1) and longwave infrared (LWIR; 10.8 µm; S8) as indicated above. The radiometric quality of the MIR brightness temperature (BT) measurements in the S7 channel degrades strongly above 311 K, when the channels response to incoming spectral radiance becomes nonlinear. This is significantly lower than 323 K originally specified as the channel saturation temperature pre-launch, and makes S7 quite commonly saturated over hotter ambient land surfaces by day, and very often saturated over active fires by day and by night. Data from F1 is therefore required to be used in the AF detection and FRP retrieval process more commonly than expected pre-launch, necessitating much of the development work conducted to adapt the pre-launch Wooster et al., (2012) algorithm post-launch. The Xu et al. (2020) algorithm represents the first iteration of the post-launch version, designed to work at night and over a subset of daytime cases. Further complexity is introduced because the F1 detectors are not spatially co-incident on the focal plane with the 'S' band detectors, and also have a different shape, meaning the F1 pixels are not co-located with those of S7 and have a different size and orientation (Wooster et al., 2012; Xu et al., 2020). This means that swapping between S7 and F1 measured BTs cannot be precisely done at the level of individual active fire pixels saturated in S7, necessitating use of the active fire pixel clustering procedures described in Xu et al. (2020) and in the detailed algorithm description provided herein. Further difficulties are presented by the so-called 'down-scan anomaly" that is present in the F7 data subsequent to viewing hot targets both day and night (see Xu et al., 2020).



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SLSTR Spectral Channel	Used for Spectral Radiance (L) and/or Brightness Temperature (T) and/or Spectral Reflectance (ρ) measures described herein	Channel Central Wavelength (µm)	Channel Width (µm)	Spatial Sampling Distance (Near Nadir View Swath / km)
S1		0.555	0.02	0.5
S2	L_{RED} and $ ho_{\!RED}$	0.659	0.02	0.5
S3	L_{NIR} and $ ho_{NIR}$	0.865	0.02	0.5
S4	-	1.375	0.015	0.5
S5	L_{S5}	1.61	0.06	0.5
S6	L_{S6}	2.25	0.05	0.5
S7	L_{MIR} and T_{MIR}	3.74	0.38	1.0
S8	L_{TIR} and T_{TIR}	10.95	0.9	1.0
S9	L_{TIR2} and T_{TIR2}	12	1.0	1.0
F1	L_{MIR} and T_{MIR}	3.74	0.38	1.0
F2	L_{TIR} and T_{TIR}	10.95	0.9	1.0

Table 1. Sentinel-3 SLSTR Spectral channels. Note that the F1 and F2 'fire channels' have greatly increased saturation temperatures compared to the matching standard ('S') IR channels operating at the same MIR and TIR wavelengths respectively (the S7 and S8 channels). However, the F1 and F2 channels have increased noise compared to S7 and S8. The middle infrared (MIR) S7 channel starts to saturate at brightness temperatures exceeding 311 K, necessitating switching to use the MIR F1 channel in the active fire detection and FRP retrieval algorithm presented here. The F1 channel can measured BTs in excess of 450 K without saturation. Note that the algorithm presented here only uses data from the SLSTR near nadir view swath, which is considerably wider than the oblique view swath and thus provides higher temporal resolution observations.

An advantage of SLSTR compared to some other moderate spatial resolution imaging radiometers is that its two SWIR bands (S5 and S6) continue to operate at night, and so can be used to support active fire detection at night. Casadio *et al.* (2012) used absolute thresholding tests to detect gas flares with night-time 1.6 μ m band SWIR data from forerunner to the SLSTR - the Along Track Scanning Radiometer (ATSR), whilst Wooster and Rothery (1997) detected and characterised volcanoes using SWIR data from the same instrument. The S6 (2.2 μ m) channel in theory provides an ability to detect slightly cooler hotspots than the S5 channel, due to its longer wavelength, though both channels are exploited herein. Fisher and Wooster (2018) first report the detection of gas flares using night-time SLSTR SWIR channel data.

Once detected, the FRP of an AF pixel can be estimated from the fire pixel signal increases identified in certain spectral channels. Generally, this is assessed with respect to the neighbouring ambient background pixel signal. One candidate for a method to estimate the FRP is simply the Stefan-Boltzmann Law, but this requires the instantaneous fire effective temperature (T_f) and subpixel fractional area (p_f) [since the fires are not resolved at the scale of SLSTR pixels]. These parameters can be determined using the so-called bi-spectral approach, based on simultaneous TIR



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and MIR channel radiance measurements made at the fire pixel and at the surrounding non-fire pixels, and this method has been used to retrieve FRP from data collected by the Bi-Spectral Infrared Detection (BIRD) Hot-Spot Recognition System (HSRS) Satellite for example (Zhukov et al., 2006). However, fire pixel signal increases in the TIR channel are much weaker than in the MIR channel, yet the bi-spectral approach requires that both be well characterised for optimum retrieval accuracy. As a result, bi-spectral retrievals can be subject to large errors when variability in the TIR brightness temperatures of the non-fire background pixels means that the degree to which the fire pixel TIR channel signal is raised above the TIR background cannot be precisely determined (Giglio and Kendall, 2001; Wooster et al., 2003). This effect will typically be much more significant for the kilometre scale SLSTR pixels than for the BIRD HSRS pixels that were ~ 10x smaller in area, since a particular fire will represent a smaller proportional area in a larger pixel and will thus increase the fire pixel signal to a lesser degree. In addition, Shephard and Kennelly (2003) indicate the significant impact that band-to-band co-registration errors can have on fire characterisations made with the bi-spectral method. They demonstrate that for a 1-km horizontal spatial resolution pixel, a 10% inter-channel co-registration error generates retrieval errors of the order of 150 K and 210 % for the effective fire temperature and fractional fire area terms respectively. In the BIRD HSRS processing chain, this effect was dealt with by clustering spatially contiguous fire pixels into individual fire clusters, and analysing the mean MIR and TIR signals recorded at the cluster scale to estimate the instantaneous cluster effective temperature (T_f) and sub-pixel area (A_t) (Zhukov et al., 2006). In this way the sensitivity to band-to-band coregistration errors was reduced considerably. However, because of the constraints of the bispectral approach, especially when applied to coarser scale remote sensing data, the MODIS Collection 5 (and earlier) active fire products used a non-linear, empirical relationship between FRP and the fire pixel MIR brightness temperature increase above the background to derive FRP (Kaufman et al., 1998, Giglio et al., 2003). This relationship was itself derived using multiple simulations of MODIS observations of sub-pixel sized fires (Kaufman et al., 1998). By using data from only a single waveband, the effect of inter-channel co-registration errors is removed, and by using the MIR waveband where the fire signal is strongest the errors induced due to uncertainty in the ambient background signal are minimised. However, the algorithm was specific only to MODIS. A new algorithm for FRP estimation was derived by Wooster et al. (2003), by approximating the Planck Function at MIR wavelengths by a power law valid over the range of temperatures seen in open vegetation fires. In this so-called 'MIR radiance method', FRP is linearly related to the fire pixel MIR radiance increase above the surrounding non-fire background. Wooster et al. (2003) used BIRD HSRS data to show that the MIR radiance method produced FRP



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estimates that agreed well with those from the bi-spectral method, as long as fire emitter temperatures (note: not pixel-integrated brightness temperatures) exceed ~ 650 K, which is generally the case for all but extremely weak or sub-surface smouldering fire events. Wooster et al. (2003) also demonstrated the MIR radiance method to be capable of producing reliable FRP retrievals in cases where the bi-spectral approach was severely affected by large variability in the brightness temperatures of the ambient background. The MIR radiance method has been adopted for use with the Meteosat FRP-Pixel product produced operationally at the EUMETSAT LandSAF (Roberts and Wooster, 2008; Wooster et al., 2015; Roberts et al., 2015), for other operational geostationary active fire products (e.g. Xu et al., 2017; 2021), for Collection 6 of the MODIS active fire products (Giglio et al., 2016), and for the VIIRS active fire products (Li et al., 2018). The MIR radiance method is the primary approach used within the algorithm described herein for characterisation of active fires using SLSTR. Recently, Fisher and Wooster (2018) demonstrated that since gas flares typically have emitter temperatures significantly higher than those of vegetation fires (often >1500 K), and Wien's Displacement law shows their spectral emittance maxima occurs well within the SWIR waveband, the FRP of these targets is best retrieved using a SWIR version of the MIR radiance method. This SWIR radiance approach was used to generate FRP data of global gas flare targets by Fisher and Wooster (2019) and provides a secondary FRP measure within the SLSTR algorithm described herein – one best suited to FRP determination over gas flares.

2.5 SLSTR Level 2 Algorithm Heritage

Though it was designed with the key purpose of providing long-term, highly accurate observations of sea surface temperature (SST), the (A)ATSR series of sensors that are the heritage instruments for SLSTR do possess the MIR and TIR spectral channels necessary for active fire detection. However, their relatively low dynamic range (optimised for cloud and SST measurements) meant that daytime saturation of the MIR channel over warm terrestrial surfaces restricted routine active fire detection to night-time cases only. Nevertheless, the resulting ATSR World Fire Atlas (WFA) is currently the longest available global active fire dataset (Orino *et al.*, 2007) and have been used to support databases representing the global fire emissions record (e.g. Van der Werf *et al.*, 2006) as well as a wide range of science studies (e.g. Thompson *et al.*, 2001; Schultz, 2002; Generoso *et al.*, 2003; Sinha *et al.*, 2004), including volcanoes (e.g. Wooster and Rothery, 1997) and gas flares (Casadio *et al.*, 2012).

The simple 'fixed threshold' active fire detection approach used within the WFA is far from optimum when considering the algorithmic possibilities for use with the SLSTR fire product,



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which is required to operate under a wide range of environmental conditions by day as well as by night. Daytime thermal conditions vary much more markedly between areas and over time than do night-time conditions, and a contextual approach with self-adapting detection thresholds is required for optimum fire detection performance and false alarm minimisation. The MODIS active fire detection algorithm (Giglio *et al.*, 2003; 2016) works on these principles, as does the Bi-Spectral Infrared Detection (BIRD) Hot Spot Recognition Sensor (HSRS) fire detection scheme (Zhukov *et al.*, 2006) and the geostationary 'fire thermal anomaly' (FTA) active fire detection algorithm of Roberts and Wooster (2008) and Wooster et al. (2015). The SLSTR fire detection algorithm is therefore based on this contextual, self-adapting approach, blending many of the tests originally formulated in these pervious schemes but adding adjustments where necessary and where it is believed it will improve performance.

Perhaps the most significant adjustment with respect to current contextual active fire detection algorithms is the need with SLSTR for use of data merging (by day) and data clustering (by night and by day) procedures to ensure best use of the S7 and F1 MIR channel data. Other differences include use of the shorter wavelength SLSTR 3.7 µm MIR observations (from S7 and F1) instead of those from the narrowband 3.9 µm channel found on MODIS. This SLSTRs shorter wavelength, wider waveband 3.7 µm channel is more affected by the atmosphere, and we introduce adjustments for this atmospheric effect based on those applied to SEVIRI-based FRP retrievals (Wooster et al., 2015). Unlike MODIS, the S3 AF detection procedure at night also makes use of measurements from the sensors SWIR bands (S5 and S6), which are available at 500 m spatial resolution, and which are also applied to detect ocean hotspots (gas flares) at night as well as landbased hotspots. The well-tested MODIS fire detection algorithm of Giglio et al. (2003; 2016) is the basis for many of the active detection tests applied herein, since in terms active fire products MODIS provide most closely matching those expected from SLSTR. However, in order to attempt to maximise performance, the method for detection of a potential fire pixels has been adjusted to become less conservative that used in the MODIS algorithm, whilst the spatial filter from the geostationary FTA algorithm of Roberts and Wooster (2008) is used to constrain the number of potential fire pixels passed to the next algorithm stage. The coefficients of this spatial filter are taken from image blocks rather than the entire image, in a manner akin to the first stage of the BIRD HSRS algorithm (Zhukov et al., 2006). Certain specific additions in relation to gas flare detection were informed by the work of Gallegos et al. (2007) and Fisher and Wooster (2019), and following hotspot detection, characterisation is conducted using the MIR radiance method of FRP retrieval (Wooster et al., 2003), though with parallel implementation of the SWIR radiance method which is more appropriate for gas flares (Fisher and Wooster, 2018; 2019). The pre-launch version



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of the SLSTR active fire detection and FRP characterisation algorithm was presented in Wooster *et al.* (2012) and focused on land-based active fires only. Xu et al. (2020) greatly extended this algorithm using analysis of real SLSTR data (albeit focusing on night-time scenes only; and with the capability also to process 'classic' daytime cases where S7 was not saturated over the background). The algorithm presented in this current ATBD now extends this Xu et al. (2020) algorithm further and is capable of processing all daytime and night-time SLSTR Level 1 granules.

3 ALGORITHM OVERVIEW – PHYSICS AND TECHNICAL DETAILS

3.1 Background

Vegetation fires exhibit a wide temperature range, generated by activity from smouldering to intense flaming combustion, but flame radiometric temperatures of ~ 750 - 1200 K appear dominant (Sullivan et al., 2003), whilst gas flares can reach significantly higher temperatures (> 1500 K). Wien's Displacement Law indicates that the peak of thermal emission from such fires occurs in or close to the shortwave infrared (SWIR; 1.6 – 2.5 µm) or middle infrared (MIR; 3 – 5 μm) atmospheric windows, depending upon the combustion temperature. Fires are typically very much more active by day than by night (see Figure 2), but by day with moderate spatial resolution EO data there is limited scope for using SWIR data in AF detection procedures due to the presence of very significant amounts of solar reflected radiation in this waveband. The use of SWIR signals in the SLSTR-based detection and FRP retrieval of hotspots is thus confined to night-time use only. Generally, daytime active fire detection algorithms are focused on exploitation of the MIR signal, where the emission from the fire is still very strong and solar reflected radiation signals typically far weaker than in the SWIR (Robinson, 1991). By day the MIR is therefore the spectral region where active fires typically show their greatest contrast with their surrounding background pixels, and they also show this by night when SWIR data can also be used. In fact, parameterisation of the Planck function with the temperatures indicative of open vegetation fires indicates that in the MIR spectral region the spectral emission from an open vegetation fire can be up to four orders of magnitude greater than that from the ambient temperature background (Figure 3). The MIR channels (S7 and F1) are therefore key to the active fire detection algorithm presented herein.



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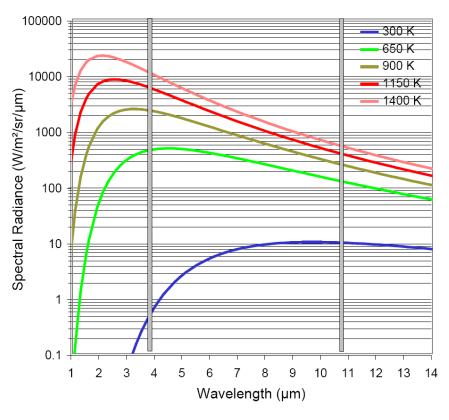


Figure 2. Spectral radiance emitted from blackbodies at differing temperatures. Earth ambient temperature is around 300 K and vegetation fires have a range of temperatures (\sim 650 to 1400 K). The 3.7 μm and 10.8 μm central wavelengths of the SLSTR MIR channels (S7 and F1) and TIR channel (10.8 μm) used in the AF detection algorithm are indicated by vertical lines are also indicated. As emitter temperature increases the spectral radiance increases more rapidly at MIR wavelengths than at TIR wavelengths. Note the logarithmic y-axis.

The intense MIR thermal signals from combusting biomass and other heat sources of similar temperature means that pixels containing actively burning fires or other sub-pixel hot targets can be discriminated via their significant increase in MIR pixel radiance or brightness temperature, even if the hot area covers as little as 10^{-3} to 10^{-4} of the pixel planimetric area (Robinson, 1991). This makes active fire detection possible using even rather coarse spatial resolution data (e.g. from geostationary systems), or even from spatially-averaged Earth observation data such as AVHRR GAC imagery (e.g. Wooster and Strub, 2002). Fire pixels generally show elevated signals in the MIR region, as already described (Robinson, 2001), and so active fire detection algorithms are



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generally based on identification of an increased MIR channel signal (here in S7 or F1) and/or by a divergent signal between the MIR and TIR brightness temperatures of a pixel (i.e. $BT_{S7} - BT_{S8}$ or $BT_{F1} - BT_{S8}$). The non-collocated data between the F1 channel and the 'S' channels, plus the quite regular saturation of S7 over even the ambient background, makes this more challenging that it would otherwise be in the SLSTR AF detection algorithm. FRP retrieval using the MIR radiance method requires that the MIR channel in particular has a wide enough dynamic range such that it does not saturate over active fire pixels (Wooster et al., 2005), and whilst saturation does occur in S7 it is almost totally avoided in F1. By night, observations in the SLSTR SWIR bands (S5 and S6; Table 1) can be used to aid hotspot detection, and a second estimate of FRP using the S6 channel is provided since this approach is more accurate for FRP retrieval over gas flares (Fisher and Wooster, 2018).

