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Satellite Remote Sensing of Active Fires: History and Current Status, Applications and Future Requirements

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Leverhulme Center for Wildfire, Environment & Society and NERC National Centre for Earth Observation (NCEO), c/o Dept. of Geography, Kings College London, Aldwych, London, WC2B 4BG, UK
martin.wooster@kcl.ac.uk
University of Southampton, Geography and Environmental Science, Southampton, UK;
G.J.Roberts@soton.ac.uk
Department of Geographical Sciences, University of Maryland, College Park, MD, USA
lgiglio@umd.edu
Department of Geography, Environment, and Spatial Sciences, Michigan State University, East Lansing, MI, USA
roydavi1@msu.edu
Missoula Fire Sciences Laboratory, Rocky Mountain Research Station, USDA Forest Service, Missoula, MT, USA
patrick.h.freeborn@usda.gov
Department of Forest, Rangeland, and Fire Sciences, , University of Idaho, Moscow, ID, USA
luigi@uidaho.edu
Department of Geographical Sciences, University of Maryland, College Park, MD, USA
cjustice@umd.edu
Interdisciplinary Studies, Atmospheric and Environmental Sciences, Howard University, Washington, District of Columbia, USA
charles.m.ichoku@nasa.gov

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NOAA/NESDIS/OSPO Satellite Analysis Branch, College Park, MD, USA
wilfrid.schroeder@noaa.gov
Trigg-Davies Consulting Ltd, Malvern UK /
GSFC, Science Systems and Applications Inc, Lanham, Maryland United States
diane.k.davies@nasa.gov
Department of Forest, Rangeland, and Fire Sciences, , University of Idaho, Moscow, ID, USA
alistair@uidaho.edu asparks@uidaho.edu
Centro de Previsão de Tempo e Estudos Climáticos/Instituto Nacional de Pesquisas Espaciais, Programa de Monitoramento de Queimada por Satélites, 12227-010, São José dos Campos, SP, Brazil
alberto.setzer@inpe.br
NOAA/NESDIS Center for Satellite Applications and Research (STAR), College Park, MD, USA
ivan.csiszar@noaa.gov
Scientific Services, South African National Parks, Skukuza, South Africa
tercia.strydom@sanparks.org
iMMAP Middle East, Mecca St. 145, Amman, Jordan
pfrost@immap.org
Kings College London, Dept. of Geography, Strand, London, WC2R 2LS, UK
NERC National Centre for Earth Observation (NCEO), Kings College London, UK
tianran.zhang@kcl.ac.uk
NERC National Centre for Earth Observation (NCEO), c/o. Dept. of Geography, Kings College London, Strand, London, WC2R 2LS, UK
Kings College London, UK
weidong.xu@kcl.ac.uk
NERC National Centre for Earth Observation (NCEO), c/o. Dept. of Geography, Kings College London, Strand, London, WC2R 2LS, UK
mark.dejong@kcl.ac.uk
Canadian Forest Service, Great Lakes Forestry Centre, Sault Ste Marie, On. Canada
Joshua.Johnston@canada.ca

Science Systems and Applications, Inc. (SSAI), NASA Goddard Space Flight Center, Greenbelt, MD 20771, USA.
lukecaj@gmail.com

NASA Marshall Space Flight Center, Huntsville, Alabama, 35811, USA
krishna.p.vadrevu@nasa.gov

Department of Geography and Geospatial Analysis Center, Miami University, Oxford, OH, USA
mccartjl@miamioh.edu

Upper ASEAN Wildland Fire Special Research Unit, Kasetsart University, Bkk, Thailand
fforvrc@ku.ac.th

Cooperative Institute for Meteorological Satellite Studies, Space Science Engineering Center, University of Wisconsin-Madison
chris.schmidt@ssec.wisc.edu

European Commission Joint Research Centre, Ispra. jesus.san-miguel@ec.europa.eu

Abstract

Landscape fire is a widespread, somewhat unpredictable phenomena that plays an important part in Earth's biogeochemical cycling. In many biomes worldwide fire also provides multiple ecological benefits, but in certain circumstances can also pose a risk to life and infrastructure, lead to net increases in atmospheric greenhouse gas concentrations, and to degradation in air quality and consequently human health. Accurate, timely and frequently updated information on landscape fire activity is essential to improve our understanding of the drivers and impacts of this form of biomass burning, as well as to aid fire management. This information can only be provided using satellite Earth Observation approaches, and remote sensing of active fire is one of the key techniques used. This form of Earth Observation is based on detecting the signature of the (mostly infrared) electromagnetic radiation emitted as biomass burns. Since the early 1980's, active fire (AF) remote sensing conducted using Earth orbiting (LEO) satellites has been deployed in certain regions of the world to map the location and timing of landscape fire occurrence, and from the early 2000's global-scale

information updated multiple times per day has been easily available to all. Geostationary (GEO) satellites provide even higher frequency AF information, more than 100 times per day in some cases, and both LEO- and GEO-derived AF products now often include estimates of a fires characteristics, such as its fire radiative power (FRP) output, in addition to the fires detection. AF data provide information relevant to fire activity ongoing when the EO data were collected, and this can be delivered with very low latency times to support applications such as air quality forecasting. Here we summarize the history of achievements in the field of active fire remote sensing, review the physical basis of the approaches used, the nature of the AF detection and characterization techniques deployed, and highlight some of the key current capabilities and applications. Finally, we list some important developments we believe deserve focus in future years.

1. Introduction

Landscape fire is a widespread natural disturbance agent involved in Earth's biogeochemical cycling, but one that can be greatly influenced by human actions, including in relation to climate and environmental change. Fire provides multiple ecological benefits (McLauchlan et al., 2020) – but in certain circumstances also poses a risk to life and infrastructure (Duff and Penman, 2021). In areas of substantial landscape fire activity and in regions downwind, air quality can also be seriously degraded - leading to major human health impacts and hundreds of thousands of early deaths per year worldwide (Roberts and Wooster, 2021). Deforestation fires, other fire involving 'permanent' land cover conversion, and fires consuming peat soils can also result in a net release of carbon to the atmosphere, since unlike savannah or grassland fires the carbon released is not balanced by a roughly equivalent uptake over subsequent growing seasons (Sommers et al., 2014; Friedlingstein et al., 2020). Active fire (AF) remote sensing from space is a key technique used to deliver information on local to global scale fire activity for all these applications and more in a timely and accurate manner. Following a recent review of EO-based burned area mapping (Chuvieco et al., 2019), here we focus on EO for active fires – a technique that has developed to now

provide information on fire activity occurring anywhere on Earth with very low data latency and updates multiple times per day. Conducted as part of the Global Observation of Forest Cover/Global Observation of Landcover Dynamics (GOFC/GOLD) Fire Programme (https://gofcgold.org/), this review summarizes the history of the AF remote sensing approach, details current capabilities and key applications, and identifies important developments deserving focus in the coming years. Appendix 1 provides a glossary and acronym list covering many of the terms used, along with a definition of some of the most relevant physical and chemical quantities.

Figure 1 shows the annual distribution of actively burning landscape fires detected via processing of data collected by the Moderate Resolution Imaging Spectroradiometer (MODIS) instrument onboard NASA's Terra satellite. The fires detected include for example wildfires, those planned for some land management objective such as support to agriculture or forestry, and those used to clear land – including forests - for future agriculture. The data of Figure 1 clearly illustrate that widespread landscape fire activity occurs on all continents except Antarctica, generally in regions with enough dry fuel and ignition sources from people or lightning. Globally an average of around 3.4% of Earth's terrestrial surface area burns annually (Giglio *et al.*, 2018), an estimate that may increase as more finely detailed EO-derived burned area (BA) data become available (Roy *et al.*, 2019; Roteta *et al.*, 2019). Landscape fires such as these play important roles in many ecological (Bond and Keeley, 2005; McLauchlan *et al.*, 2020) and wider Earth system processes (Bowman *et al.*, 2009), including in relation to the carbon cycle (Sommers *et al.*, 2014). But their annual consumption of billions of tonnes of vegetation and organic soil also results in globally significant emissions of smoke to the atmosphere (van der Werf *et al.*, 2017), even from individual fire events (Hirch and Koren, 2021), and this affects air quality (Jaffe *et al.*, 2020), and human health (Roberts and Wooster, 2021). Those fires resulting in permanent landcover change, such as deforestation, and/or which consume carbon-rich organic soil such as peat built up over long-timescales also represent a net release of carbon to the atmosphere (e.g. Sommers *et al.*, 2014; Huijnen *et al.*, 2015) and so contribute to rises in atmospheric greenhouse gas concentrations. One of the earliest stimuli for use of satellite EO in studying landscape fires came from uncertainties on their net carbon budget impact (Seiler and Crutzen,

1980), though a century earlier von Danckelman had drawn attention to their role in large-scale aerosol radiative forcing (Bronnimann *et al.*, 2009).

Satellite EO can be used to probe many fire characteristics, including burned area (Giglio *et al.* 2018; Chuvieco *et al.*, 2019) and the concentration and composition of smoke plumes (e.g. Kaufman *et al.*, 2002; Coheur *et al.* 2009; Ross *et al.*, 2013). Active fire (AF) remote sensing such as that used to produce the data of Figure 1 primarily focuses on identifying the location, timing and radiative strength (Fire Radiative Power; FRP) of fires that are actually consuming vegetation and/or organic soil at the time the observations were made. The FRP is somewhat akin to a spatial integration of the intensity of the overall combustion zone, and is measured in Watts. AF remote sensing is based primarily on infrared (IR) spectral measurements, and we begin by summarizing the historical development of the approaches used to exploit these measures (Section 2). We then review the fundamental physics (Section 3) and strategies for AF detection (Section 4), detailing approaches for FRP retrieval and the extraction of related variables such as fire effective temperature and area (Section 5). We examine how such data relate to fuel consumption and atmospheric impacts (Section 6), fire characteristics and ecosystem variables (Section 7), and how they are increasingly provided via online portals and in 'analysis ready' formats (Section 8). Finally, to aid future planning, we examine types of sensors, datasets and research activities we consider important for further development of AF applications, so as to point the way to areas of further fruitful research (Section 9).