By day solar-heated bare ground and specularly reflected sunlight can also increase MIR pixel signals far above those of surrounding areas, and thus active fire detection algorithms must use a series of additional multi-spectral optical and thermal channel tests to discriminate true fire pixels from such "false alarms" (particularly by day). Pixels that are homogeneously hot due to solar heating of, for example, bare rock or soil surfaces should have similar MIR and TIR brightness temperatures (albeit somewhat different due to differing atmospheric, surface emissivity and solar reflection effects). This contrasts with pixels containing sub-pixel sized fires which are expected to have larger MIR and TIR brightness temperature differences if the fires cover a large enough pixel proportion. Pixels that show a high MIR signal due to sunglint from (potentially sub-pixel sized) water bodies also show a markedly increased VIS or NIR channel signal, but pixels containing sub-pixel fires typically do not. Solar panels and other reflective surfaces can cause similar glint effects, but multispectral testing can discriminate these false alarms from true fire pixels. Once an active fire pixel is detected, the FRP of the fires present within it can be determined.

3.2 Active Fire Detection Principles

Consider a pixel ground field of view of uniform background temperature T_b , containing a subpixel fire of effective radiant temperature T_f and effective fractional area P_f . Assuming a unitary emissivity and neglecting atmospheric and solar reflected radiation effects for the present case, the observed spectral radiance (L_λ) in two different spectral bands that can be approximated by central wavelengths in the MIR and TIR regions can be simply assumed to be the area weighted sum of that from the two individual thermal components (Dozier, 1981; Giglio and Justice, 2003).

$$L_{MIR} = p_f B(/_{MIR}, T_f) + (1 - p_f) B(/_{MIR}, T_b)$$
 (1)



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$$L_{TIR} = p_f B(/_{TIR}, T_f) + (1 - p_f) B(/_{TIR}, T_b)$$
(2)

Where $B(\lambda, T)$ is the Planck function at wavelength λ and brightness temperature T.

Given the type of Planck function relationships shown in Figure 3, the presence of a subpixel sized fire within a pixel will enhance the pixel integrated spectral radiance (L_{λ}) much more in the MIR than in the TIR. Converting L_{MIR} and L_{LWIR} into the equivalent brightness temperatures T_{MIR} and T_{TIR} through the inverse Planck function therefore results in $BT_{MIR} >> BT_{TIR}$. Termed here the $T_{MIR} - T_{TIR}$ brightness temperature difference (and sometimes referred to as $\Delta T_{MIR-TIR}$), this value increases with increasing T_f and p_f up to the point where a fire starts to cover a very large proportion [>10%] of the pixel (Figure 4). More than 10% by area coverage of the pixel footprint by a fire is very rare for a moderate spatial resolution sensor such as SLSTR. Active fire detection algorithms are therefore generally based on thresholding pixel level observations of T_{MIR} and $T_{MIR} - T_{TIR}$ to discriminate fire pixels from non-fire pixels. Thresholds must be carefully chosen, since even certain non-fire pixels can have substantially increased values of T_{MIR} and $T_{MIR} - T_{TIR}$, due for example to solar heating. An approach using fixed spatially and/or temporally thresholds is therefore not generally effective where an algorithm is required to be applied globally across all regions and seasons and by day and by night, so a contextual approach is adopted whereby fire pixels are identified based on their signal contrast with the surrounding non-fire ambient 'background' pixels (Flasse and Ceccato, 1996; Giglio et al., 2016). Strong contrast with the background in terms of the T_{MIR} and T_{MIR} - T_{TIR} measures is the basic detection criteria used in the SLSTR AF detection algorithm, with additional multi-spectral tests aimed at preventing false alarms from, for example, uniformly warm surfaces and reflected sunglint (Giglio et al., 2003; Wooster et al., 2012; Xu et al., 2020). The details of these tests are described in full in Section 3.



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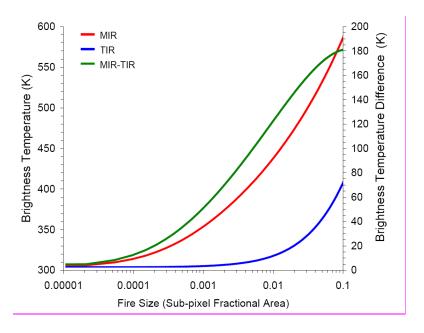


Figure 3. Simulated MIR and TIR channel brightness temperatures for an active fire pixel containing a landscape fire having an effective brightness temperature of 900 K and covering a varying fraction of the pixel area. The fire is superimposed on an ambient background with a brightness temperature of 300 K. As the proportional area of the pixel covered by the fire increases, the brightness temperature measured in both the MIR and TIR channels also increase, but more rapidly in the MIR due to the fires' spectral radiance signal peaking in or close to this wavelength region (see Figure 3). Thresholding of the MIR-TIR brightness temperature difference between these two spectral channels is commonly used to detect active fire pixels, as is the case with the SLSTR algorithm detailed herein. Fires of 900 K covering even 10⁻³ of the SLSTR pixel area raise the MIR-TIR brightness temperature difference by more than 10 K, and are thus very likely detectable with the algorithm presented herein. Emissivity and atmospheric effects have been neglected in this simulation (see Wooster et al., 2005 for details).

3.3 Fire Characterisation Principles

Once an active fire pixel has been detected, it can be characterised through estimation of its fire radiative power. As previously described, FRP quantifies the rate of release of radiant energy by a fire over all wavelengths (albeit primarily in the infrared) and over the viewing hemisphere above the fire. For reasons stated earlier, the SLSTR algorithm adopts the single channel MIR radiance method for fire characterisation - originally presented in Wooster *et al.* (2003). This approach is based on a power law approximation to the Planck function (Wooster *et al.*, 2003) and exploits the fact that for the temperature range of active fires the Planck function relationship between emitted



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spectral radiance and emitter temperature approaches a 4th order power law at MIR wavelengths (see Wooster et al., 2003; 2005). Since the same fourth order power law is found in Stefan's Law, which relates total energy radiated per second per unit area (i.e. over all wavelengths and over the hemisphere above the surface; so the Fire Radiative Power per unit area) to emitter temperature, the per unit area fire radiative power (FRP_A) can be expressed as a linear function of the fire emitted spectral radiance measured in a MIR spectral band (Wooster *et al.*, 2005):

$$FRP_A = \left(\frac{\sigma.\varepsilon_f}{a.\varepsilon_{f,MIR}}\right) L_{f,MIR}$$
 [Wm⁻²] (3)

where σ is the Stefan-Boltzmann constant (5.67x10⁻⁸ W.m⁻².K⁻⁴), ϵ_f is the broadband emissivity of the fire and ϵ_{MIR} is the MIR spectral emissivity. Gray body behaviour is at present assumed ($\epsilon_f = \epsilon_{f,MIR}$), which is understood to be a realistic approximation for vegetation fires (Langaas, 1995; Johnson et al., 2014). α (W.m⁻².sr⁻¹. μ m⁻¹·K⁻⁴) is the power-law scaling constant whose derivation is described in Wooster et al. (2005). $L_{f,MIR}$ (W.m⁻².sr⁻¹. μ m⁻¹) is the spectral radiance of the fire itself.

With the coarse spatial resolution pixels of SLSTR, we cannot directly measure $L_{f,MIR}$ and can only measure the pixel integrated spectral radiance given by the mix of fire and ambient background (Equation 1). Thus $L_{f,MIR}$ is generally estimated as the difference between the MIR spectral radiance of the fire pixel and the mean of the immediately surrounding non-fire ambient 'background' pixels. However, Equation (2) is a simplification that neglects many other contributions to the pixel integrated radiance, yet these must be included to obtain the full description of the fire pixel radiance to include both emissivity, atmospheric and solar radiation effects. Thus, under the assumption of cloud free conditions, for a pixel containing a sub-pixel sized fire, the at-sensor MIR spectral radiance (L_{MIR}) will be the summation the following terms; emitted fire thermal radiance, solar and atmospheric downwelling irradiance reflected from the fire, emitted thermal radiance from the non-fire background, the solar and downwelling atmospheric irradiance reflected from the non-fire background, and the upwelling atmospheric thermal radiation:

$$L_{MIR} = \tau_{MIR} p_f \varepsilon_{f,MIR} B(\lambda_{MIR}, T_f) + \tau_{MIR} p_f (1 - \varepsilon_{f,MIR}) (\tau_{d,MIR} I_{sun,MIR} \cos \varphi + I_{atm,MIR}) / \pi$$

$$+ \tau_{MIR} (1 - p_f) \varepsilon_{b,MIR} B(\lambda_{MIR}, T_b) + \tau_{MIR} (1 - p_f) (1 - \varepsilon_{b,MIR}) (\tau_{d,MIR} I_{sun,MIR} \cos \varphi$$

$$+ I_{atm,MIR}) / \pi$$

$$+ L_{atm,MIR}$$
 (4)



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where τ_{MIR} is the upward atmospheric transmission in the sensors MIR spectral channel, ϕ is the solar zenith angle, $\tau_{d,MIR}$ is the downward atmospheric transmission in the sensors MIR spectral channel at angle ϕ , $I_{sun, MIR}$ is the extraterrestrial solar irradiance in the sensors MIR spectral channel, $I_{atm,MIR}$ is the diffuse downwelling atmospheric irradiance in the MIR spectral channel, and $L_{atm,MIR}$ is the upwelling atmospheric spectral radiance in the MIR spectral channel. T is land surface temperature, ϵ is emissivity and p the proportion of the pixel covered by that component, with subscript f corresponding to their value at the fire and b at the non-fire background.

Similarly, for a neighbouring non-fire 'background' pixel:

$$L_{b,MIR} = \tau_{MIR} \varepsilon_{b,MIR} B(\lambda_{MIR}, T_b) + \tau_{MIR} (1 - \varepsilon_{b,MIR}) (\tau_{d,MIR} I_{sun,MIR} \cos \varphi + I_{atm,MIR}) / \pi + L_{atm,MIR}$$
 (5)

The fire emitted spectral radiance in the MIR spectral channel, $L_{f,MIR}$, required as input into equation (3) is in fact the $p_f \varepsilon_{MIR}$ $B(\lambda_{MIR}, T_f)$ term on the right hand side of equation (4) (i.e. the spectral emissivity of the fire multiplied by its spectral emittance). The value of this term can be obtained numerically by combining Equations (4) and (5) and re-arranging:

$$p_f \varepsilon_{MIR} B(\lambda_{MIR}, T_f) = \frac{1}{\tau_{MIR}} \left(L_{MIR} - (1 - p_f) L_{b,MIR} + p_f L_{atm,MIR} \right) - p_f (1 - \varepsilon_f) (\tau_{d,MIR} I_{sun,MIR} \cos \varphi + I_{atm,MIR}) / \pi$$
(6)

The right side of Equation (6) represents the true value of $p_f \varepsilon_{MIR} B(\lambda_{MIR}, T_f)$ for use as $L_{f,MIR}$ in Equation (3). Multiplying the output of (3) by the sensor ground field of view then provides an estimate of the fire radiative power in Watts. Further detail on this is included in Wooster et al. (2005).

However, certain of the parameters in Equation (6) cannot be readily determined, for example the unresolved fire fractional area, p_f , whilst others, for example the atmospheric parameters, are likely to be imperfectly known. By neglecting the (relatively) unimportant terms, Equation (6) can be greatly simplified and then parameterised using the SLSTR measured radiances, in order to provide an estimate of $L_{f,MIR}$ for input into Equation (3).



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The first assumption is that the atmospheric term $p_fL_{atm,MIR}$ on the right hand side of Equation (6) will always be small compared to at least one of the first two terms and is therefore negligible. Next, the requirement to know the fire fractional area (p_f) is removed by assuming that $(1-p_f)L_{b,MIR} \approx L_{b,MIR}$, which is considered workable when p_f is sufficiently small. As p_f increases, the error introduced by this assumption remains negligible, since in that case the spectral radiance of the fire pixel will be increasingly dominated by emittance from the (increasingly large) fire rather than from the much cooler ambient background. This is because $B(\lambda_{MIR}, T_f)$ is many orders of magnitude larger than $B(\lambda_{MIR}, T_b)$ at MIR wavelengths (Figure 3). The final term in Equation (6) corresponds to the solar and downwelling atmospheric radiation reflected from the fire, and is assumed negligible for the same reason.

Via these simplifications the fire-emitted spectral radiance ($L_{f,MIR}$) for input into Equation (3) can be estimated from the difference between the MIR spectral radiance of the active fire pixel (L_{MIR}) and that of the surrounding non-fire 'background' ($L_{b,MIR}$), which is generally estimated from the average signal of the valid (i.e. non-fire, non-water, non-cloud) pixels within a 'background window' surrounding the fire pixel. Thus:

$$L_{f,MIR} = p_f \varepsilon_{f,MIR} B(\lambda_{MIR}, T_f) \simeq \frac{1}{\tau_{MIR}} \left(L_{MIR} - L_{b,MIR} \right) L_{f,MIR} = p_f \varepsilon_{f,MIR} B(\lambda_{MIR}, T_f) \simeq \frac{1}{\tau_{MIR}} \left(L_{MIR} - L_{b,MIR} \right)$$

$$(7)$$

Combining Equations (3) and (7) we obtain a method (applicable at night and day) for calculating FRP averaged over a coarse spatial resolution pixel in units of W.m⁻². Multiplying by the ground projection of the sensor FOV (A_{sampl}) provides the FRP in Watts:

$$FRP_{MIR} = \frac{1}{10^6 \cdot t_{MIR}} \left(\frac{S \cdot e_f}{a \cdot e_f} \right) \left(L_{MIR} - L_{b,MIR} \right)$$
 [MW]

An adaption for gas flares, which are typically much higher in temperature than vegetation fires (>1500K) and which have their spectral radiance peak around the shortwave infrared band (S6; 2.2 µm) of SLSTR (as shown in Figure 3), means that (at night when solar-sourced SWIR radiation is absent) the FRP of Gas flares is best calculated using the excess spectral radiance assessed in the S6 channel (Fisher and Wooster, 2018):



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$$FRP_{SWIR} = \frac{1}{10^6.t_{SWIR}} \left(\frac{S.e_f}{a.e_f} \right) \left(L_{SWIR} - L_{b,SWIR} \right)$$
 [MW]

3.4 Details of the SLSTR MIR Channel Intricacies

MIR channel measurements are key to active fire detection and fire characterisation (Section 2.2 and 2.3 respectively). SLSTR has two MIR channels (Table 1) to provide both highly accurate brightness temperatures up to 311 K (in S7) and unsaturated brightness temperatures over very strongly emitting pixels (in F1). As already mentioned however, the pixel shape and area of the S7 and F1 pixels are not identical, and nor are the measurements made at the same line and sample of an image perfectly co-located. The F1 channel has a far more consistent pixel area across the nearnadir view swath, and across much of the swath its pixel area is significantly smaller than that of S7 (Figure 5). This means that any sub-pixel fire will have its spectral radiance signal diluted more when recoded by S7 than F1, reducing its detectability against the ambient background. On the other hand, F1 has more noise than S7, and also is affected by the 'downscan' anomaly phenomena shown in Figure 6. Any joint use of F1 with the 'S' channels also requires that the spatial offset between the F1 data and the data from these other channel needs to be overcome.



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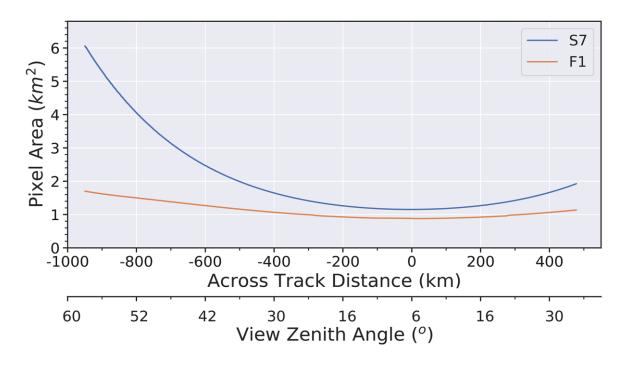


Figure 5. Ground pixel area (km²) of the SLSTR F1 and S7 channels across the near-nadir view swath. Note the F1 channel data has a far more consistent pixel area across the swath than does the S7 channel data, increasing from 0.9 km² to 1.8 km² at the far-left swath edge compared to an increase from 1.1 km² to 6 km² for the S7 channel over the same view zenith angle range. Pixel size data courtesy Science and Technology Facilities Council Rutherford Appleton Laboratory (STFC-RAL).



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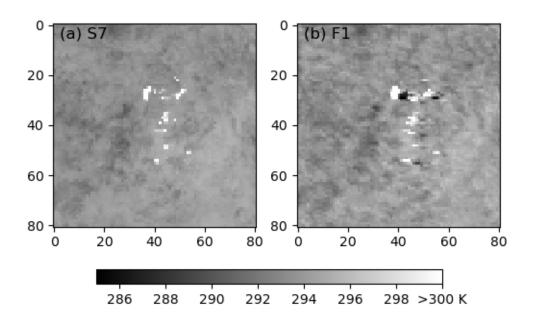


Figure 6. Example of a large wildfire burning in northern Ontario, Canada (51.25° N, 94.68° W) as observed in the SLSTR near-nadir view scan at 03:46 UTC on 12 August 2018. (a) S7 channel data, and (b) F1 channel data. AF pixels have elevated BT values and are shown as bright in this rendition. Whilst the same fires are identified in both S7 and F1, the number of AF pixels in a fire cluster and the shape of the cluster are slightly different between the two channels, due to the different pixel footprint characteristics. Some AF pixels are saturated in S7, whilst none are saturated in F1. However, F1 data show higher noise over the ambient temperature non-fire background, have a small spatial offset from the matching S7 pixels, and possess anomalously low BT values down-scan of the fires (dark areas to the bottom right of each fire cluster in (b), which are not present in the S7 data shown in (a)). See Xu et al. (2020) for further details.