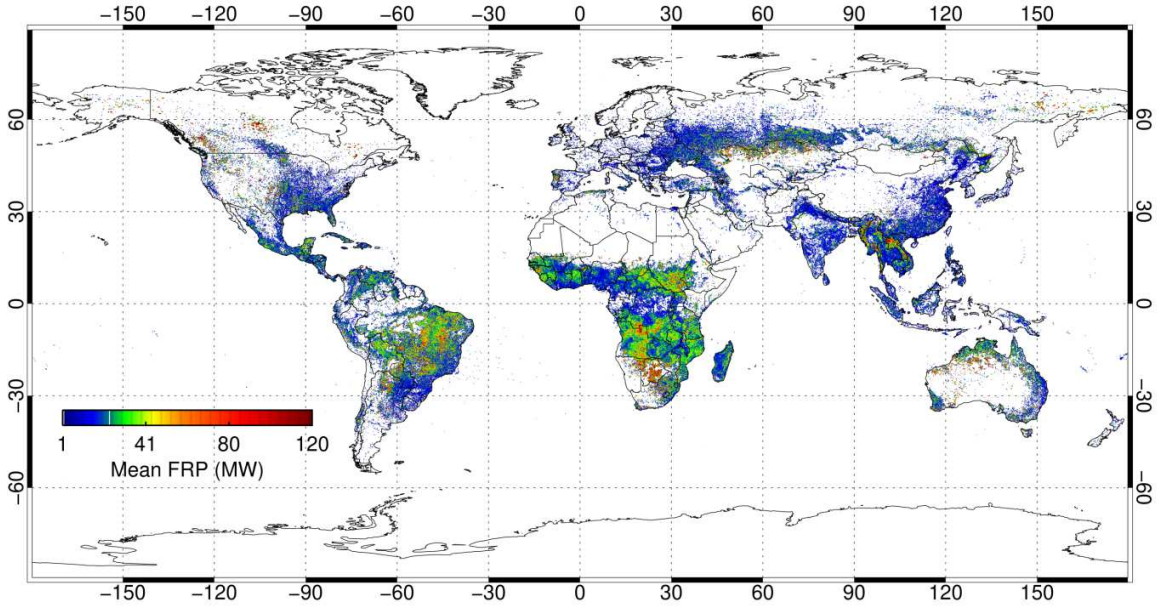


Figure 1. One year of actively burning landscape fire radiative power (FRP), derived from MODIS observations made from the Terra satellite. Data are the mean FRP of all active fire pixels detected in each 0.5° grid cell, as defined by the MODIS MCD14ML Active Fire and Thermal Anomaly product generated for 2010 (Giglio *et al.*, 2016).

2. The Historical Development of Satellite Active Fire (AF) Methods

The origins of active fire remote sensing extend back to 1960's and 1970's, with airborne thermal imaging of forest and coal seam fires (e.g. Hirsch, 1965; Ellyett and Flaming, 1973). Satellite-based studies commenced in the early 1980's, primarily using data from the Advanced Very High Resolution Radiometer (AVHRR) operating onboard NOAA's Polar-orbiting Operational Environmental Satellites (POES). AVHRR data played a key role in the development of AF detection methods (e.g., Flasse and Ceccato, 1996; Giglio *et al.* 1999; Ichoku *et al.*, 2003). Research was largely based on the strong 'active fire sensitivity' of spectral bands located in the middle infrared (MIR) atmospheric window (3 – 5 μm) (Section 3), with the AVHRR 3.7 μm channel shown to discriminate areas of combustion covering < 1% of the pixel area (Dozier; 1981; Matson and Dozier, 1981; Muirhead and Cracknell, 1985; Flannigan and Vonder Haar, 1986; Lee

and Tag, 1990; Setzer and Periera, 1991; Justice *et al.*, 1993). The sensitivity of MIR measurements to sub-pixel thermal anomalies still underpins most AF remote sensing today, and AVHRR itself is still used (e.g., in the Brazilian 'Queimadas' fire monitoring system described in Appendix 2). During the 1980's the first AVHRR-based active fire initiatives were unable to use the full spatial resolution (1 km) data globally due to the limited 'local area coverage' (LAC) onboard storage capacity of POES. However, a global network of AVHRR ground stations collected the directly downlinked High Resolution Picture Transmission (HRPT) 1 km data broadcast from the POES within their coverage areas, and in 1992 the International Geosphere Biosphere Programme Data and Information System (IGBP-DIS) provided specifications for the first global 1 km data set (Eidenshink and Faundeen 1994). This led to the first ever day and night global AF data set, produced by Europe's Joint Research Center (JRC; Ispra) covering April 1992 to December 1993 (Stroppiana *et al.* 2000). The nighttime only ESA World Fire Atlas (WFA) was developed at a similar time using initially ATSR-2 observations (Arino *et al.*, 1999). The call for such global fire products originated in the requirements set by the IGBP Global Change and Terrestrial Ecology (GCTE) Core Project and the response by IGBP Data and Information Systems (IGBP-DIS), and was taken up more comprehensively by the international community through the GOFC/GOLD program (Ahern *et al.*, 2003, Csiszar *et al.* 2013). Most recently the nearly 40-year archive of global, lower (~ 3 × 5 km) spatial resolution subsampled AVHRR global area coverage (GAC) data has been mined to generate some of the longest AF records currently available, initially regionally (e.g. Wooster *et al.*, 2012a) and now being extended globally. **Figure 2** shows an example of a three-decade AVHRR-GAC AF analysis of southern Canadian provinces (**Figure 2a**), where extreme fires burned in Manitoba in May, July and August 1989 (**Figure 2b**).

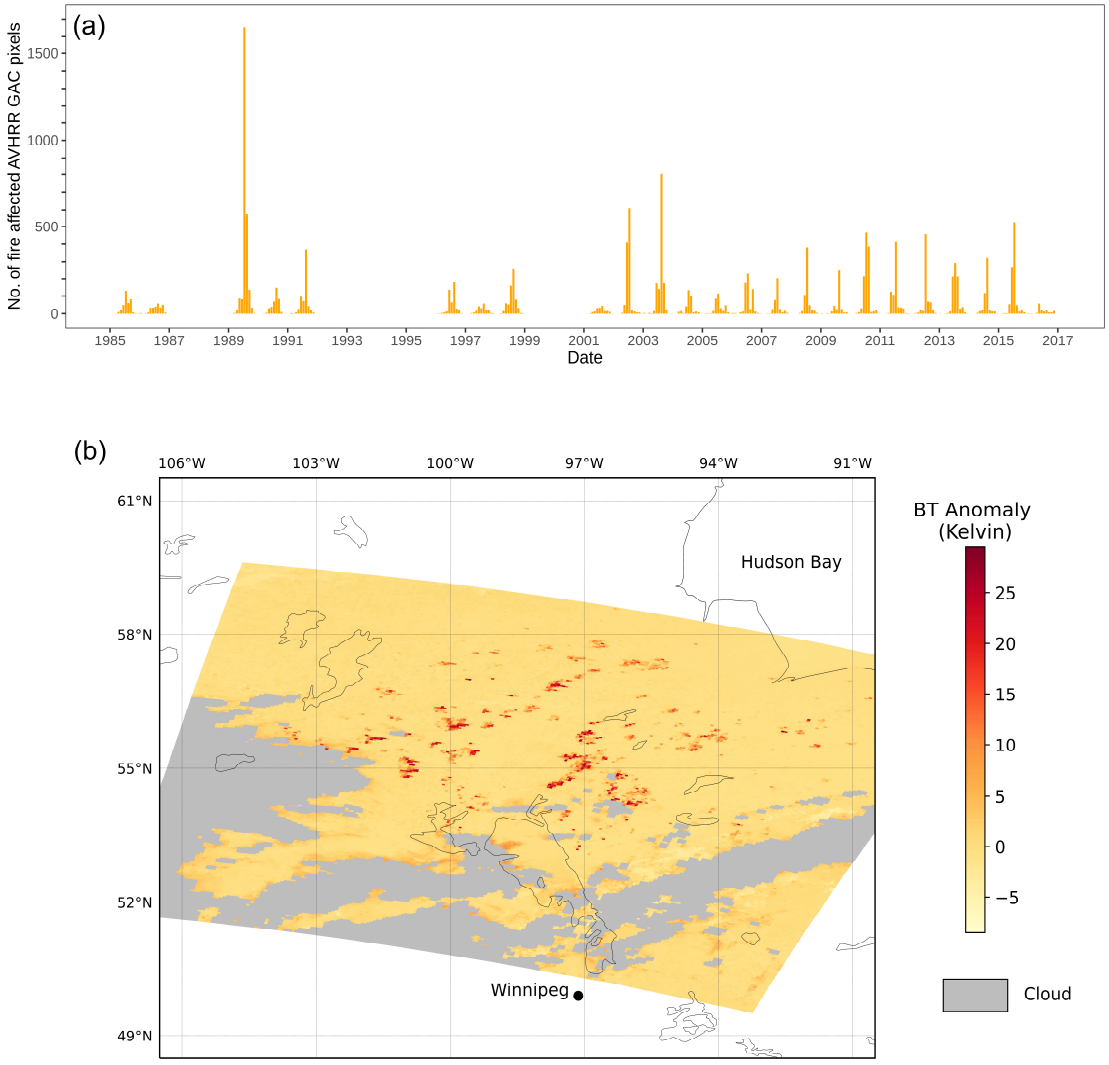


Figure 2. Example of (a) long term and (b) extreme landscape fire activity recorded in southerly Canadian provinces, as depicted via analysis of AVHRR GAC data. (a) AF detection time series derived using nighttime GAC data from 1985 to 2016. (b) Example AVHRR GAC image of 24th July 1989 (09:00 UTC) taken during the extreme 1989 Manitoba fire season (see the peak in (a) and Hirsch, 1991). Cloudy

pixels are masked as grey and active fire pixels shown by the high MIR (3.7 μm) channel brightness temperature elevation over the ambient background (red areas).

Work with AVHRR fundamentally changed our understanding of the global presence of fire, but the low sensor saturation temperature (c. 325K) of AVHRRs 3.7 μm MIR band (Csiszar and Sullivan, 2002), significant POES orbital drift (Csiszar *et al.* 2003) as well as other issues (Giglio and Roy, 2020) provided limits to its utility. However, such work greatly influenced the presence of an AF detection and characterization capability within NASA's Earth Observing System (EOS; Justice *et al.*, 1998), specifically that of the EOS flagship sensor - MODIS (Justice *et al.* 2002a). MODIS was designed with two 3.96 μm MIR channels having different saturation temperatures and dynamic ranges to support FRP retrieval as well as AF detection (Kaufman *et al.*, 1998; Justice *et al.* 2002b). FRP retrieval (Section 5) enables the AF application to go beyond fire presence/absence mapping to quantify the amount of radiant energy a fire is emitting per unit time, which is now considered linearly related to rates of fuel (vegetation and/or organic soil) consumption and smoke emission (e.g. Kaufman *et al.*, 1996; Ichoku and Kaufman, 2005; Wooster *et al.*, 2005; Kaiser *et al.*, 2012; Nguyen and Wooster, 2021). The MODIS AF detection algorithms were built on the AVHRR experience and prototyped using MODIS airborne simulator data (Kaufman *et al.*, 1998). They exploited the increased brightness temperature (BT) difference found between the MIR and long-wave infrared (LWIR) channel measurements at pixels containing actively burning fires (Section 3). The MODIS AF detection algorithm (Section 4) has been used by NASA to generate a suite of AF products having better than daily temporal resolution since the year 2000, and these remain to the present time one of the most widely used MODIS products. Other satellites in the 1990's and 2000's also supported AF detection, including the Defense Meteorological Satellite Program nighttime low-light imaging Operational Linescan System (DMSP-OLS) (e.g. Cahoon *et al.*, 1992; Elvidge *et al.*, 2013) and the Tropical Rainfall Mapping Mission (TRMM) which relied on evolutions of AF detection methods first used with AVHRR (e.g. Giglio *et al.*, 2000).