The different sizes of the F1 and S7 pixels provides also different image characteristics when fires are viewed by these two channels, as shown in Figure 6. This is especially true at the far-left edge when the pixel area of S7 is around six times that at nadir (Figure 5). At this far-left swath edge, any fire seen by S7 will be greatly oversampled in a manner similar to the so-called "Bow-Tie" effect of MODIS (Giglio et al., 2003). The effect is far less in the smaller F1 pixels. Figure 7a,b shows data from the same fire viewed by F1 and S7 at a view zenith angle of 52° (far-left swath edge). Whilst F1 shows effectively only one strong active fire pixel (FRP = 10.8 MW), S7 shows eight pixels, three of which are cosmetic fill pixels that are more common at the swath edge (total FRP = 25.2 MW from the five discrete and unique non-cosmetically filled pixels). Figure 7c, d further illustrate this issue using a simulation of SLSTR data taken of a fire at the far-left swath



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edge conducted using the procedures detailed in Xu et al. (2021). Here an 800 K active fire with a size of 1600 m² (0.16% of a 1 km² pixel) is used as a target, superimposed on a homogeneous background of 290 K. The fire has an FRP of 37.2 MW. Simulations indicate that in the F1 channel at the swath-edge this fire would result in only one active fire pixel (BT of 334.5 K) being detected by the active fire detection algorithm detailed herein (FRP = 35.6 MW, close to the 'true' value), whilst in the S7 channel data of the same fire three active fire pixels would result from pixel oversampling and be detected by the algorithm (BTs of 310.5, 306.2 and 311.9 K after removal of cosmetically filled pixels, and total FRP = 94.2 MW though one pixel would be affected in reality by saturation). The S7-derived FRP is ~ 2.5× that recorded by F1, and far away from the 'true' value – similar to the situation found in the real data of Figure 7a,b. Further details of these investigations are included in Xu et al. (2021), but they indicate the theoretical value of deriving the FRP_{MIR} measures from F1 observations at all fires. In the algorithm this is termed the 'F1 ON' option. However, since F1 has increased noise which may in reality hamper the FRP retrieval of lower FRP fires, the 'F1 OFF' option is also included for night-time granule processing, whereby the FRP of fires having no saturated S7 pixels is still retrieved from S7. This has to be done on a 'whole fire' basis because of the differing nature of the S7 and F1 data of active fires shown in Figure 6 and 7.

In the algorithm structure therefore, AF pixels are first detected first using the (low noise) S7 channel data where possible, and then clustered into individual 'fires' based on the identification of spatially contiguous S7 AF pixels, and then the matching cluster and its constituent AF pixels are identified in the F1 data. By night, FRP retrieval for the AF pixels in a cluster containing no S7 saturated pixel can then use either S7 (the so-called "F1_OFF option") or F1 (the so-called "F1_ON option"), whilst FRP retrieval by night for a cluster containing one or more S7 saturated pixels uses F1 in either case. See Xu et al. (2020) for further details, and based on the analysis conducted by Xu et al. (2021) the operational non-time critical (NTC) version of the Sentinel-3 SLSTR FRP products available from the Sentinel data hub (https://scihub.copernicus.eu/) are recommended to use the F1 ON option by night as well as by day. By day, the situation is further complicated by the fact many S7 pixels are saturated even over the ambient background with no fires present. To deal with this fact the F1 data alone could be used, but this would preclude making use of the lower-noise S7 band data where it is unsaturated over the background – and whose use generally is expected to improve the ability to detect lower FRP fires close to nadir (in part also because of the greater S7 co-location with the S8 LWIR channel data than is the case with F1). To make use of S7 data when appropriate by day, the S7 and F1 data are merged to form a new synthetic 'BT₄' (named because of the 3.7 µm bands closeness to 4 µm). In areas unaffected by S7



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saturation this 'BT₄' band is composed of S7 data, but elsewhere it takes data from F1. The initial AF detection procedure implemented by day then uses the MIR brightness temperatures stored in this BT₄ band, rather than those of the original S7 data alone. By night it uses the S7 band data since that remains unsaturated over the ambient background.

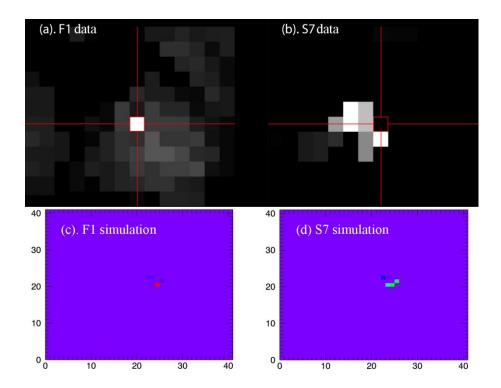


Figure 7. Demonstrated differences in the shape and size of the same active fire recorded simultaneously in the F1 and S7 channels of Sentinel-3 SLSTR. Both channels operate across the same middle infrared waveband, but with different pixel area (Figure 5) and thus pixel overlap characteristics (see Xu et al., 2021). (a, b) show real SLSTR data, whilst (c, d) show simulated data of an 800 K fire having an area of 1600 m² imaged by S7 and F1 towards the left-hand swath edge. The fire is strongly sub-pixel in both the F1 and S7 channel data, and in both the real data and the simulations, the active fire pixels appear oversampled in S7 compared to F1 due to the increased pixel overlap in S7 that comes as a result of the far larger pixels found in that channel towards the scan edge (see Figure 5). As a result, the retrieved FRP using the S7-detected active fire pixels are more than twice that retrieved using F1. Simulations based on code provided by the Science and Technology Facilities



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Council (STFC) Rutherford Appleton Laboratory. See Xu et al. (2021) for more details on the variations between S7- and F1-derived active fire imagery and the resulting FRP measures.



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4 ALGORITHM DESCRIPTION

4.1 Overview of Algorithm Structure

The SLSTR algorithm for active fire detection and fire characterisation can be considered a six-stage process (see Figure 8). The algorithm is applied to SLSTR granules already cloud masked and separated into two subsets based on geographic location, namely the land (i.e. the land surface with the locations of larger lakes and rivers masked out) and the ocean (which includes areas that could be the site of offshore gas flares). The Sentinel-3 SLSTR channel naming convention and the matching scientific notation used throughout this document was already shown in Table 1 and the six active fire pixel detection stages utilise a series of spatially varying thresholds to detect the set of confirmed fire pixels in the scene under consideration, with the thresholds varying between day and night conditions. Furthermore, the thresholds vary between the detection of hotspots on land and over the ocean. Night-time pixels are those defined as having a solar zenith angle \geq 85 ° unless otherwise stated, and all other pixels are defined as daytime pixels.

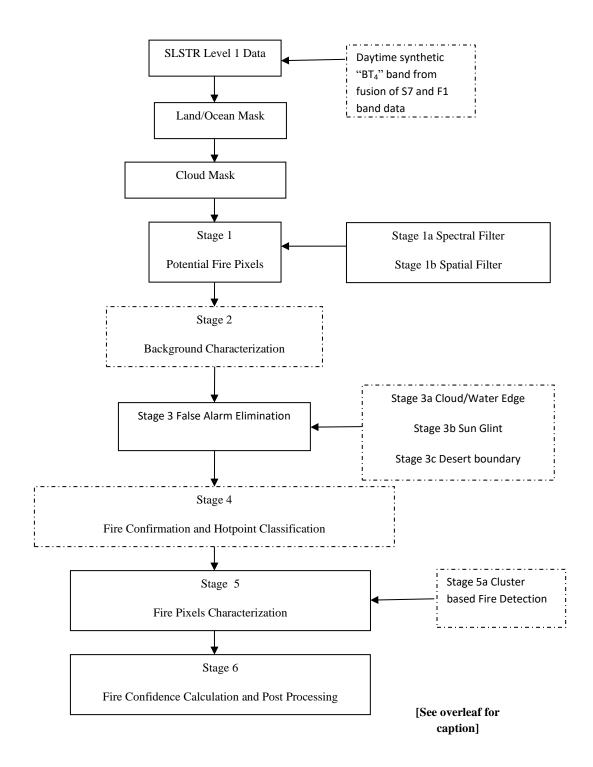
By day, solar reflected radiation from cloud tops or cloud edges can lead to high MIR brightness temperatures at cloud-contaminated pixels, whereas the clouds will typically be cold and thus have a low TIR brightness temperature. Therefore, the T_{MIR} , T_{TIR} and $(T_{TIR} - T_{TIR}; \Delta T_{MIR-TIR})$ measures recorded at certain cloud-contaminated pixels may appear similar to those of active fire pixels. Furthermore, inland water bodies (lakes and rivers), together with mixed land-water pixels at coastlines, may have rather different MIR and TIR brightness temperatures to their neighboring land surface pixels, and might also be affected by specifically reflected sunglint. Therefore, the availability of an accurate and appropriate cloud mask (which does not identify smoke as cloud) and also a high-quality land/water mask is important for the active fire application, and only SLSTR pixels confirmed as clear-sky, land pixels via the use of such masks should be used within the land hotspot tests. Of course, some small or seasonally varying water bodies may not be present in the land-water mask, and certain small or semi-transparent clouds may not be identified by the cloud mask. To assist in these instances, the algorithm contains some simple tests aiming to reduce problems introduced by such cases. Masks of "(semi-) permanent high temperature events" (e.g. gas flares, volcanoes) will also be applied after fire detection in order to classify detections into different type of hotspot based on their geographic locations.



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Figure 8. Structure of the Sentinel-3 SLSTR Active Fire Detection and Characterisation algorithm (prior page). Note the algorithm has evolved considerably from the pre-launch version presented in Wooster *et al.* (2012). The night-time version is described in Xu et al. (2020), and this ATBD now covers both full daytime and night-time processing. Prior to Stage 1 active fire detection commencement, two separate geographic subsets of data are determined: namely the cloud-free land area potentially capable of supporting land-based hotspots (i.e. the land surface with the locations of clouds, larger lakes and rivers masked out) and cloud-free ocean areas that might potentially be the sites of offshore gas flares. A new synthetic BT4 band is created from merging of the S7 and F1 data - supporting daytime active fire detection when much of the ambient background land maybe saturated in S7. Each of the algorithm stages is then applied to each of the two geographic subsets of data (Land and Ocean), though with some alterations to the thresholds used, and in a few cases some tests being de-activated or added. Stage 4b 'desert elimination' is not necessary over the ocean or over the land at night. For the Land geographic subset, thresholds and test details sometimes vary between observations made under night-time and daytime conditions. For the Ocean geographic subset, only night-time processing is conducted. The dashed rectangles outline procedures where certain differences exist in the tests applied during daytime and night-time processing.

4.2 Creation of the Synthetic BT₄ Band by Day and Use of SWIR Data at Night

Whilst the algorithm presented here uses data from many of the SLSTR spectral channels listed in Table 1, it is mainly reliant on data from the middle infrared (MIR; 3.7 µm) channels (S7 and F1) and from the first thermal (long-wave) infrared channel (TIR; 10.8 µm) channel (S8). As already mentioned, the precision of the MIR brightness temperature measurements is far better in the S7 channel than the wider dynamic range (but nosier) F1 channel, but S7 becomes strongly non-linear above 311 K and saturates soon after. This makes S7 quite commonly unusable over hotter regions, whose 3.7 µm BTs often exceed 311 K by day. Even in cooler regions, S7 is very often saturated at active fire pixels. For this reason, F1 is required to be used in the AF detection and FRP retrieval process more commonly than expected pre-launch, but F1 is not perfectly co-located with the S7 and S8 channels and has a different pixel area size and shape, making switching between use of S7 and F1 data non-trivial as detailed in Sections 2.4 and 3.2. F1 also suffers a so called "downscan anomaly" which means that after it has scanned a high brightness temperature pixel (e.g. an active fire pixel) it records anomalously lower BTs in the immediate down-scan area (see example in Figure 6b). A similar "down-scan anomaly" also occurs after F1 has scanned very cold BT pixels (e.g. high cold clouds), with the down scan region now showing elevated brightness temperatures in F1. All these phenomena make joint use of data from F1 and the standard 'S' channels more complex than would otherwise be the case. To cope with this, a clustering algorithm is used that exploits the AF detections made in the S7 channel data (by night) or the BT₄ band data (by day) - and groups spatially contiguous AF pixels as belonging to the same "fire cluster". Once



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these AF clusters are formed, the clusters in F1 that match those identified in S7 (by night) or the BT₄ band (by day) are identified and characteristised. This approach is described in Section 3.3,7 and also in Xu et al. (2020). When synthesising the BT₄ band from the individual S7 and F1 data, consideration of the previously-mentioned down-scan anomaly phenomena is required, and also of the fact that at location of saturated S7 pixels the F1 channel data should not be used for that pixel alone, but F1 data for surrounding pixels should also be used (due to the pixel overlap and the different size and shape of the S7 and F1 pixels detailed in Section 2.4 and in Xu et al. (2020, 2021)). Specifically, BT₄ is formed by first copying the S7 data array. Then, pixel locations in S7 having brightness temperatures considered saturated ($T_{S7} > S7_{AT}$; where $S7_{AT} = 311$ K) are identified, and in BT₄ these pixels and any others having $T_{S7} > p_1$ ($p_1 = 300$ K) OR $T_{S7} - T_{S8} > p_2$ $(p_2 = 10 \text{ K})$ in the surrounding 11×11 pixel window are replaced with their matching F1 channel brightness temperatures. It is possible that F1 pixels affected by the down-scan anomaly phenomena are included in these initially created BT₄ band data however, though any such F1 pixels having a matching $T_{S7} < p_1$ will not be present. To deal with the possibly remaining F1 down-scan anomaly pixels now present in the BT₄ band data, for example those from pixel locations having $T_{S7} > 300$ K, we exclude any BT₄ pixels coming from a location with $T_{S7} > 300$ K from use in the background characterisation step detailed in Section 3.2.2.

To demonstrate synthesis of the BT_4 band data, Figure 9 shows an SLSTR subscene taken over southeast Australia from 3^{rd} January 2020, when significant numbers of large active fires were burning. In this subscene, more than 85% of the land pixels have $BT_{S7} > 311$ K, and therefore the active fire pixels are not easily identifiable in the S7 channel data (Figure 9a). However, they are identifiable in the F1 channel data (Figure 9b), since this remains unsaturated over the ambient background. The final synthesised BT_4 band - which uses S7 where possible and F1 where necessary - is shown in Figure 9c. The BT_4 pixels coming from F1 are coloured in this rendition, leaving just the S7-sourced pixels as greyscale.



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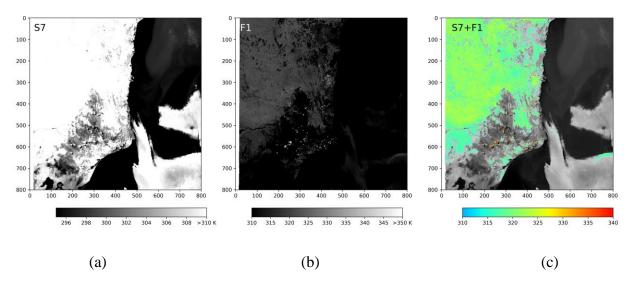


Figure 9: Example of a large wildfire burning in Australia as observed in the SLSTR near-nadir view scan at 23:08 UTC on 3 Jan 2020. (a) S7 channel data where \sim 85% land pixels have BT_{S7} > 311 K and (b) F1 channel data where pixels containing actively burning fires appear bright (high brightness temperature). (c) The new BT₄ band which combines data from the S7 and F1 channel as detailed in Figure 10.

Figure 10 shows the detail of methodology used to combine the S7 and F1 channel data into the synthesised BT₄ band. The green pixel is the pixel under analysis, and it has $T_{S7} > S7_{AT}$, where $S7_{AT}$ is the threshold above which S7 brightness temperatures are considered inaccurate and starting to saturate (currently 311 K). The red outlined pixel is a pixel that will later be identified as an AF pixel, and the blue, black and yellow pixels all lie within the 11 ×11 pixel window surrounding the green pixel. Within this window, the black pixels are those having $T_{S7} < 300$ K and $T_{S7} - T_{S8} < 10$ K, the blue pixels $T_{S7} > 300$ K or $T_{S7} - T_{S8} > 10$ K, and the yellow pixels are those down scan of the AF pixel where the F1 BTs are colder than otherwise because they are affected by the F1 down-scan anomaly.

During generation of these BT₄ data, the green pixel and all blue pixels take their values from F1, whilst the black pixels take their values from S7. If the pixels at the location of the down-scan anomaly have $T_{S7} < 300$ K then they will have their values provided by S7 since F1 is imprecise below ~ 300 K, but if they have $T_{S7} > 300$ K they will have their BTs provided by F1 (but they will be excluded from use in the background characterisation stage; Section 3.3.3). When two or more spatially contiguous pixels have $T_{S7} > 7_{AT}$, the surrounding window is expanded according to the number of these pixels. The window size in each direction is taken as 11 plus the number of pixels



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having $T_{S7} > S7_{AT}$ in that direction For example, if a block of pixels of size 2 ×3 have $T_{S7} > S7_{AT}$, then the surrounding window size will be 13 × 14 pixels.