AF detection accuracy assessment is challenging due to the ephemeral and highly dynamic nature of landscape fire, difficulties in obtaining independent reference data coincident with the satellite observations, and because surface fires are complex to characterize *in situ*. However, for MODIS, the inclusion of the higher spatial resolution (15, 30 and 90 m) Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) instrument operating concurrently on the Terra satellite and itself able to be used for AF detection enabled simultaneous reference data to be collected. A systematic evaluation of the minimum fire sizes detectable by MODIS was produced (Morisette *et al.,* 2005; Schroeder *et al.,* 2008), and further refinements to the MODIS AF detection algorithm were informed by this validation. This culminated in the latest Collection 6 dataset reprocessing (Giglio *et al.,* 2016). These developments also influenced algorithms used with subsequent low earth orbit (LEO) satellite sensors, such as the Visible Infrared Imaging Radiometer Suite (VIIRS) (Csiszar *et al.*, 2014) and Sentinel-3 Sea and Land Surface Temperature Radiometer (SLSTR) (Wooster *et al.*, 2012b; Xu *et al.*, 2020). Inter-comparisons of AF data derived from observations made by different LEO sensors are commonly used to understand their varying performance characteristics (**Figure 3)**, with one aim being to derive transfer functions enabling data from multiple sensors to be combined into single time-series.

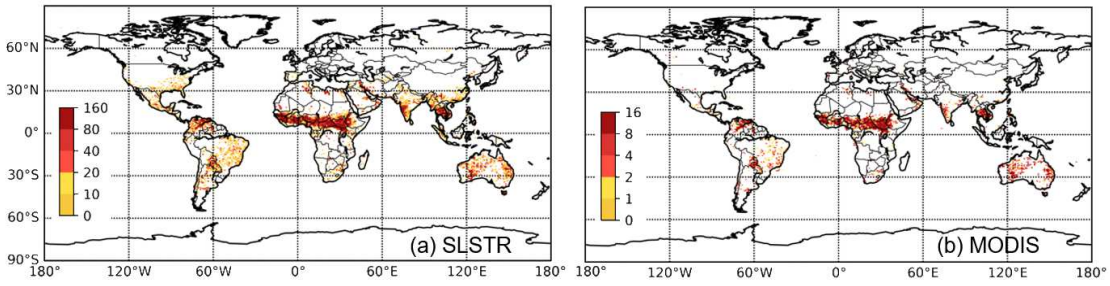
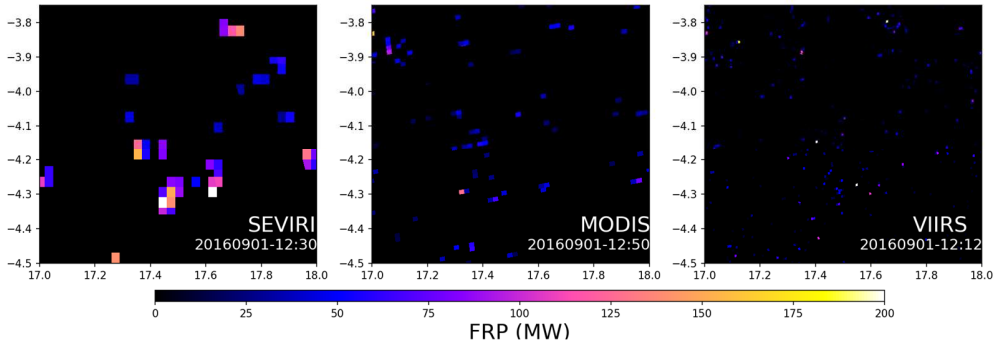


Figure 3. Nighttime active fire pixel counts detected in 0.1° grid cells in January 2019 from (a) Sentinel3B SLSTR and (b) Terra MODIS. These sensors have similar local overpass times and show similar spatial patterns of AF detection, but the SLSTR data record shows far higher AF pixel counts. Analysis shows this is in part due to the detection of many lower FRP fires by SLSTR than MODIS. This is a result of the former sensors smaller pixel area growth around the swath compared to MODIS (Wooster *et*

298 *al.*, 2012a; Xu *et al.,* 2020), and the fact that lower FRP fires are typically the most
299 numerous (e.g. Wooster and Zhang, 2004).
300
301 A similar AF detection algorithm development cycle has occurred for geostationary
302 (GEO) satellite AF products as with LEO products. Compared to LEO systems, GEO
303 products offer higher temporal resolutions but coarser spatial resolutions, and each
304 sensor only provides data over a specific region of the Earth (**Figure 4**). Geostationary
305 AF products were first generated over the America's using the Geostationary
306 Operational Environmental Satellite Visible Infrared Spin Scan Radiometer
307 Atmospheric Sounder (GOES-VAS) (e.g. Prins and Menzel, 1992; 1994; Weaver *et al.*,
308 1995), and this led to the development of the long-standing GOES WildFire Automated
309 Biomass Burning Algorithm (GOES WFABBA) product (Prins *et al.*, 1998). The GOES
310 WFABBA products represent the longest geostationary AF dataset currently available,
311 and in addition to AF location and time included an estimate of effective AF
312 temperature and area - derived using the Dozier (1981) 'bi-spectral' approach (Section
313 4). Wooster *et al.* (2005) and Roberts *et al.* (2005) first demonstrated the retrieval of
314 FRP from geostationary EO data, doing so via an approach avoiding use of bi-spectral
315 data (see Section 5), and went on to develop a full 'fire thermal anomaly' (FTA) AF
316 detection and FRP retrieval algorithm for GEO systems. This was first applied to data
317 from Meteosat Second Generation (Roberts and Wooster, 2008), and an operational
318 version is now used to generate a series of geostationary AF detection and FRP retrieval
319 products spanning much of the globe, including from Meteosat over Africa and Europe
320 (Wooster *et al.*, 2015), GOES-East and -West over the America's (Xu *et al.*, 2010; 2021)
321 and Himawari over Asia (Xu *et al.*, 2017). Similar product intercomparisons and
322 evaluations have been conducted as for LEO AF products (e.g. Roberts *et al.*, 2015).



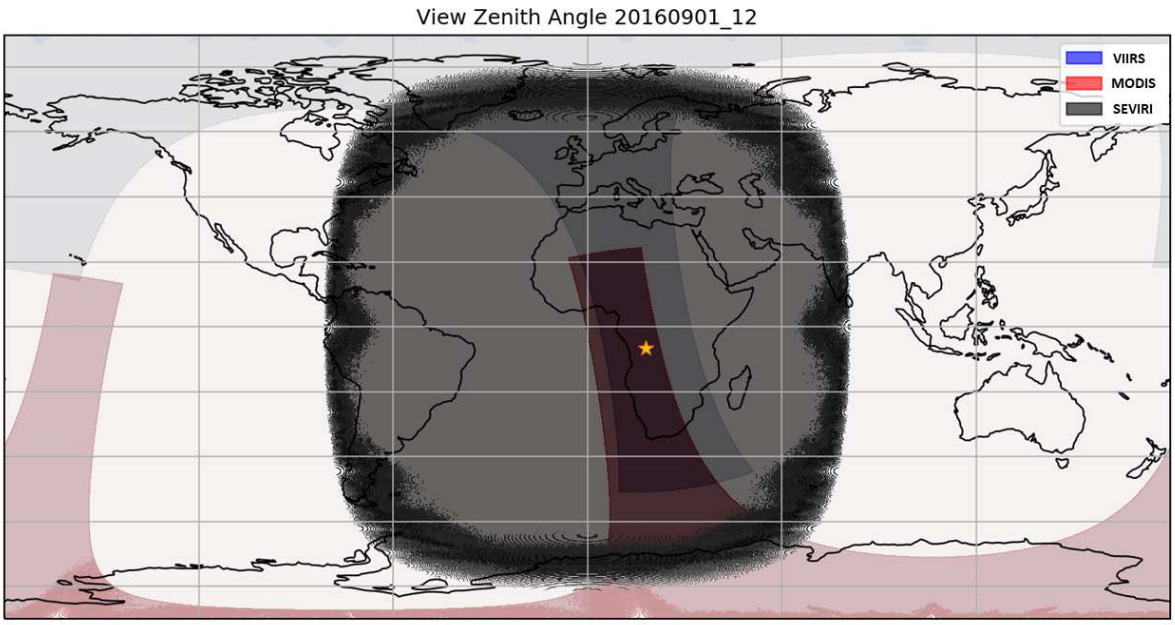


Figure 4. Active fire data and coverage maps derived from observations made by the geostationary Meteosat Second Generation SEVIRI instrument (SEV), and the polar-orbiting Aqua MODIS (MYD) and VIIRS (VNP) at approximately the same time of day. An approximately 80 × 100 km region of southern Africa is shown at top, where the coarser spatial detail of SEVIRI is apparent but also the higher per pixel FRP values due to the capturing of more fires within a pixel. The spatial

coverage of each of these systems obtained in a single hour is shown in the global map, with the location of the focus region highlighted.

3. Basic Physics of Active Fire Remote Sensing

AF detection and characterization is based on remote sensing of some of the approximately 20 $MJ.kg^{-1}$ of energy released when vegetation and organic soil burns (Cheney and Sullivan, 2008). 'High heat of combustion' describes the maximum total energy release per unit of dry matter consumed, and so live, i.e., moist, fuels release somewhat less (Smith *et al.*, 2013). Of the total energy released, only about 10 - 20% is released as (primarily IR) electromagnetic radiation (Freeborn *et al.* 2008, Kremens *et al.*, 2012). This radiative energy release rate is far higher than from the same area of ambient land however, and its spectral distribution follows Planck's Radiation Law and its derivative Wien's Displacement Law which serve as the physical basis for most AF remote sensing.

Figure 5 shows the modeled blackbody emitted spectral radiance for surfaces at 300 K, 600 K and 1000 K (typical temperatures of the Earth's land surface, smoldering, and flaming combustion respectively; Kaufman *et al.* 1998; Sullivan *et al.* 2003; Dennison *et al.* 2006). The emitted spectral radiance from a 1000 K flaming fire in the longwave IR (LWIR) atmospheric window (8 – 14 μm) is more than an order of magnitude higher than from the ambient land surface, but in the MIR (3 – 5 μm) atmospheric window it is almost three orders of magnitude higher – demonstrating why MIR observations are so sensitive to the presence of actively burning fires. Cooler smoldering fires show lower but still very significant levels of MIR and LWIR emittance. The very strong radiative signal of areas of combustion in the MIR spectral region, and the contrast between this and that seen in the LWIR from the same location, and in the MIR from nearby ambient non-fire areas, mean that active fires can be detected in appropriately remotely sensed imagery even if they cover an extremely small fraction of a pixel.