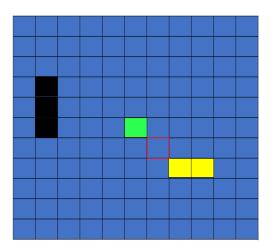


Figure 10. Illustration of the method for synthesising the BT_4 band from the separate S7 and F1 band data. The green pixel in the middle is the saturated S7 pixel, and the blue, black and yellow pixels are the pixels surrounding the saturated pixel in 11×11 pixel window. The black pixels are the those having an S7 channel brightness temperature < 300 K and a S7 minus S8 (T_{S7} - T_{S8}) brightness temperature difference less than 10 K. Blue pixels are those with an S7 brightness temperature > 300 K or T_{S7} - T_{S8} >10 K, and yellow pixels those affected by the F1 down-scan anomaly. To create the BT_4 band, S7 data are copied first and then the green and blue pixels from S7 in that data replaced by data from F1. The black pixels are kept as S7, and the yellow pixels will be kept as F1 – but the latter will be excluded from use in the latter background characterisation stage. The pixel outlined in red contains an active fire, which is why the down-scan anomaly occurs where it does.

In addition to the creation and use of the BT₄ band by day, the next main change from the prior algorithm version is that night-time processing now exploits the SLSTR SWIR channels. The SLSTR VIS to SWIR channels (S1 to S6) are recorded at 500 m spatial resolution in the near-nadir view scan (at the sub-satellite point), whereas the thermal channels have a 1000 m spatial resolution. The SLSTR Active Fire algorithm now uses data from both types of channels, and the difference in pixel size needs to be taken account of during data processing where measurements from both types of channel are combined (e.g. in a band ratio). Where the SWIR channels are used alone in a night-time test, it is desirable to undertake the analysis at the original SWIR channel spatial resolution since the hotspot signals will be maximized at this smaller pixel area. This will then enable the algorithm to be most sensitive to the smaller sub-pixel hotspots. However, where the SWIR data are needing to be combined with thermal channel data – such as in a band ratio (e.g.



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an S7/S2 ratio) then a re-mapping method is used to move the 500 m pixel size data to the 1000 m pixel size grid is performed as detailed in Section 3.3.7 (the method is essentially similar to a coordinate division by two). For the clustering to find a corresponding fire in the 1000 m MIR-detected data as in the 500 m SWIR channel data (or vice versa) a similar procedure is required.

4.3 Land Hotspot Detection

4.3.1 Orphan Pixels, Cosmetically Filled Pixels and MIR-band merging

The Level 1 granules upon with the AF detection and FRP retrieval algorithm acts contain both orphan pixels and cosmetically filled pixels. Orphan pixels are currently not used in the AF detection and characterisation algorithm, but some cosmetically filled pixels are.

Cosmetic fill pixels in the F1 channel should be masked out at the initial stage prior to the AF detection process starting. However, cosmetic fill pixels in the S7 and S8 channels should remain to be included in the potential AF detection stage (including in the spectral filter, spatial filter) and in the background characterisation process of the contextual detection stage. They should not however be able to be detected as an AF pixel, so at night AF pixels corresponding to cosmetically filled observations in S7 should be masked out before they are passed to the contextual detection stage. This means that in the case of F1_OFF processing, the AF detection and FRP processing reported on the S7 grid does not include cosmetically filled AF pixels. Similarly the FRP derived from S7 or F1 does not include a contribution from cosmetically filled pixels, and any AF pixel location reported under F1_ON processing on the F1 grid does not include the location of F1 cosmetically filled pixels either.

For night-time granules, the initial AF detection stage uses the S7 data to supply the MIR waveband data, except for the absolute threshold tests which use F1 data. For daytime granules however, the initial AF detection stage relies on the synthesised BT₄ band as detailed above (termed 'BT₄' since it is formed of data collected at close to $4 \mu m$). This BT₄ data is used for the initial AF detection stage by day, as outlined in Section 3.2, in place of the S7 channel data used at night. We can expect that daytime active fire detection performance is somewhat reduced compared to that at night because of the use of the requirement to use the higher noise F1 data within the BT₄ band where the S7 channel observations were saturated. To keep the description contained in Section 3 relatively simple – in the Sections below the term 'S7' refers to the S7



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channel data when dealing with night-time (ascending node) pixels, but for day-time pixels it refers to data from the synthesised BT₄ band. By day, FRP is retrieved using the F1 channel data via the clustering algorithm outlined in Section 3.3.7, whereas by night the F1_ON and F1_OFF options can be set to determine which of the S7 and F1 channels are used to retrieve the FRP of fires whose pixels all remain unsaturated in S7.

4.3.2 Detection of Potential Active Fire Pixels (Stage 1)

The purpose of this stage is to identify all pixels whose spectral and spatial signals suggest that they may potentially contain an actively burning vegetation fire. The aim is to successfully include all the true fire pixels within the potential fire pixel set, whilst minimizing the number of non-fire pixels included so as to minimize data processing overheads and avoid later false alarms. A spectral filter using a set of spectral thresholds is applied to detect a set of potential fire pixels PF_I , based on their thermal channel BT signals. In some circumstances, much of the cloud-free land surface maybe returned as a potential fire pixel by the spectral filter, particularly when thresholds are set low so as to minimize errors of omission (i.e. the missing of fire events). For this reason, a spatial (edge detection) filter is used to detect a second set of potential fire pixels PF_2 , based on the spatial variation of $\Delta T_{MIR-TIR}$, and the final set of potential fire pixels PF_f is the intersection of these two:

$$PF_f \in \{PF_1 \cap PF_2\} \tag{10}$$

At night this potential active fire pixel detection stage (Stage 1) is conducted using the S7 channel data, whereas by day it is conducted using the BT_4 band detailed in Section 3.2. Whilst most tests use day and night thresholds based on a pixel being classified as day or night based on its solar zenith angle, there are some instances where this classification is required at the granule or quarter scene level. Any granule of quarter scene containing more than p% of its pixels classified as day-time pixels based on their solar zenith angle is considered a day-time granule or quarter scene. At present, p = 1.

In the descriptions below, unless explicitly stated and as introduced above, for night-time pixels or granules or sub-scenes the T_{MIR} measures come from the S7 channel data, whilst for daytime pixels or granules or sub-scenes they come from BT_4 .

Spectral Filter Detail (Stage 1a)

Stage 1a identifies potential fire pixels belonging to set PF_1 using two adaptive thresholds. Firstly, the granule is divided into equal sized quarter sub-scenes having dimensions on half of those of the original granule in terms of along- and across-track coordinates, and is classified as a day-time



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or night-time sub-scene based on the criteria above. For each sub-scene being tested, the number of land (N_{land}) and cloud free land (N_{cf_land}) pixels is calculated. The subscene is classified as valid for use in adaptive threshold determination if the number of land pixels is greater than 10% of the total number of pixels in the subscene, and if the number of cloud free land pixels is greater than 1% of the total number of pixels in the subscene. In this case the mean values of T_{MIR} , T_{TIR} and $\Delta T_{MIR-TIR}$ for all cloud-free land pixels in that subscene are used as the spectral filter thresholds (\overline{T}_{MIR}^{cf} , \overline{T}_{TIR}^{cf} and $\overline{\Delta T}_{MIR-TIR}^{cf}$ respectively) against which each cloud-free land pixel in the subscene is tested for inclusion into potential fire pixel set PF_2 :

$$T_{MIR} > \overline{T}_{MIR}^{cf} + p \times \theta_{S}$$
 (11a)

where p = -0.3 for day time pixels and p=0 for night-time pixels

and

$$\Delta T_{MIR-TIR} > \overline{\Delta T}_{MIR-TIR}^{cf}$$
 (11b)

 θ_s is the solar zenith angle (in degrees), and use of this parameter enables adjustment of the MIR band detection threshold to cope with the fact that at locations where the solar elevation is high, the ambient background temperature and the solar reflectance component of the MIR signal are typically greater. All parameters in these tests come from previous applications of the same tests made using SEVIRI or MODIS (e.g. Wooster et al., 2015; Giglo et al., 2003; 2016), updated with testing using real SLSTR data.

Tests (11a) and (11b) are targeted at identifying the spectral signature of fires, whose pixel integrated T_{MIR} and $T_{MIR-TIR}$ difference should in general be higher than those of the subscene ambient background. Using adaptive thresholds for the detection of potential fire pixels, rather than fixed thresholds such are used in the MODIS fire product (e.g. $T_{MIR} > 310$ K and $T_{MIR-TIR} > 10$ K; Giglio *et al.*, 2003) provides the algorithm a chance at identifying the more weakly burning and/or smaller component of the fire regime – which can be rather numerous in areas such as disturbed tropical forests. The disadvantage is that many more non-fire pixels may also be returned.

If N_{land} and/or N_{cf_land} are too low to meet the 10% and 1% criteria specified above, then the weighted mean of the spatial filter thresholds \overline{T}_{MIR}^{cf} , \overline{T}_{TIR}^{cf} and $\overline{\Delta T}_{MIR-TIR}^{cf}$ calculated from the



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(maximum five) valid spatially neighboring subscenes are used (with the weighting for each subscene given by its value of N_{cf_land}). If no valid neighboring subscenes are available, which we expect to be relatively rare over most land areas given the non-stringent requirement for only 1% of land pixels to be cloud free, then default thresholds are used:

By day,

$$T_{MIR} > 310 \text{ K} + p \times \theta_s \tag{11c}$$

Where p = -0.3

and

$$\Delta T_{\text{MIR-TIR}} > p$$
 (11d)

where p = 8 [Kelvin]

Noting that by day T_{MIR} tested here comes from BT₄.

By night,

$$T_{MIR} > p$$
 (11e)

Where p = 290 [Kelvin]

and

$$\Delta T_{\text{MIR-TIR}} > p$$
 (11g)

where p = 3 [Kelvin]

Noting that at night T_{MIR} tested here comes from S7.

Pixels failing these preliminary tests are immediately classified as non-fire pixels. Pixels passing these tests belong to set PF_1 and relate to the land area.

Spatial Filter Detail (Stage 1b)

The spectral filter of Stage 1a is designed to be very liberal (in order to catch any possible AF pixels), with the disadvantage that it can return very large numbers of potential fire pixels many of which are not fires. Such pixels include those containing large areas of solar-heated bare rocks,



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soil or other "warm" surfaces, such as are found in arid or desert areas for example. In order minimize the inclusion of such areas in the final potential fire pixel set (PF_f) and so reduce potential commission errors and computational cost, a series of spatial thresholds is employed in conjunction with an edge detection filter. This test is used to identify locations where the $\Delta T_{TIR-MIR}$ signal shows a marked spatial change such as is found at fire pixels but not at areas of homogeneous warm land. A series of high-pass filters \mathbf{K} are applied to $\Delta T_{MIR-TIR}$ to identify a second potential fire pixel set PF_2 [with, as before, one PF_2 for land areas and one PF_2 for ocean areas]. Since the contrast between fire and non-fire pixels is greater in $\Delta T_{MIR-TIR}$ than in the MIR channel alone, the spatial filter is applied to the latter brightness temperature difference data (Roberts and Wooster, 2008).

The idea behind the use of the high pass spatial filter is that since each SLSTR pixel measures the spatially averaged radiance over ~ 1 square kilometer, $\Delta T_{MIR-TIR}$ recorded at non-fire "background" pixels generally changes rather gradually from pixel to pixel. In contrast, a pixel containing an active fire represents a high spatial frequency change in $\Delta T_{MIR-TIR}$, which can thus be isolated via a high-pass spatial filter. Filter kernels of size f_K x f_K are used, where f_K is taken sequentially as 3, 5, 7 and 9, with the 3 x 3 filter having the coefficients shown in Figure 11.

-1	-1	-1
-1	8	-1
-1	-1	-1

Figure 11. Coefficients of the 3×3 pixel high pass spatial filter.

The use of multiple filter kernel sizes attempts to ensure that the spatial filter is appropriate for detecting both single fire pixels and those belonging to larger spatial clusters of fire pixels. The



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edge detection filter is applied to the entire subscene, and pixels passing the test are those where the filter output (h_K) exceeds a threshold defined in relation to the filter output standard deviation calculated from all the clear sky, land surface pixels in the SLSTR subscene within which the test pixel resides. A subscene has the same definition as in Stage 1a.

$$PF_2 \in h_K \ge p \times \delta_{fK}$$
 (12)

where p = 1.5

Where σ_{fK} is the standard deviation (Kelvin) of the clear sky, land surface pixels in the subscene, high-pass filtered with filter size f_K , and p is the threshold multiplier taken as 1.5 currently. We use the same criteria for defining valid subscenes as per Stage 1a, and for calculation of the thresholds in the case that the current subscene under consideration fails to contain sufficient cloud free, land pixels. In the case where there are no valid subscenes available for a particular fire pixel (which is expected to be a rare occurrence), default values of 3 for σ_{fK} are used instead, for all the filter sizes.

A pixel having $\Delta T_{MIR-TIR}$ belongs to set PF_2 if condition (11) is valid for at least one of the four filter kernel sizes f_K .

Stage 1 selects the final potential fire-pixel set as those pixels passing both Stages 1a and 1b. In the subsequent stages these pixels will then be further tested to confirm whether they do in fact contain an active fire. As with other stages, the processing is conducted independently for land and ocean geographic subsets, so two potential fire pixel sets are ultimately produced, those corresponding to the land and those corresponding to the ocean respectively.

4.3.3 Background Characterisation (Stage 2)

The objective of the background characterization step is to provide an estimate of what the radiometric signal of the potential fire pixel would be in the absence of fire, based on statistics derived from the set of valid "background" pixels P_b located within a window W of size $b_W \times b_W$ immediately surrounding the potential fire pixel being tested. Stage 3 will use this estimate to determine whether the observed potential fire pixel signal is sufficiently different to this value such that it can be confirmed as a true fire pixel.



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At each potential land fire pixel belonging to set PF_f , b_W is initially set as 5. The center pixel of this 5×5 window is the potential fire pixel itself and so is discounted, and the immediately surrounding eight background pixels are also discounted since their closeness to the potential fire pixel can result in their radiances being contaminated by the fire radiance itself. Thus, for the 5×5 pixel window, a total of 16 pixels are initially included. From these 16 pixels, the set of valid background pixels P_b are selected based on their being identified as clear-sky, land pixels that for daytime observations are not influenced by strong sun glint and which have:

$$T_{MIR, w} < T_{MIR, pf} \tag{13a}$$

$$\Delta T_{MIR-TIR,w} < \Delta T_{MIR-TIR,pf}$$
 (13b)

$$T_{MIR,w}$$

Where p = 311 [K] at night and p = 330 [K] by day

$$\Delta T_{MIR-TIR,w} < p$$
 (13d)

Where p = 10 [K] by night and p = 20 [K] by day

$$\theta_g < p$$
 (13e) where $p = 2$ [degrees]

To cope with the down-scan anomaly in the F1 channel observations that potentially form part of the BT₄ band data, the following masking test is used to exclude such pixels from the background window used to define detection thresholds at the contextual test stage:

NOT
$$(T_{S7}, w > p_1 \text{ AND } T_{F1}, w < p_2)$$
 (13f)

where $p_1 = 300$ [K] and $p_2 = 290$ [K], this test only used at daytime pixel locations

Where $T_{MIR,w}$ and $\Delta T_{MIR-TIR,w}$ are the middle infrared brightness temperature and the middle infrared minus thermal infrared brightness temperature difference of the pixel in the background window respectively; $T_{MIR,pf}$ and $\Delta T_{MIR-TIR,pf}$ are the middle infrared brightness temperature and the middle



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infrared minus thermal infrared brightness temperature difference of the potential fire, θ_g is sunglint angle defined in Equation 14 and used here to attempt to ensure that the background pixels are in a region of the Earth unaffected by sunglint. The purpose of Tests 13a-13e is, as far as possible, to remove other fire pixels from the background pixel set and to thus select P_b as being representative of the uncontaminated ambient background signal. For nighttime observations, only Tests 13 a-d are used because Test 13e (the sun glint test) is not required at night, and the thresholds for Test 13c and 13d are lowered to 310 K and 10 K respectively.

Test 13f is only enacted during daytime processing and aims to exclude from use in the background characterisation step any remaining F1 down-scan anomaly pixels remaining in the MIR data (which by day comes from the BT_4 band). As outlined in Section 3.2, in the BT_4 data any pixels where F1 shows a down-scan anomaly have their brightness temperature provided by S7, as long as $BT_{S7} < 300$ K. Some BT_4 band pixels may therefore still come from F1 pixels that are affected by the down-scan anomaly, but these should be excluded from use in the background window characterisation step via Test 13f.

If the number of valid background pixels in set P_b is no less than 25% of the total number of background pixels (excluding from the total number of background pixels the potential fire pixel itself and the 8 immediate surrounding pixels; so 16 pixels for the smallest bw of 5) [and for the smallest b_W of 5 the total number of pixels is eight or more] then the background window statistical characterization process proceeds immediately using a window size b_W of 5. If this condition is not met, the window size b_W is increased through 7, 9, 11, 13,15, 17, 19 and 21 and the test repeated at each stage until the conditions are met. For each window size the 8 pixels spatially neighboring the potential fire pixel itself (along with the potential fire pixel being tested and any other potential fire pixels within the window, so the total excluded number of pixel will be 9) are excluded from the background pixel set, and thus for example the maximum number of background pixels in the case where $b_W = 7$ is 40 (i.e. $[7 \times 7] - 9$).

If an insufficient number of valid neighboring pixels is identified using even the 21 x 21 window, the background characterization is unsuccessful and the fire pixel is classed as "unknown". The approach inherently assumes that the spatially closest pixels to the potential fire pixel being tested have a signal most similar to that which the potential fire pixel would have in the absence of fire. The 21×21 background window maximum size, though somewhat arbitrary, ensures that the background signal is sampled within ~ 11 km of the potential fire pixel location, a scale that (Giglio



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et al., 2003) found empirically to be appropriate for preventing false alarms induced by the unrepresentative selection of background pixels.