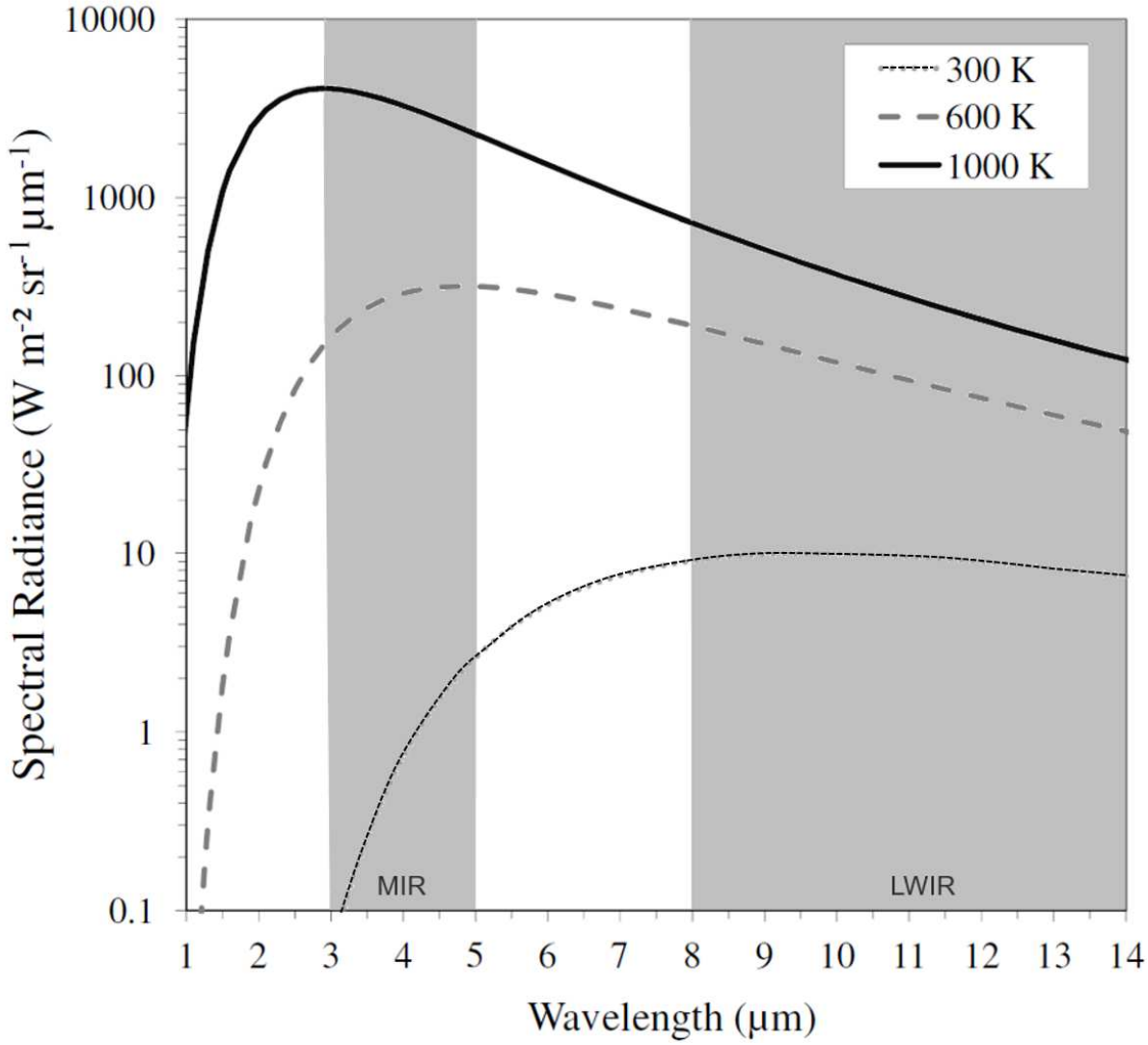


Figure 5. Emitted spectral radiance for blackbodies at typical flaming (1000 K) and smoldering (600 K) temperatures along with that from an ambient 300 K surface. Note the logarithmic scale of the y-axis. The MIR and LWIR atmospheric window regions are shaded grey.

To demonstrate that even small sub-pixel fires generate very detectable changes in the signal of the pixels they are contained within, **Figure 6** shows an example of modelled top-of-atmosphere (TOA) spectral radiance for different pixel situations, fully taking into account both emitted and reflected radiation and atmospheric effects. The figure contrasts a 300 K savannah land surface pixel (green line) with the same pixel but also

containing 0.5 % areal coverage of flaming 1000 K combustion (red line). In the MIR spectral region (3 – 5 μm), there is around an order of magnitude difference between the spectral radiance of these two pixels, equivalent to an easily detectable brightness temperature (BT) difference of around 80 K - even though the fire covers less than 1% of the pixel area. Whilst there is a dependency on issues such as day/night operation, and certain instrument-specifics, most AF detection algorithms can identify pixels in remotely sensed imagery that contain active fires if they have induced a minimum 5 to 10 K increase in the pixels MIR brightness temperature compared to the non-fire background. As such, fires covering down to perhaps ~ 0.01% of the pixel area are potentially identifiable. A far lower (but still likely detectable) signal difference between the fire and non-fire savannah pixels is apparent in the 10 – 12 μm LWIR spectral region of **Figure 6**, indicating that fires essentially have to cover a far larger portion of the pixel area to be identified using LWIR observations than MIR observations. These types of spatial and spectral contrast differences are the basis of most AF detection algorithms, with various additional tests employed to discriminate AF pixels from 'false alarms'. Pixels containing homogeneously warm (e.g. solar heated) land would be expected to have more similar MIR and LWIR BTs than would AF pixels, enabling the latter to be discriminated using this characteristic (see Section 4), whilst geographic masks can be used to screen out land-based gas flaring and active volcanoes for example.