Following Giglio *et al.* (2003) the number of valid background pixels within the background window is recorded as N_b . The number of pixels excluded from the background window is also recorded for later use in false alarm reduction and in defining the fire pixel confidence measure. The number of pixels (N_f) excluded as being "background fires" is set as the total number failing test 13c and test 13d, and the number excluded as being water/land pixels (in the land/ocean hotspot testing respectively) or cloud-contaminated pixels is recorded as N_w and N_c respectively. The MIR brightness temperature mean and mean absolute deviation of those spatially neighboring pixels that were rejected as background fires by test 13c and test 13d are also computed and denoted as \hat{T}_{MIR} and $\hat{\delta}_{MIR}$, respectively, since they can prove useful for rejecting certain 'warm surface' false alarms. As suggested by Giglio et al. (1999), we employ the mean absolute deviation as a measure of dispersion, rather than standard deviation, since it is more resistant to outliers (Huber, 1981). For contextual fire detection algorithms, this is a highly desirable feature since as far as possible contamination of the background window statistics by pixels containing cloud, water, or fire that have not been correctly identified as such is to be avoided.

For each potential fire pixel where a sufficient number of valid background pixels are identified (which is the vast majority or cases), the background characterisation is classed as successful and a number statistical measures computed from the valid background pixel set P_b . These are \bar{T}_{MIR} and σ_{MIR} , the respective mean and mean absolute deviation of T_{MIR} ; \bar{T}_{TIR} and σ_{TIR} the respective mean and mean absolute deviation of T_{TIR} ; and $\bar{\Delta T}_{MIR-TIR}$ and $\sigma_{\Delta T_{TIR-MIR}}$, the respective mean and mean absolute deviation of $\Delta T_{MIR-TIR}$, and by day $\bar{R}_{S1/MIR}$ the mean spectral radiance ratio of the Red channel (S1; 0.86 μ m) and the MIR channel (from BT₄) calculated over the valid background pixel set.

4.3.4 False Alarm Elimination (Stage 3)

Locations having a radiometrically strong spatial contrast across a geographic boundary in the S7 and S8 channels can potentially cause either errors of omission or commission for a contextual AF detection algorithm. Cloud/Water edge and desert boundaries are the most common features to



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induce such false alarms. Strong radiance from sun glint also causes false alarms. These false alarms need to be removed before FRP characterisation stage.

3.2.3.1 Cloud/water edge rejection (Stage 3a)

Potential active fire pixels located next to a "Cloud/water" pixel are currently recommended to be disregarded from further processing, since experience shows that a large proportion of these are false detections caused by the spectrally varying signatures of undetected cloud or land-water boundaries. If there is one or more cloudy pixels in the immediately surrounding 3×3 pixel window, the AF pixel is recommended to be rejected as cloud edge false alarm if the potential fire pixels MIR brightness temperature (BT) is less than a pre-set threshold 330 K for daytime from new BT₄ band and 310 K for nighttime. Similarly, if there is one or more water pixel in the surrounding 3×3 pixel window that are water pixels, and if the potential fire pixels MIR BT is less than the 330 K at daytime and 310 K at nighttime, then the AF pixel is rejected as a water edge false alarm. For the gas flare detection on the ocean, if there is one or more land pixel in the 3 × 3 window that are land pixel. These pixels discounted by these tests are flagged as CLOUDEDGE and WATEREDGE respectively. Whilst these test limit the number of false AF detections associated with unmasked cloud edges and water bodies, they will likely result in a number of "true" active fire pixels going undetected if they lie next to water bodies or cloud identified by the land/sea and cloud mask. As cloud and water masking with SLSTR become more mature, these tests can potentially be considered for removal from the AF detection algorithm.

Since only basic cloud masking and landcover-based water masking are used in the algorithm, there maybe undetected cloud and water pixels in the scene. These may cause false AF pixel detections, so further tests are used to remove any such false alarms.

For daytime pixels, the spectral radiance ratio between the MIR channel (which comes from BT₄ by day) and the S2 (RED waveband) channel is used, along with the radiance ratio between the MIR and TIR channels. These are employed in the test below. If a potential fire pixel has $BT_{MIR} < 330$ K and the ratio between the MIR and RED channel radiances OR that between the MIR and TIR channel radiance is less than a certain threshold - then the pixel will be removed and classed as CLOUDEDGE.

[
$$\frac{L_{MIR}}{L_{RED}} < p_1 \text{ OR } \frac{L_{MIR}}{L_{TIR}} < p_2 \text{] AND } BT_{MIR} < p_3$$
 (13f)



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Where
$$p_1 = 0.018$$
, $p_2 = 0.08$ and $p_3 = 330$ K

Where, since this test is applied at daytime pixels only, both L_{MIR} and BT_{MIR} come from BT₄.

For night-time pixels, if there are one or more cloud contaminated pixels in the background window (i.e. $N_c > 0$), the MIR and TIR spectral radiance ratio is employed in Equation 13g to further remove false alarms arising around cloud edges. If this ratio is less than 0.05 at the potential AF pixel under test, and the AF pixel has a BT_{MIR} < 310 K, then it is classed as CLOUDEDGE and removed from further processing.

$$\frac{L_{MIR}}{L_{TIR}} < p_1 \quad \text{AND } BT_{MIR} < p_2 \tag{13g}$$

Where
$$p_1 = 0.05$$
 and $p_2 = 310 \text{ K}$

It is possible that Test 13f-g can be discarded later on if a cloud mask optimized for the AF application is available to use.

3.2.3.2 Sun Glint Identification (Stage 3b)

By day, sun glint over small-unmasked water bodies or cloud, or even from areas of wet or sometimes bare soil, can increase the MIR pixel signal considerably above the LWIR signal and lead to false alarms. Such instances are rejected using a scheme based on a combination of those in Giglio (2003) and Zhukov *et al.* (2006), using the glint angle (θ_g) calculated between the sensors viewing direction and the direction of the sun rays specifically reflected from the horizontal (usually water) surface:

$$\theta_g = \cos \theta_v \cos \theta_s - \sin \theta_v \sin \theta_s \cos \theta_{\varphi} \tag{14}$$

Where, θ_{v} and θ_{s} are the view zenith angle and solar zenith angle respectively, and θ_{φ} is the relative azimuth angle between them.

In daytime conditions, the following conditions are then evaluated using data from the MIR (BT₄), RED (S2) and NIR (S3) bands:



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$$\theta_g < p$$
 (15a)

Where p = 2 [degrees]

$$\theta_g < p_1$$
 AND ($\rho_{RED} > p_2$ OR the Red Channel (S2) is saturated) (15b) Where $p_1 = 25$ [degrees], $p_2 = 0.15$, $p_3 = 0$

$$\theta_g < p_1 \text{ AND } \frac{L_{MIR}}{L_{RED}} < p_2$$
 (15c)

Where $p_1 = 15$ [degrees] and $p_2=0.01$

$$\theta_g < p_1 \text{ AND } L_{NIR} > p_2 \text{ OR the NIR Channel (S3) is saturated}$$
 Where p1=25, and p₂ = 175 mW.m⁻².sr⁻¹.nm⁻¹

$$\theta_g < p_1 \text{ AND } L_{RED} > p_2 \text{ OR the RED Channel (S2) is saturated}$$
 (15e)
Where p1=25, and p₂ = 150 mW.m⁻².sr⁻¹.nm⁻¹

Test 15a rejects as a false alarm all active fire pixels in the strongest region of potential glint (based on them having a very small glint angle). Test 15b rejects as a false alarm all active fire pixels having a far larger glint angle AND a high red (S2) channel reflectance. Note that in the case when the S2 channel saturated at certain pixels, those pixels will be treat as sunglint contaminated pixels. Test 15c also rejects daytime active fire pixels with a reasonably small glint angle and which show an insufficiently large ratio of MIR to RED spectral radiance (since only the MIR channel signal will be increased substantially by a fire, whereas both will be increased by glint).

Test 15d and 15e tests for very high clear sky land NIR spectral radiances – in order to identify forms of sunglint that lie outside of the normal sunglint angle range (e.g. from angled roofs or solar panels). The glint angle is restrained at < 25 degrees, and at any pixel where a high NIR spectral radiance is observed that is greater than the identified threshold or which is saturated - an 11×11 pixel window in the matching BT_4 band is considered potentially sun-glint contaminated and is masked out. It is possible that Test 15d-e can be discarded later on if a sun-glint mask optimized for the AF application is available for the algorithm to use.



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3.2.3.3 Desert Boundary Rejection (Stage 4c)

Over land surface, spatial boundaries between surfaces having significantly different ambient temperatures can pose problems for active fire detection algorithms, since the pixels on the hotter side of the boundary can sometimes be excluded from the background window tests in Stage 2. This can lead to a cooler background window and to the possibility that the hotter land surface pixels may then be falsely identified as active fire pixels. Investigation shows that this problem is largely confined to daytime observations, so this 'desert boundary rejection test' is only applied during daytime sub-scene analysis.

The method of Giglio et al. (2003) is used to reject such falsely detected AF pixels in these daytime subscenes. This uses outputs of Test 13c, d which quantify the number of pixels considered to possibly be 'fire pixels' that are present in the background window – as detailed in Section 3.3.3, along with a series of spectral thresholds. During the day, most desert areas that might lead to such false alarms are expected to have a high and relatively uniform surface temperature, expected to be above 335 K and with a standard deviation of around 0.5 K. For a background containing highly radiating fire pixels however, the T_{MIR-TIR} will be much larger (perhaps 40 K or above), and T_{MIR} will be somewhat larger at maybe 350 – 380 K. Tests 16a-16f from Giglio et al. (2003) exploit these characteristics as a means of rejecting daytime false alarms arising along "desert boundaries":

$N_f > p \times N_b \tag{16a}$

Where p = 0.1

$$N_f > p$$
 (16b)

Where p = 4

$$\rho_{\text{NIR}} > p$$
 (16c)

Where p = 0.15

$$\acute{T}_{MIR} < \mathbf{p}$$
(16d)

Where p = 345 [Kelvin]

$$\delta_{MIR} < p$$
 (16e)

Where = 3 [Kelvin]

$$T_{MIR} < \dot{T}_{MIR} + p \times \dot{\delta}_{MIR}$$
 (16f)



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Where p = 6

If all the above tests are satisfied, the active fire pixel is rejected as a false alarm caused by a hot desert boundary. This test is only applied to land pixels, and not oceanic areas, and only to subscenes considered to be daytime.

4.3.5 Fire Pixel Confirmation (Stage 4)

This stage uses the statistics from the potential fire pixel and the matching background window to confirm whether or not the potential fire pixel actually contains an active fire. An absolute threshold and a series of contextual thresholds, varied on the basis of the background window statistics, are employed.

3.2.4.1 Absolute Threshold Test and SWIR Detection Tests

Prior to the series of contextual tests, an absolute threshold test is used to identify the most radiant active fire pixels in a scene. Such a test maybe required for example if a high intensity fire pixel is located within a very large cluster of surrounding fire pixels, from which it has proven impossible to gain a sufficient number of valid background window pixels, or where the background window statistics have for some reason become contaminated by radiance from the immediately surrounding fires. We use the absolute threshold test defined by Kaufman *et al.* (1998) which is still used in the current MODIS AF detection algorithm. Because of the high BTs involved, these tests use F1 channel data at night, and by day use the BT₄ band data. A potential fire pixel is confirmed as a true fire pixel (even if at Stage 2 it was classed as "unknown") if:

 $T_{F1} > p$ by day (17a)

Where p = 360 [Kelvin]

and for night-time observations

 $T_{F1} > p$ by night (17b)

Where p = 326 [Kelvin]



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Thresholds in Test 17a and 17b are chosen on the basis that no ambient non-fire pixels are expected to attain these high brightness temperatures due to thermal emission and daytime near lambertian reflection of MIR wavelength solar radiation. However, as Giglio *et al.* (2003) pointed out, despite the high daytime threshold, by day the use of this test must be accompanied by adequate sun glint rejection, otherwise sunglint-induced false alarms may occur.

Since the S7 channel saturates above 311 K, both tests 16a and 16b are applied to data from the F1 channel rather than S7 (either F1 directly by night, or as part of BT₄ by day). However, due to the spatial offset between S7 and F1 (even after ortho-geolocation) the location of any AF pixel identified by these two tests applied to the F1 band data may be different than if the same AF were detected by S7. Furthermore, the shape and size of the same 'fire cluster' can also differ between F1 and S7 (see Figure 6), a 'fire cluster' being defined as a group of spatially-connected AF pixels (e.g. Figure 14a). For this reason, the FRP calculation and the reported coordinates of all AF pixels belong to a 'fire cluster' having one of more active pixels detected with Test 16a or 16b will be reported at the locations of the relevant F1 pixels (i.e. the F1 image domain), and these AF pixels are classified as "Detected by F1". The entire clustering approach is described in Section 3.3.7.

If some AF pixels in a fire cluster have a signal strong enough to be detected with the contextual detection approach as well as the absolute threshold test, then adjustment maybe needed to avoid double counting. As shown in Figure 12, two AF pixels (A and B) are detected by the absolute threshold test in this large fire cluster – and then other pixels are detected around them based on the "F1 contextual detection" approach described in Section 3.3.5 - but these pixels are also detected with the standard S7 based contextual detection tests, so those duplicated pixels should be removed to avoid the double counting issue. In the event of larger active fire clusters, there maybe two or more AF pixels in the cluster that are detected with the absolute threshold test, but they maybe spatially separated from one another. When the AF clustering around each of these absolute fire pixels is conducted (as detailed in Section 3.3.5), the same AF pixels surrounding them could be detected twice or even more. These duplicated AF pixels should also therefore be removed. Also shown in Figure 12, A and B denote the two AF pixels detected with the absolute threshold test in F1. When A is detected, the whole cluster of F1 AF pixel are subsequently also detected using the "F1 contextual detection" - including B which was also detected by the absolute threshold test. When B is detected, the whole cluster is also detected, including pixel A. Therefore, all these duplicated AF pixels should be removed from the final set of AF pixel results. In the case

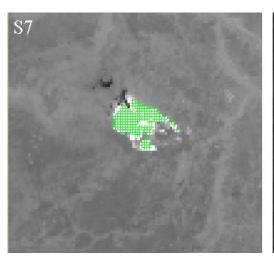


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of F1 "ON" or "OFF" this is done by removing the contextually detected AF pixels from the S7-detected AF pixel set <u>if</u> they belong to the same AF cluster as the F1 detection.



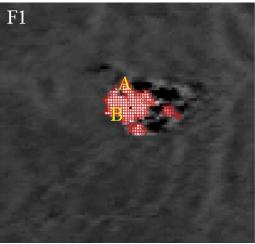


Figure 12. Night-time large-scale fire, containing two pixels (A and B) detected by the absolute threshold test. At left, the green markers represent the S7 contextual AF pixel detections, whilst at right the red markers represent the AF pixel detections in F1 based on the two absolute threshold detections at A and B and the identification of the other F1 AF pixels based on the clustering from these two. Most AF pixel detections are common between the left and right image. The S7 contextual AF pixel detections (green) are removed as they will otherwise be counted twice. A and B illustrate the AF pixel positions which are detected by the absolute threshold test.

At night, signals from the two SLSTR SWIR channels (S5 at 1.6 μ m and S6 at 2.25 μ m) can additionally be used to detect AF pixels. These SWIR channel signals should essentially be very close to zero over ambient temperature surfaces, but fires emit significantly at these wavelengths (see Figure 3) so these SWIR signals can be used to detect nighttime fire pixels. It is possible thats some of these detected pixels might be missed by the MIR-channel based tests, particularly since the pixel size of these SWIR channels is 500 m as opposed to 1 km for the MIR and TIR channels. Any fire will thus comprise a higher proportion of the SWIR pixel area. An additional absolute threshold test is used to make use of this capability, and the definition of "night" here is a pixel having $\theta_s > 90^\circ$ (solar zenith angle), slightly higher than that used in the prior-stages of the algorithm to avoid issues associated with twilight.

$$\left[L_{S6} > \left(p_1 + \overline{L}_{S6} + \left(p_2 \times n_{S6}\right)\right)\right] \text{ AND } (L_{S6} > p_3) \qquad \text{for night pixels only}$$
 (17c)



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Where $p_1 = 0.03 \text{ mW} \cdot \text{m}^{-2} \cdot \text{sr}^{-1} \cdot \text{nm}^{-1}$, $p_2 = 2$, and $p_3 = 0.25 \text{ mW} \cdot \text{m}^{-2} \cdot \text{sr}^{-1} \cdot \text{nm}^{-1}$

Where p_1 is a minimum spectral radiance set for the S6 channel signal and p_2 a multiplier. Only those 'valid' pixels having $L_{S6} > p_1$ contribute to the calculation of the mean (\overline{L}_{S6}) and median (n_{S6}) S6 channel statistics. \overline{L}_{S6} is the mean spectral radiance signal determined from the valid pixels from S6 at night over ambient cloud free land in the subscene, and n_{S6} is a measure of the S6 channel noise level (i.e. the median spectral radiance of the valid S6 pixels in the subscene). These tests are not applied in any other case than this "night" definition.

Within a bounding box on the Earth any AF pixel detected by Test 17c with the S6 also has to be confirmed by Test 17d using S5. Currently the bounding box covers the whole Earth, Latitude from -90 to +90 and Longitude from -180 to +180, but this maybe adjusted later to focus on areas such as the South Atlantic Anomaly (SAA) only if found appropriate.

$$\left[L_{S5} > \left(p_1 + \overline{L}_{S5} + \left(p_2 \times n_{S5}\right)\right)\right] \text{ AND } (L_{S5} > p_3) \qquad \text{for night pixels only (17d)}$$

Where $p_1 = 0.05 \text{ mW} \cdot \text{m}^{-2} \cdot \text{sr}^{-1} \cdot \text{nm}^{-1}$, $p_2 = 2$, and $p_3 = 0.24 \text{ mW} \cdot \text{m}^{-2} \cdot \text{sr}^{-1} \cdot \text{nm}^{-1}$

Where p_1 is a minimum spectral radiance set for the S5 channel signal and p_2 a multiplier. Only those 'valid' pixels having $L_{S5} > p_1$ contribute to the calculation of the mean (\overline{L}_{S5}) and median (n_{S5}) S5 channel statistics. \overline{L}_{S5} is the mean spectral radiance signal determined from the valid pixels from S5 at night over ambient cloud free land in the subscene, and n_{S5} is a measure of the S5 channel noise level (i.e. the median spectral radiance of the valid S5 pixels in the subscene).

Some night-time fires maybe detected by the SWIR band tests whilst failing to be detected by the MIR based tests. Figure 13 shows an example of this, where some fires are clearly identifiable in the SWIR band (S6 shown, circled in green) but not in S7 (MIR). There are also some fires that are detected by the MIR based tests (circled in red) but not by the SWIR tests. In the product output files, the MIR- and SWIR-based active fire detections are reported in different files, partly to cope with this but also because the SWIR active fire detections can then be presented on the 500 m grid and take advantage of the higher spatial resolution observations. In the MIR-detected AF pixel set in the final product only the FRP derived from the MIR radiance method is included (Equation 20), but in the SWIR-detected AF pixel set the FRP derived from the MIR radiance method and the SWIR radiance method (Equation 23) is included. The way the MIR radiance method FRP is distributed across the SWIR-detected AF pixels is detailed later in Section 3.3.7 on AF pixel clustering, but any MIR-detected AF cluster that does not have a matching SWIR-detected AF



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cluster is not included in the SWIR product output. Any SWIR-detected AF cluster for which a matching MIR-detected AF cluster cannot be found also has no MIR-radiance based FRP reported.



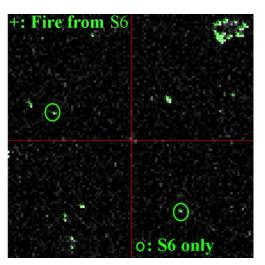


Figure 13. Night-time fires observed in the SLSTR S6 and S7 spectral bands. Red crosses show the AF pixels fire detected by the MIR-based contextual algorithm (based on S7 data), whilst green crosses denotes those detected using the SWIR-based thresholding method (based on S6 data). The background image on the left is in fact the brightness temperature difference between the S7 and S8 bands (which shows up AF pixels well), whilst that on the right is from the S6 band only. Note that most AF pixels in the scene are detected by both S7 and S6 active fire pixel detection approaches, but those circled in red at left are detected only by the S7 based AF detection procedures, whilst those circled at right in green are those detected only by the S6-based AF detection procedures. For those AF pixels detected by the contextual algorithm based on S7 data, only the FRP value from S7/F1 will be given.

Those active fire pixels detected with the F1 channel absolute threshold tests (Test 17a and 17b), do not require background characterization values to be confirmed as true active fire pixels. However, the background characterization is still required to estimate the FRP of those fires using the MIR radiance method (Equation 20), as well as its FRP uncertainty. In this case, the background characterization algorithm described in Section 3.3.2 is employed to characterise the MIR channel background statistics for those AF pixels detected using the F1 channel absolute threshold test. By night these MIR background statistics come from S7, and by day from BT₄. Note however that this means that it is possible to have AF pixels detected by these absolute thresholding tests even when the MIR channel background characterization process fails. Where



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this occurs, the background window should continue to be expanded beyond 21×21 pixels to a maximum of 51 × 51 pixels until at least 50 background pixels are available to perform the background characterization process and thus provide the estimate of background window spectral radiance required to estimate FRP and its uncertainty. Since all active fire pixels detected by the absolute thresholding tests will by definition be very large fires, the fact that the background statistics in these cases will come from areas further away from the fire pixel than normal (and so maybe less representative of the fire pixel background itself) is less important than for lower FRP AF pixels, due to the very large MIR fire signals involved (i.e. in Equation 20; $L_{f, MIR} >> L_{b, MIR}$). If even with the 51×51 pixel window upper limit, there remains insufficient background pixels to meet the 50 pixel criteria, which is expected to be a very rare occurrence, then the FRP should be estimated with $L_{b,MIR}$ taken as the median of the non-cloud, non-sunglint pixels of the sub-scene pixels having the same land/ocean classification as the fire pixel itself, and with the absolute uncertainty (δ_{L_h}) in the estimate of the fire pixel background radiance [used in Equation (20)] taken as that equivalent to a fixed uncertainty in the equivalent brightness temperature. Currently this value is set at 10 Kelvin (i.e. ±10 K uncertainty). The same absolute thresholding tests are used for land and ocean hotspots. For the equivalent S6 radiance derived FRP value (Eqn. 23) the background $L_{b,S6}$ value can be taken as the median of the S6 signal in the sub-scene.

3.2.4.2 Contextual Threshold Tests

For potential fire pixels from the set PF_f corresponding to land hotspots and where the background characterization was successful but the potential fire pixel MIR brightness temperature was not high enough to pass the absolute threshold test (17a or 17b), a series of contextual threshold tests are used to test confirmation of the potential fire pixel. These tests examine the T_{MIR} , T_{TIR} and $T_{MIR-TIR}$ potential fire pixel signals and compare these to the mean signals from the background window, with the exact thresholds adjusted to take into account the variability of the background window as measured by the mean absolute deviation. The contextual tests employed are:

$$L_{MIR/RED} > \bar{L}_{MIR/RED} \tag{18a}$$

$$\Delta T_{MIR-TIR} > \Delta \bar{T}_{MIR-TIR} + p \times \sigma_{\Delta T_{MIR-TIR}}$$
 (18b)

Where p = 3.2 at night and p = 5 in the day

$$\Delta T_{MIR-TIR} > \Delta \bar{T}_{MIR-TIR} + p$$
 (18c)



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Where p = 5.6 [Kelvin] at night and p = 10 in the day

$$T_{MIR} > \bar{T}_{MIR} + p \times \sigma_{T_{MIR}}$$
 (18d)

Where p = 3 at night-time pixels and p = 5 in the day

$$T_{TIR} > \bar{T}_{TIR} + p \tag{18e}$$

Where p = -4 [Kelvin]

Where $L_{MIR/RED}$ is the ratio between the spectral radiance by day in BT_4 and S2 of the potential fire pixel and $\bar{L}_{MIR/RED}$ is the mean of this ratio for the valid background pixels.

These tests are based on those in Giglio *et al.* (2003) and are adapted for SLSTR which performs differently because of its wideband 3.7µm MIR channel compared to MODIS' narrowband 3.9 µm channel for which the tests were originally designed. Test (18a) has been added by day to help in the removal of potential fire pixels caused by sunglints, since at such pixels both RED (S2) and MIR (BT4) radiances will be increased, whereas at fire pixels only the latter will be.

A daytime potential land fire pixel from PF_f will be classified as a confirmed fire pixel if:

{The absolute threshold test (17a) is true}

OR

 $\{\text{Tests } (18a) - (18e) \text{ are true}\},\$

Otherwise it is classified as a non-fire pixel.

A night-time potential land fire pixel from PF_f is classified as a true fire pixel if:



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{The absolute threshold Test 17b is true; OR both Tests 17c AND 17d are true}

OR

{Tests (18b) to (18d) are true},

Otherwise, the potential fire pixel is classified as a non-fire pixel

At pixels for which the background characterization fails, i.e. due to an insufficient number of valid background pixels being identified in the background window, only Tests 17a to 17d can be applied. In this case, if any of Tests 17a OR 17b are true OR both 17c AND 17d are true then the pixel is classified as a fire pixel, otherwise the pixel is classified as "unknown".

3.2.4.3 Gas flare / Volcano Classification

Gas flares and volcanoes are often detected by the procedures detailed here, as they also have high temperatures and thus can have high contrast with the surrounding background in the MIR and SWIR bands. It is useful to identify when a detected AF hotpot is more likely to be due to either of these phenomena rather than a landscape fire, because applications of these data differ. A global map showing the location of gas flares and volcanoes is provided for this purpose.

The list of active volcano locations was generated from https://catalog.data.gov/dataset/global-volcano-locations-database, whilst that for the gas flares was from https://www.skytruth.org/viirs/. If a detected active fire pixel falls within a set distance of a location identified as a gas flare or active volcano (as specified within either of these two datasets), then it is classified as a suspected industrial hotspot or volcanic hotspot respectively (otherwise classed as a suspected landscape fire). Since the location of the gas flares and active volcanos is provided in world geodetic system latitude and longitude coordinates, Equation (19) is used to calculate the distance (d) in kilometers between the identified hotspot pixel and any active volcano or gas flare location:

$$d = a\cos(\sin(lat_f) * \sin(lat_c) + \cos(lat_f) * \cos(lat_c) * \cos(lon_f - lon_c)) * p$$
(19)

Where p = 6371 [km] and lat_f and lon_f are the latitude and longitude of the detected hotspot pixel, and lat_c and lon_c are the latitude and longitude of the volcano/gas flares.

Where d for a particular detected AF pixel is less than a preset value, currently assumed as 10 km, then the hotspot is given the relevant classification as probable volcano or probable gas flare, otherwise it is classed as probable vegetation fire. The classification is placed in the relevant flag



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file. Users may also use the ratio of the S5 to S6 spectral radiance reported in the SWIR-detected AF pixel output file to classify fires and fire pixels into likely landscape fires or gas flares. The higher values of this ratio are more likely to relate to gas flare targets (see Fisher and Wooster, 2018; 2019).

4.3.6 Fire Characterisation (Stage 5)

At each confirmed active fire pixel on land which has a valid number of background pixels, the MIR-radiance based FRP is calculated from the MIR channel spectral radiance measure as:

$$FRP_{MIR} = \frac{A_{sampl}}{10^6 \cdot t_{MIR}} \left(\frac{S}{p}\right) \left(L_{MIR} - L_{b,MIR}\right)$$
 [MW]

Where
$$p = 3.327 \times 10^{-9} [\text{W} \cdot \text{m}^{-2} \cdot \text{sr}^{-1} \cdot \mu \text{m}^{-1} \cdot \text{K}^{-4}]$$

Where A_{sampl} is the ground projection area of the sensor FOV (in m²), which generally varies with view zenith angle (Figure 5). Two look up tables (LUTs) stating the value of A_{sample} (m²) to use in Equation 20 are provided for the two SLSTR near-nadir view MIR Bands (S7 and F1) in the auxiliary data files. These LUTs provide the value of A_{sample} according to the pixel index (0-1199) expressed in the original instrument domain (not the image domain). The indices file in the L1 data record are used to convert between the image domain and instrument domain pixel indices to select the correct A_{sample} value from the LUTs.

 σ is the Stefan-Boltzmann constant (5.67x10⁻⁸ W.m⁻².K⁻⁴), L_{MIR} is the spectral radiance of the fire pixel in the MIR channel (W·m⁻²·sr⁻¹·μm⁻¹) and \overline{L}_{MIR} is the mean spectral radiance of the valid background window pixels in the MIR channel (W·m⁻²·sr⁻¹·μm⁻¹), and p is the constant from the power-law linking radiance to 4th power of emitter temperature (W·m⁻²·sr⁻¹·μm⁻¹· K⁻⁴; see Section 2.3). The actual value of p will depend on the exact spectral response function of the SLSTR MIR spectral band, which is slightly different for each SLSTR instrument. The division by 10⁶ converts the FRP into units of MW.

The value of atmospheric transmission in the MIR band (τ_{MIR}) will be taken from a further LUT that uses the total column water vapour (TCWV) and the pixel view zenith angle as input search criteria (see Section 3.3.8).



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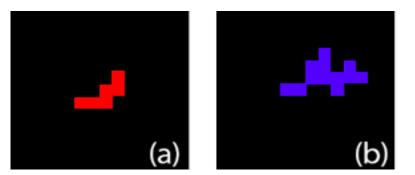
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4.3.7 Fire Pixel Clustering

Clustering groups of AF pixels into fire 'clusters' is the basis of swapping between use of the S7 and F1 channel data beyond the simple use of these two datasets in the creation of BT₄. This fire pixel clustering is required because of the S7 and F1 different pixel shapes and sizes makes the same fire appear different in the two MIR channel datasets (see example in Figure 6 and 7). Importantly, clusters (i.e. spatially connected groups) of active fire pixels are much more common than isolated single active fire pixels (e.g. see example in Figure 14). The clustering is also used to find the same fires in the MIR-based detections that appear in the SWIR-based detections, so that the MIR-radiance FRP can be reported at the locations of the SWIR-detected active fire pixels.

4.3.7.1 MIR Radiance Method FRP Retrieval at Fire Pixel Clusters



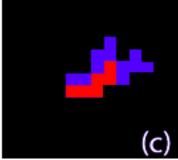


Figure 14. Example of an active fire (AF) pixel cluster. (a) AF pixel detections made using the MIR channel data from S7, where each AF pixel value still retains its BT_{MIR} value in the S7 band. (b) shows the AF pixel detection and clustering result using the alternative MIR channel data from F1. (c) The two sets of AF pixels overlain, showing their clearly different locations and cluster shapes.

The L_{MIR} value for an isolated or cluster-based active fire pixel for use in Equation (20) can only be read from S7 if that band has a BT_{MIR} value less than or equal to the S7 accuracy threshold (termed here $S7_{AT}$), currently taken as 311 K. For isolated AF pixels, or for AF pixels in clusters where all the AF pixels have a BT_{MIR} value lower than $S7_{AT}$, the L_{MIR} value for the AF pixel(s) can be derived from the S7 measurements (in the case of F1_OFF processing). However, in F1_OFF processing, for AF pixels where T_{MIR} from S7 exceeds the $S7_{AT}$ threshold and is less than absolute detection threshold (Test 17 a and b), the L_{MIR} values cannot be taken from S7 and values from F1



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must be used instead (note for For F1_ON processing, all L_{MIR} values come from F1). However, there are two issues associated with the F1_OFF situation as detailed earlier:

- 1) Spatial mis-registration between S7 and F1 (even after ortho-geolocation) means that the location of an AF pixel identified in S7 cannot simply be taken as the same location in F1. Study of a limited number of ortho-geolocated Level 1b data show that whilst the F1 and S7 active fire pixels are geometrically quite well matched close to the centre point of the nadir view scan, they can have an increased offset further away from the nadir point. Thus, whilst the F1 AF pixel locations matching S7 will certainly be close to the S7 AF pixel locations, their exact locations must be newly identified.
- 2) Differences in the shape and size of the S7 and F1 pixels mean that a cluster of AF pixels need to have their 'fire cluster' FRP retrieved from either S7 or F1, and not a mixture of both. Thus, if even a single S7 pixel in a cluster has an T_{S7} exceeding the $S7_{AT}$ threshold, all pixels in the cluster must have their FRP estimated using L_{MIR} values derived from F1.

There are two situations envisaged:

Situation 1 (common at night):

AF pixels whose T_{S7} exceeds the $S7_{AT}$ threshold but is less than absolute threshold, but which have values below this threshold at every one of their valid background window pixels.

In this case the Stage 2 background characterisation results taken from within the AF pixel's background window (Section 3.3.2) can still be used in the AF characterisation process - and specifically the mean and mean absolute deviation of the qualifying background window pixels in both the MIR (S7) and TIR (S8) bands.

Even in F1_OFF processing, the AF pixels still have to be identified in the F1 channel however because one or more of them in the cluster exceeds the S7_{AT} threshold. The approach to identify them employs a pixel clustering algorithm and an AF pixel detection approach that uses only the F1 channel. The approach is expressed via the eight stages detailed below:

i) Cluster the S7 band AF fire pixels into individual clusters. This can be done using "connected-component labelling" - an approach used in computer vision to identify connected regions in imagery (e.g. https://en.wikipedia.org/wiki/Connected-component_labeling). The method groups a spatially connected set of AF pixels into a single cluster, based on a series of Steps.



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Step 1: The AF detections made in S7 are used to create a binary image "mask" that has.

 $V=\{1\}$ where a pixel is an AF pixel

 $V={0}$ where a pixel is not an AF pixel.

Step 2: Starting from the first pixel in the binary image mask. Set a current label (C) counter to 1.

Step 3: If this pixel is an AF fire pixel [i.e. has $V=\{1\}$] and it is not already labelled with the current label value then give it the current label (C) and add it as the first element in a queue, then go to Step 4. However, if this pixel is not an AF pixel [i.e. has $V=\{0\}$] or it is already labelled, then repeat Step 2 for the next pixel in the binary mask.

Step 4: Pop out an element from the queue, and look at each of its neighbours in the binary image mask (based on any type of connectivity [up, down, left, right or diagonal]. For each neighbour that is itself an AF pixel (and which is not already labelled), give it the current label and add it to the queue. Repeat Step 4 until there are no more elements in the queue.

Step 5: Goto Step 3 for the next pixel in the binary image mask and increment current label (C) by 1.

Each AF cluster now has its individual AF pixels coded with a different label value, one for each cluster. The size of each cluster in samples and lines (F_x, F_y) is then recorded from the maximum and minimum sample and line positions of the AF pixels making up the relevant cluster, and the total number of AF pixels making up each cluster (N_f) is also stored, along with the number of AF pixels in the cluster having $T_{S7} > S7_{AT}$ (N_s) .

- ii) Using Equation (20), the FRP of those AF pixels in the cluster that have $T_{S7} \le S7_{AT}$ is calculated and its total stored as FRP_{S7}. The mean and mean absolute deviation of the qualifying background window pixels in S7 are also carried forward to the next step.
- iii) From the centre of the top left AF pixel in the cluster having $T_{S7} > S7_{AT}$, a window of size ($F_x + 10$) samples and ($F_y + 10$) lines around that location in the F1 band is selected. This window will be used to identify the corresponding AF fire pixels of the cluster in the F1 band. All F1 pixels within this window are checked to determine whether they are an AF pixel or not using the "F1 contextual detection" method. This is based on their F1 signals and the average of all mean and



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mean absolute deviation of the S7 background window pixels identified for the particular S7 AF pixel cluster. The tests used are:

During daytime:

{The absolute threshold test (16a) is true}

or

(if the $\sigma_{T_{S7}}^{'}$ (average of all mean absolute deviation of the MIR background window) >= 1 then:

$$T_{F1} > \bar{T}'_{MIR} + (p_1 \times \sigma'_{T_{MIR}}) + p_2$$
 (21a)

else

$$T_{F1} > \bar{T}'_{MIT} + \sigma'_{T_{MIR}} + p_3 (21b)$$

Where \bar{T}'_{S7} is the mean of all mean S7 pixel signals in the background window, $p_1 = 4.0$, $p_2 = 0.0$ and $p_3 = 4.0$.

At night:

{The absolute threshold Test 16b is true}

OR

{if the $\sigma_{T_{S7}}^{'} \ge 1$ then:

$$T_{F1} > \bar{T}'_{MIR} + p_1 \times \sigma'_{T_{MIR}}$$
 (22a)

ELSE

$$T_{F1} > \bar{T}_{MIR}^{'} + \sigma_{T_{MIR}}^{'} + p_2 (22b)$$

Where $p_1 = 3.0$ and $p_2 = 2.0$.

For F1_OFF:

iv) Once the AF pixels have been identified in the F1 band, cluster these using the same connected-component_labeling approach as in (i) above.



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- v) Identify the F1 cluster that matches the detected S7 cluster. In Figure 14c for example, the blue coloured AF fire cluster detected in F1 should be identified as the same cluster as the red coloured cluster detected in S7. The same connected-component labeling as in (i) can be used to identify whether the two clusters are connected. If they are connected, then the blue F1 fire cluster will be regarded as the corresponding fire cluster to that shown in red in S7.
- vi) Assuming that the total FRP for a fire cluster should be the same whether it is measured in F1 or in S7, use the F1-derived FRP values to calculate the FRP for the F1_ON case, and report the F1 location for all the AF pixels. For F1_OFF, for pixels where $T_{S7} > S7_{AT}$, the FRP is retrieved from F1 in the case where a cluster contains S7 pixels with $T_{S7} > S7_{AT}$, but the FRP is redistributed back to the matching S7 clusters AF pixel locations in order to ultimately have all FRP records corresponding always to AF pixel locations detected in S7 (and not F1). To accomplish this, the total FRP of the cluster is calculated from the clusters F1 AF pixels using Equation 19 (and the background window parameters measured in S7) and recorded as FRP_{F1}.
- vii) For F1_ON, the FRP recorded as FRP_{F1} for an F1 detected cluster, and the location of fire pixels are reported in F1 domain. For F1_OFF, then the FRP_{F1} needs to be distributed around the S7-detected AF pixels of the matching S7 cluster. First, in the S7 cluster AF pixels with $T_{S7} \le S7_{AT}$ have their FRP coded as that derived earlier using the S7 band data. The FRP total of these pixels is termed FRP_{S7}. Then, the remaining S7 pixels that have $T_{S7} > S7_{AT}$ are given their FRP value (FRP_{F1}- FRP_{S7})/N_s. The total FRP of the cluster in S7 will therefore be the same as recoded in the matching F1 cluster.

The approach is illustrated in Figure 14, assuming that the AF pixels are detected in S7 and F1 as shown in Figure 14a and 14b respectively using the methods outlined above. The corresponding S7 and F1 AF clusters partly but not wholly overlay, as shown in Figure 14c, due to the differing pixel sizes and shapes and the spatial offset between the S7 and F1 channels. The total FRP of the AF cluster detected in F1 is calculated (as FRP_{F1}), then the total FRP for those AF pixels detected in the matching S7 cluster that have $T_{S7} \leq S7_{AT}$ (FRP_{S7}) is subtracted from this value. The result of this calculation is divided by the number of S7 cluster AF pixels having $T_{S7} > S7_{AT}$ (N_s) and the final value stored as the FRP for each of the N_s pixels whose $T_{S7} > S7_{AT}$. In this way, all the AF pixels detected in the S7 cluster have a valid FRP value, and the total FRP recoded for them is equal to FRP_{F1}. For example, in Figure 14a there are six AF pixels identified in S7, and two of these have an $T_{S7} > S7_{AT}$ which means their FRP cannot be accurately calculated from their saturated S7 signals. The remaining four S7 pixels have $T_{S7} \leq S7_{AT}$ and thus can have their FRP



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accurately calculated from their unsaturated S7 signals. We assume in this example that the total FRP of these four pixels recorded in S7 (i.e. FRP_{S7}) is 40 MW for example. Now the corresponding fire cluster detected in F1 (Figure 14b) has twelve AF pixels within it, and lets say that these have a total FRP of 300 MW as calculated via their F1 signals (i.e. FRP_{F1}). In the final FRP output, at the location of the two S7 pixels having $T_{S7} > S7_{AT}$ the FRP is recorded as (300-40)/2=130 MW each.

viii) The MIR radiance FRP uncertainty value for the cluster is calculated using Equation (25a) along with the AF pixel spectral radiances from F1, whilst the background window values still come from S7.

For F1_ON, the approach for retrieving the FRP value for each fire pixel is very similar to the eight stage description for Situation 1 above, except for the following minor changes:

- i) Cluster the S7 band AF fire pixels into individual clusters.
- ii) We do not need the FRP value from S7 AF pixel detections, since in this case all the FRP and fire pixel positions will be reported in F1 domain. However, the mean and mean absolute deviation of the qualifying background window pixels in S7 for all the pixels in the fire cluster will be carried forward to the next step.
- iii) Centre at the top left AF pixel in the cluster, notice this does not have to be the top pixel having a $T_{S7} > S7_A$. Select a window of size (Fx + 10) samples and (Fy + 10) lines around that location in the F1 band. This window will be used to identify the corresponding AF fire pixels of the cluster in the F1 band. The method to detect the fire will be the same as for Situation 1.
- iv) Once the AF pixels have been identified in the F1 band, cluster these using the same Connected-component_labeling approach as in (i) above.
- v) Identify the F1 cluster that matches the detected S7 cluster. In Figure 14c for example, the blue coloured AF fire cluster detected in F1 should be identified as the same cluster as the red coloured cluster detected in S7. The same connected-component-labeling as in (i) can be used to identify whether the two clusters are connected. If they are connected, then the blue F1 fire cluster will be regarded as the corresponding fire cluster to that shown in red in S7.
- vi) Assuming that the total FRP for a fire cluster should be the same whether it is measured in F1 or in S7, use the F1-derived FRP values to calculate the MIR radiance FRP using Equation (20).



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vii) The FRP recorded as FRP_{F1} for an F1 detected cluster, and the location of fire pixels are reported in F1 domain. The corresponding S7 cluster will be discarded as all the location and FRP for the fire cluster are reported in F1 domain already.

viii) The FRP uncertainty value for the cluster is calculated using Equation (25a) along with the AF pixel spectral radiances from F1, whilst the background window values are still come from S7. If a corresponding F1 fire cluster cannot be found through this approach, the fire position and FRP will be reported in the S7 domain.

Situation 2 (common by day):

For AF pixels having $T_{S7} > S7_{AT}$ when measured in the S7 channel, and for which their background window also contains pixels having $T_{S7} > S7_{AT}$ in the same channel, the background window characterisation of Stage 2 needs to be conducted using the new BT₄ data in place of S7. Then the same Stages 3 and 4 are also applied, but to BT₄ instead of S7. Once all the AF pixels are detected, the clustering method outlined in situation 1 is used to retrieve the FRP from the F1 channel data.

4.3.7.2 SWIR Radiance Method FRP Retrieval at Fire Pixel Clusters

For most active fire pixels detected at night, two FRP values can be provided. The two values come from application of the MIR and SWIR radiance methods of FRP derivation, and we term here FRP_{MIR} and FRP_{SWIR} respectively (Equation 20 and 23). Users are recommended to use FRP_{SWIR} for suspected gas flares and FRP_{MIR} for suspected vegetation fires -see Fisher et al (2018; 2019). Classification of the detected hotspot pixels into these two classes is provided in the product, based on pre-set geographic coordinates, but it is also possible for users to consider their own interpretation of a hotspots class (see below).

Active volcanoes are also detected by the hotspot detection algorithm, and present a very wide range of temperatures, including below the minimum threshold for accurate application of the FRP_{SWIR} and FRP_{MIR} methods (Wooster et al., 2005; Fisher and Wooster, 2018). Thus, whilst these FRP metrics will be useful in assessing thermal changes at active volcanoes, they are unlikely to provide unbiased estimates of active volcano radiative power output.

As introduced in Section 1.2, users are provided with the S5 to S6 spectral radiance ratio and can use this to interpret the geographic based hotspot classification of hotspots if they so wish. In particular they may wish to make their own interpretation of which land-based hotspots are in fact



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gas flares and which are landscape fires – and thus which of the FRP_{MIR} and FRP_{SWIR} metrics to select as optimum. This maybe preferrable since industrial gas flaring locations will change over time so a static map alone cannot provide a 100% accurate classification. The ratio of the S5 and S6 spectral radiances is thus perhaps better means by which the classification can be made (Fisher et al., 2018, 2019), and is presented in the final SWIR-based AF detection product file. Values of this ratio greater than a certain threshold are likely to be gas flares, whereas values less than this are likely to be landscape fires or other non-flaring hotspots (see Product Handbook for recommended threshold). As Fisher et al. (2018) detail, FRP_{SWIR} for landscape fires tends to be low-biased, whereas FRP_{MIR} for gas flares tends to be low-biased. Volcanoes could in theory be below or above the aforementioned S5 to S6 spectral radiance ratio threshold, but are likely to be below. However, they can be quite easily identified by the geographic mask classification since volcanoes do not typically change their location over time.

The MIR radiance FRP (appropriate for gas flares) is calculated with Equation (20). The SWIR radiance FRP (appropriate for gas flares) is calculated with the similar Equation (23), fed with the SWIR spectral radiance signals from the S6 channel:

$$FRP_{SWIR} = \frac{A_{sampl}}{10^6 f_{SWIR}} \left(\frac{S}{p}\right) \left(L_{SWIR} - L_{b,SWIR}\right)$$
(23)

Where p is the S6 equivalent of the factor used in (20) [W·m⁻²·sr⁻¹· μ m⁻¹· K⁻⁴]. This is currently calculated at 6.1 x 10⁻⁹ W·m⁻²·sr⁻¹· μ m⁻¹· K⁻⁴ but will depend on the exact spectral response function of the SLSTR MIR spectral band, which is slightly different for each SLSTR instrument. $L_{b,SWIR}$ is the background radiance estimate, taken as the median spectral radiance of all S6 pixels in the subscene. If this calculation of $L_{b,SWIR}$ is negative then it should be reset to zero before use in Equation [23].

Where A_{sampl} is the ground projection area of the sensor FOV (in m²), which generally varies with viewing angle. A look up table (LUT) stating the value of A_{sample} (m²) to use in Equation 23 will be provided for the SLSTR nadir view S6 band in the auxiliary data files, and this will provide the value of A_{sample} according to the pixel index (0-2399) expressed in the original instrument domain (not the image domain). The indices file in the L1 data record is used to convert between the image domain and instrument domain pixel indices to select the correct A_{sample} value from the LUTs. The value of atmospheric transmission in the S6 channel (τ_{SWIR}) will be taken from a further LUT that uses the total column water vapour (TCWV) and the pixel view zenith angle (see Section 3.3.8).



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Since there exist remaining spatial offsets between the MIR channels and S6 even when the line and sample number of the S6 detected pixel is divided by two, the same cluster-based searching strategy detailed in Section 3.3.7 for the F1 and S7 channels is used to identify the corresponding active fire cluster in the MIR channel data that relates to the cluster detected in S6. This clustering is applied after the S6 line and sample number is divided by two in order to give a matching coordinate for the estimated MIR pixel location. The final AF location and FRP will be reported in the 500 m spatial resolution S6 domain using the clustering algorithm outlined in Section 3.3.7.

Since the pixel size of the S6 pixels is nominally 500 m, and since there remain spatial offsets between the S6 and S7 channels, the data of the MIR-detected AF pixels will be redistributed back to the S6 grid using the cluster based algorithm outlined in Section 3.3.7. Firstly, the AF pixels from S6 will be grouped into fire clusters, then the coordinate of S6 will be divided by 2 to find the corresponding location in the MIR data (S7 channel since this is night-time only). After this, the cluster and search procedure of Section 3.3.7 is enacted to find the corresponding fire cluster in S7 which matches that detected in S6. Finally, the FRP for that fire cluster derived using the MIR-radiance method (FRP_{MIR}) is redistributed back to the S6-detected AF pixels of the matching cluster (on the 500 m grid). The re-distribution of FRP_{MIR} is simply based on the distribution of FRP_{SWIR} among the SWIR-detected active fire pixels of the cluster. So, for example if a SWIR-detected AF cluster contains two AF pixels, and one has a SWIR-derived FRP of 20 MW and the other 30 MW (total FRP = 50 MW), and the total FRP_{MIR} of the matching AF cluster is 60 MW, then the corresponding FRP_{MIR} given to the two S6 pixels is $(20/50 \times 60 = 24$ MW and $(30/50 \times 60 = 36$ MW respectively).

In most cases of nighttime fires, as shown in Figure 13, the active fire pixels will be detected by both the MIR-based and SWIR-based tests. However, if a fire was detected by the MIR tests but not by the SWIR tests at night then its FRP is not reported in the SWIR-AF pixel detection output. Any fire conversely that is detected by the SWIR-tests but where the matching MIR-AF pixel cluster cannot be identified will have no MIR-radiance based FRP reported.

4.3.8 Atmosphere Transmittance

Wooster et al. (2015) demonstrate that the primary atmospheric effect of significance with regard to FRP derivation is the non-unitary atmospheric transmittance (τ_{MIR}) in the MIR atmospheric window. The impact of upwelling atmospheric path radiance and reflected downwelling atmospheric radiance can be neglected due to their similarity at the fire pixel and surrounding



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background pixels and the subtraction of these signals during FRP calculation. A similar situation exists for the SWIR-derived FRP.

Values of atmospheric optical depth (t) have in the MIR and SWIR bands been pre-computed as a function of the total column water vapour (TCWV). These values (t_{MIR} and t_{SWIR} respectively) are shown in Table A1. Corresponding values of atmospheric transmittance in the MIR and SWIR (t_{MIR} and t_{SWIR} respectively) are then derived from these pre-computed optical depth values, including at different view angles.

For each value of TCWV, the mean optical depth was estimated for varying CO₂ concentrations of 380 to 420 ppmv, aerosol optical thicknesses between 0.2 and 1.0 for various aerosol types, different atmospheric vertical profiles and surface brightness temperatures. The ozone concentration was set to 354 DU. Atmospheric transmittance in the MIR (τ_{MIR}) is then estimated from the values in Table A1 using the following expression, as a function of the satellite view zenith angle θ_{ν}

$$\tau_{MIR} = exp\left(\frac{-t_{MIR}}{cos(A + Bq\theta_v + C(q\theta_v)^2)}\right)$$
(24)

with $q = \pi/180$. Values of A, B and C have been adjusted to fit exactly the variations of t_{MIR} with θ_{ν} . The appropriate optical depth (t_{MIR}) for use in Equation 24 is linearly interpolated from the Tabel A1 LUT according to the actual water vapour concentration U_{H2o} .

This same procedure is used to estimate (τ_{SWIR}) and the equivalent LUT for the SLSTR SWIR band (S6) is provided in Table A2.

4.3.9 FRP Uncertainty Estimation

The FRP uncertainty estimation (Stage 6) for the FRP_{MIR} measure is described in this section.



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The estimation of FRP via the MIR radiance method of Equation (20) is subject to random errors resulting from uncertainties in the value of a and τ and in the assessment of L_{MIR} and $L_{b, MIR}$. Assuming that these are uncorrelated, the corresponding uncertainty (δ_{FRP} ; MW) in FRP is:

$$\delta_{FRP_{MIR}} = FRP_{MIR} \sqrt{\left(\frac{\delta_a}{a}\right)^2 + \left(\frac{\delta_{\tau_{MIR}}}{\tau_{MIR}}\right)^2 + \left(\frac{\delta_{L_{MIR}}}{L_{MIR} - L_{b,MIR}}\right)^2 + \left(\frac{\delta_{L_{b,MIR}}}{L_{MIR} - L_{b,MIR}}\right)^2}$$
(25a)

Where δ_a is the absolute error (in MW) resulting from the power law approximation to the Planck function used in deriving Equation (20). Assuming a fire temperature range of 675 to 1300 K the value of $\frac{\delta_a}{a}$ is about 0.1 at one sigma (Wooster et al., 2005)

 δ_{τ} is the absolute error in the estimation of atmospheric transmission in the channel used for FRP derivation: (i) the uncertainty on the actual atmospheric vertical composition except the water vapour concentration and (ii): the atmospheric correction error resulting from the uncertainty on the water vapour concentration. This total error writes:

$$\delta_t = \sqrt{\delta_b^2 + \delta_{H_2O}^2} \tag{25b}$$

The former error is

$$\delta_b = 10^{-5} \tau (816.1 - 27.5\theta_v + 2.3\theta_v^2 - 0.0585\theta_v^3 + 0.0005\theta_v^4$$
 (25c)

And the latter

$$\delta_{H_2O} = \frac{\partial \tau}{\partial U_{H_2O}} \sigma_{U_{H_2O}} \tag{25d}$$

with

 $\sigma_{U_{H_2O}} = 0.24287 + 0.11172 U_{H_2O} - 0.00090 U_{H_2O}^2$ (25e) and $\frac{\partial \tau}{\partial U_{H_2O}}$ taken as -0.00404 using the data of Table A1.



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Equation (25e) holds for the total column water vapour field delivered by ECMWF.

 $\delta_{L_{MIR}}$ represents the absolute radiometric error resulting from the combination of: (*i*) the radiometric noise (σ_n) of the SLSTR MIR channel, (*ii*) the random errors (ϵ_{b1}) related to the Level 1b processing effects and finally (*iii*) the instrument saturation above 500K. For this latter effect, the error term $(\sigma_{\tilde{l}_s})$ corresponds to the uncertainty on the estimation of the radiance \tilde{l}_s that would have been observed if SLSTR were not subject to saturation. Systematic errors such as calibration uncertainty are not included in this term. This error is

$$\sigma_{L_f} = \sqrt{(\sigma_n)^2 + (\tilde{l}\epsilon_{b1})^2 + (\sigma_{\tilde{l}_s})^2} \ \sigma_{L_f} = \sqrt{(\sigma_n)^2 + (\tilde{l}\epsilon_{b1})^2 + (\sigma_{\tilde{l}_s})^2}$$
(25f)

The value of σ_n is taken from the level 1b product, it set as 0.01 at present. $\tilde{I}\epsilon_{b1}$ represents the fractional uncertainty induced by the image processing chain used to deliver the version of the SLSTR data input into the algorithm. At present this is considered negligible.

 $\sigma_{\tilde{I}_s}$ is the error associated with the saturated pixel default radiance value. This term is non-zero only over saturated F1 pixels, which with SLSTR are expected to be extremely rare. $\sigma_{\tilde{I}_s}$ is set at 0.05 over saturated F1 pixels, and set to 0 elsewhere.

 $\delta_{L_{b,MIR}}$ is the atmospherically corrected standard deviation of the background radiance (i.e. the MIR channel background radiance of the fire pixel divided by the MIR atmospheric transmittance).

The estimation of the FRP uncertainty associated with the SWIR radiance method of Equation (23) follows that used for the MIR radiance method:

$$\delta_{FRP_{SWIR}} = FRP_{SWIR} \sqrt{\left(\frac{\delta_a}{a}\right)^2 + \left(\frac{\delta_{\tau_{SWIR}}}{\tau_{SWIR}}\right)^2 + \left(\frac{\delta_{L_{SWIR}}}{L_{SWIR} - L_{b,SWIR}}\right)^2 + \left(\frac{\delta_{L_{b,SWIR}}}{L_{SWIR} - L_{b,SWIR}}\right)^2} \quad (26a)$$



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Where δ_a is the absolute error (in MW) resulting from the power law approximation to the Planck function used in deriving Equation (23). Assuming a gas flares temperature range of 1600 to 2200 K the value of $\frac{\delta_a}{a}$ is about 0.1 at one sigma.

 δ_{τ} is the absolute error in the estimation of atmospheric transmission in the SWI channel used for FRP derivation: (i) the uncertainty on the actual atmospheric vertical composition except the water vapour concentration and (ii): the atmospheric correction error resulting from the uncertainty on the water vapour concentration. This total error writes:

$$\delta_t = \sqrt{\delta_b^2 + \delta_{H_2O}^2} \tag{25b}$$

The former error is

$$\delta_b = 10^{-5} \tau (620.5 - 28.6 \theta_v + 2.5 \theta_v^2 - 0.0645 \theta_v^3 + 0.0005 \theta_v^4)$$
 (25c)

and the latter

$$\delta_{H_2O} = \frac{\partial \tau}{\partial U_{H_2O}} \sigma_{U_{H_2O}} \tag{25d}$$

with again

 $\sigma_{U_{H_2O}} = 0.24287 + 0.11172 U_{H_2O} - 0.00090 U_{H_2O}^2$ (25e) for the total column water vapour field delivered by ECMWF

and now $\frac{\partial \tau}{\partial U_{H_2O}}$ taken as -0.00087 using the data of Table A2.

Similar to the uncertainty on the MIR-derived FRP, the third term inside the square root of Equation [26a] is taken as the uncertainty of the SWIR radiance measurements – taken at present as 0.03 mW.m⁻².sr⁻¹.nm⁻¹.

 $\delta_{L_{b,SWIR}}$ is the atmospherically corrected standard deviation of the background radiance. Given the fact that the ambient background emits no radiance at the S6 channel wavelengths, this is also – taken at present as 0.03 mW.m⁻².sr⁻¹.nm⁻¹.



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4.4 Oceanic and Coastal Hotspots

Whilst the pre-launch active fire detection and FRP retrieval algorithm of Wooster *et al.* (2012) was designed only to detect and characterize hotspots on the land surface, the detection of gas flares in coastal and oceanic regions is desirable. Gas flare detection over the ocean and coastal areas are therefore conducted at night using the SLSTR SWIR bands with Equation 17 (c) and (d). All the cosmetic pixels from S5 and S6 bands are removed to prevent them being detected as gas flares over the ocean.

The FRP of ocean hotspots are calculated with Equation 23 since they are all assumed to be gas flares and thus it is relevant to have their FRP calculated using the SWIR radiance method, and their FRP uncertainty is also retrieved.

5 PRACTICAL CONSIDERATIONS

5.1 Cloud masking

Cloud masking is essential to an active fire product, due to the fact that optically thick clouds make it impossible to identify active fires through passive remote sensing, and solar reflected MIR radiation from certain clouds can appear similar to fire signals. Thus, some cloud-contaminated pixels will likely be falsely classified as fires if they are not masked out prior to active fire detection.

However, it is also the case that some cloud masking algorithms use tests (e.g. those based on thermal channel differences) that can erroneously identify fire-related hotspot pixels as cloud. Furthermore, some cloud mask algorithms also identify optically thick smoke as cloud, even though fire detections can typically be made through smoke since it is relatively transparent at MIR wavelengths (unlike meteorological cloud). Therefore, care should be taken in the deployment of the generic SLSTR cloud mask with regard to its use in masking the SLSTR observations prior to Stage 1 of the fire detection algorithm (Figure 8), and it is possible that only some of the cloud masking tests will be relevant to masking data prior to application of the fire detection and characterization algorithm.



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To try to ensure that the cloud mask available for SLSTR is of maximum relevance to the fire product, over the land it can potentially be enhanced or even replaced by a further simple mask developed for the fire product based on the following simple tests taken from Giglio *et al.* (2003b):

For daytime

```
 \{ (\rho_{RED} + \rho_{NIR} > 0.9) \text{ or } T_{TIR} < 265 \text{ K} \}  or  \{ (\rho_{RED} + \rho_{NIR} > 0.7) \text{ and } T_{TIR} < 285 \text{ K} \}   \{ (abs(T_{MIR} - T_{TIR}) > 4) \text{ and } T_{TIR} < 273 \text{ K} \}
```

For nighttime

 $\{ T_{TIR} < 273 K \}$

The same tests, possibly with adjusted thresholds, can also be applied over oceanic areas.

5.2 Water masking

Given the contextual nature of the AF detection algorithm, when analyzing potential land AF pixels it is important to accurately exclude water and mixed land-water pixels during the background characterization stage. Such pixels are usually cooler than adjacent land pixels during the day. Unknowingly including water and mixed land-water pixels in the background window can cause false alarms due to altered brightness temperature signals. Also contributing to this phenomenon is the fact that compared to land, water pixels frequently have lower values of $\Delta T_{MIR-LWIR}$ due to more similar spectral emissivity's than land. Water and mixed land-water pixels contaminating the background window can therefore decrease $\Delta \bar{T}_{MIR-TIR}$ and thus increase the likelihood that a false alarm AF detection will occur. Therefore prior to the AF detection algorithm being applied, a set of tests is used in daytime areas to identify any additional water contaminated pixels that have not been masked out by the land-water mask. Following Giglio *et al.* (2003), we use a simple test based on the 0.86 μ m and 2.1 μ m reflectance (ρ) values, and the Normalized Difference Vegetation Index (NDVI) of the valid background pixels, where NDVI=(ρ_{NIR} - ρ_{NI



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 $\rho_{RED})/(\rho_{NIR}+\rho_{RED}).$ This particular combination was chosen to reduce the likelihood of confusing cloud shadows and burn scars, which also have low surface reflectance, with water. Valid background pixels having $\rho_{S6}<0.05$ and $\rho_{NIR}<0.15$ and NDVI <0 are considered to be water pixels. The number of such pixels is denoted as $N_{uw}.$ If the absolute threshold test (Section 3.3.5) is not satisfied and $N_{uw}>0$, the tentative fire pixel is rejected and classified as a non-fire pixel, otherwise it is classified as an active fire pixel.

6 ASSUMPTIONS AND LIMITATIONS

Main Assumptions

- Unsaturated, spatially co-located data from all SLSTR channels required by the algorithm are available.
- Pixels containing cloud and water bodies have been masked out before the algorithms application, though pixels containing smoke remain unmasked.
- The SLSTR radiance measurements are well calibrated across the full range of spectral radiances measured over active fire pixels and background pixels.
- Duplicate pixels created during the data remapping process at level 1 will be identified as such so that duplicate fire pixels can be removed if desired.
- The area of the Earth (in m²) covered by each SLSTR pixel to be processed is available to the algorithm.
- An estimate of the atmospheric transmissivity in the SLSTR MIR channel is available to the algorithm, together with an estimate of the uncertainty in this value.
- The algorithm ignores the effects of increased aerosol and trace gas concentration above fires on the atmospheric transmissivity in the MIR channel (and indeed other channels).
- The fire and background emission are isotropic and approximate greybodies.



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- The Planck's radiation law is well approximated by a fourth order power law in the wavelengths that the MIR channel of SLSTR is sensitive to.
- The pixel fire fraction can be neglected in the calculation of FRP.
- The fire pixel background radiance can be estimated from the radiance of the surrounding non-fire pixels.

Main Limitations

- The smallest/most weakly burning component of the fire regime will not be able to be detected with the moderate spatial resolution SLSTR instrument (fires covering down to perhaps 10⁻³ 10⁻⁴ of a pixel will however be detectable).
- The FRP for a fire pixel may have some dependence on where the sub-pixel sized fire lies within the pixel area.
- The overpass time of the Sentinel-3 satellite is non-optimum for capturing the peak of the fire diurnal cycle (Figure 2).



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7 INPUTS AND OUTPUTS

Inputs (at each SLSTR pixel)

- Cloud masked radiances and reflectances in the SLSTR Optical Channels (S1 to S6)
- Radiances and brightness temperatures in the SLSTR Thermal Channels (S7 to S9 & F1 and F2)
- Pixel coordinates (latitude/longitude)
- Water vapor fields
- Satellite zenith angles
- Solar zenith angles
- Ground pixel (km²)
- Mask representing the land area potentially capable of supporting land based hotspots (i.e. the land surface with larger lakes and rivers masked out).
- Mask representing the location of industrial hotspots and volcanically active zones
- Mask representing the area of oceans and large lakes that might potentially be the sites of
 offshore gas flares.

Suggested Outputs

At each detected fire pixel

- Hotspot pixel coordinates (column/row and latitude/longitude)
- Hotspot date and time
- FRP (MW)
- FRP uncertainty (MW)
- Fire pixel confidence
- Hotspot class (land hotspot in industrial region, land hotspot in volcanic region, vegetation fire, oceanic hotspot, detected from F1, unknown, Not Processed due to S7 background saturation)
- Atmospheric transmittance
- Ground pixel area (km²)
- Size of background window (b_w)
- Satellite zenith angle ()



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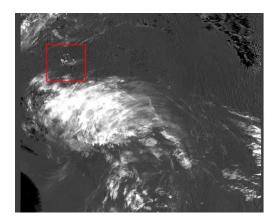
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- MIR brightness temperature of fire pixel
- LWIR brightness temperature of fire pixel
- Mean MIR brightness temperature of the valid background window pixels
- Mean LWIR brightness temperature of the valid background window pixels

Raster mask covering the enLWIRe SLSTR scene classified into the following classes: cloudy land pixels; cloud free land pixels; cloudy water pixels; cloud free water pixels; confirmed fire pixels coded according to the hotspot class (land hotspot in industrial region, land hotspot in volcanic region, vegetation fire, oceanic hotspot, unknown). This raster mask can compress to a small size and be similar to that used in the MOD14 and MYD14 MODIS Fire Products (Giglio *et al.*, 2003).

8 EXAMPLE VISUAL EXAMINATION

SLSTR-3A was launched on 16 Feb 2016. Soon after the pre-launch algorithm of Wooster *et al.*, (2012) was tested with real SLSTR data, and this led to the updated algorithm in Xu et al. (2020). Figure 15 shows an example application to SLSTR imagery collected at 05:15 UTC on 13 May 2016, when a large fire affected Fort McMurray, Alberta (Canada). Almost all the active fire pixels appear to be correctly identified in this case.



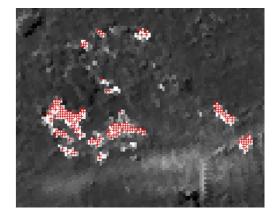


Figure 15. Example of the outputs of the SLSTR active fire detection process applied to night-time S3A data of the Fort McMurray fire in Alberta, Canada. Data were captured by SLSTR at 05:15 UTC on 13 May 2016. Background image is the MIR – LWIR brightness temperature difference scene, with the zoom around the Fort McMurray region at right. Red crosses indicate the locations of detected active fire pixels.



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In terms of oceanic hotspots, the following figures show examples of these detections.

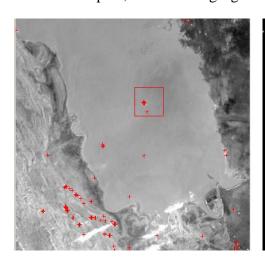
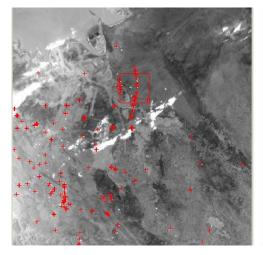




Figure 16. Example of oceanic gas flares detected at night in Iraq. Data is from a night-time S3A overpass at 18:48 UTC on 24 May 2016. Background image on the left is the MIR – TIR brightness temperature difference image, whilst that at right is the matching S6 spectral radiance image. Red crosses indicate locations of detected hotspot pixels.



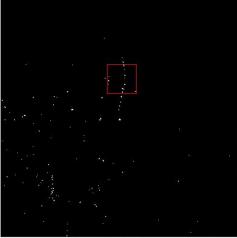


Figure 17. Further detection of gas flares, but this time onshore in Iraq. Same scene as in Fig. 17, but the location is further south. Background image on the left is the MIR – TIR brightness temperature difference image, whilst that at right is the matching S6 spectral radiance image. Red crosses indicate locations of detected hotspot pixels. S6 is very effective at detecting the gas flares.



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Appendix 1

Table A.1 Look up table of atmosphere optical depth and associated parameters for the calculation of atmospheric transmission in the SLSTR MIR band (S7 and F1)

UH ₂ O	t _{MIR}	A	В	С
5	0.132334	0.03464	0.807271	0.109722
10	0.167676	0.034524	0.797931	0.109198
15	0.198686	0.035494	0.783314	0.113246
20	0.226906	0.036565	0.769342	0.118173
25	0.253197	0.037469	0.757317	0.12285
30	0.278131	0.038189	0.7473	0.126978
35	0.305502	0.0387	0.740741	0.130468
40	0.333303	0.039033	0.736158	0.133339
45	0.361108	0.039229	0.732941	0.135641
50	0.384307	0.039393	0.728737	0.137681
55	0.408425	0.03947	0.725873	0.139317
60	0.429562	0.039525	0.722495	0.140805



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Table A.2 Look up table of atmosphere optical depth and associated parameters for the calculation of SWIR atmospheric transmission in the SLSTR S6 spectral channel.

UH ₂ O	tswir	A	В	С
5	0.091512	0.025336	0.906913	0.068176
10	0.093408	0.02535	0.906199	0.068415
15	0.095506	0.025457	0.904962	0.06897
20	0.097827	0.025735	0.903378	0.069727
25	0.100405	0.025856	0.901969	0.07049
30	0.103267	0.026111	0.900464	0.071322
35	0.109065	0.026232	0.899956	0.072059
40	0.117152	0.026288	0.900193	0.072621
45	0.125948	0.026283	0.900696	0.073006
50	0.1311	0.026351	0.900172	0.07351
55	0.137673	0.02628	0.900231	0.073817
60	0.142018	0.026331	0.899626	0.074247