Figure 6 also shows the signal of a pixel containing sunglint over water, which is a key cause of potential false alarms since sunglint affected pixels can have similar MIR and LWIR signals to AF pixels. However, sunglints can be masked out based on their typically strong visible wavelength and/or near infrared (NIR) signals (e.g. Zhukov *et al.,* 2006). Sunglint does not occur at night, and so nighttime AF detection algorithms can often be deployed with increased sensitivity, including because nighttime ambient surface temperatures are typically lower and more homogeneous than by day - leading to potential increases in the contrast provided by AF pixels. Some nighttime AF detection algorithms employ analysis of short-wave infrared (SWIR) signals (typically between 1.6 and 2.2 μm), which Figure 5 and 6 shows are also raised by the presence of

sub-pixel active fires. By day however such emitted SWIR signals can be masked by variations in solar reflected radiation unless the fire covers a substantial fraction of the pixel area. Such methods are thus best suited to use with higher spatial resolution imagery (e.g. Giglio et al., 2008).

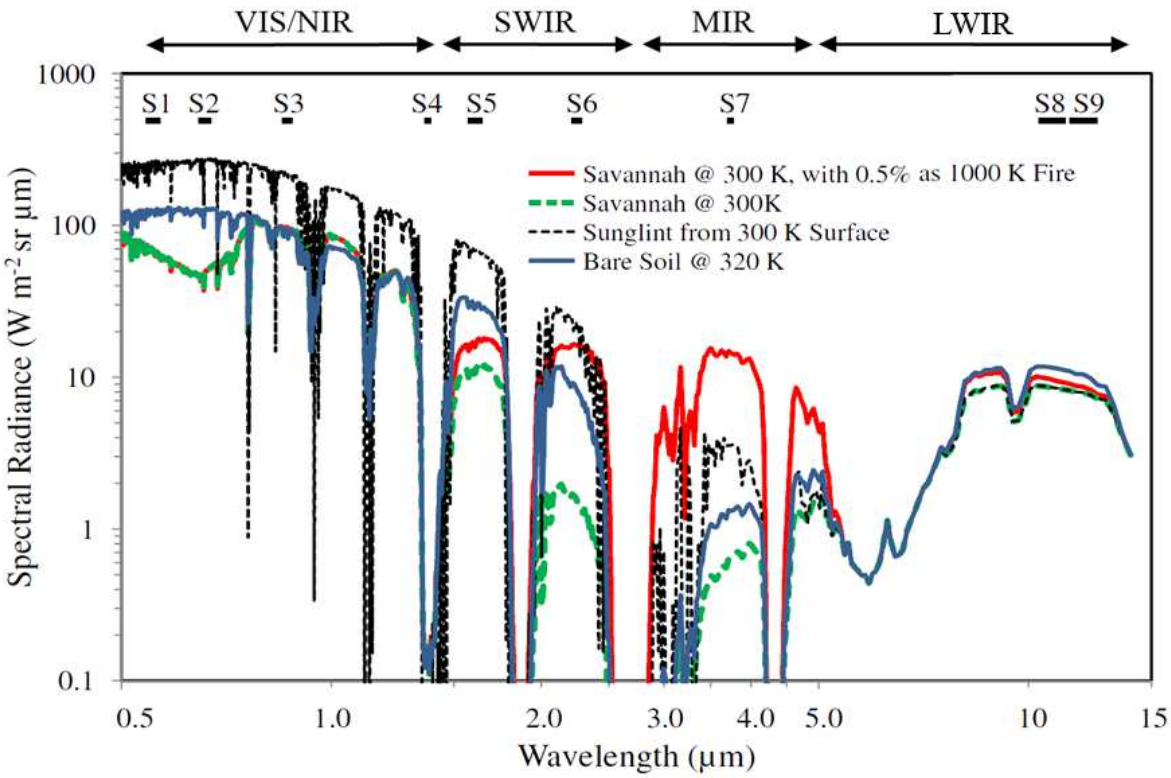


Figure 6. Modeled top-of-atmosphere emitted spectral radiance for four pixels – containing ambient (300 K) savannah; the same but with a 1000 K actively burning fire covering 0.5% of the pixel area, specularly-reflected sunglint from a 300 K surface, and solar-heated bare soil at 320 K. Examples of typical spectral bands of a satellite based imaging radiometer used to detect AF pixels are shown at top (here those from the Sentinel-3 SLSTR sensor; Wooster *et al.*, 2012a). Savannah pixels which contain a sub-pixel active fire are best separated from non-fire pixels in MIR spectral region, which is targeted by the SLSTR S7 spectral band. SLSTR also has a second (low-gain) MIR band (F1) to avoid saturation effects that impact S7 over warmer areas and active fires (see Section 10).

Few active fires completely fill a satellite image pixel, and extremely rarely at the scale of MODIS, SLSTR and VIIRS pixels. Thus subpixel AF situations such as is modelled in Figure 6 are by far the most common type. However, reliable detection of extremely small subpixel (e.g. < 0.01% pixel area), sub-canopy smouldering, or particularly cool (e.g. subsurface peat) fires remains a challenge. A fire of a given size and temperature will also occupy a smaller areal fraction of a larger pixel than a smaller pixel, reducing its detection reliability. However, moderate spatial resolution EO data such as provided by AVHRR, MODIS, VIIRS, and SLSTR are available with a daily or better update frequencies, enabling detection of active fires covering around 100 m² and in some cases even smaller (Schroeder *et al.*, 2014; Zhang *et al.*, 2017). **Figure 7** shows an AVHRR 1 km image captured over Indonesia during a period when flaming vegetation fires and cooler (often sub-surface) smoldering peat fires were widespread. These fires are generally strongly sub-pixel in size, and in agreement with **Figures 5** and **6** their influence on the MIR BT image (a) is far greater than in the LWIR BT image (b). The BT difference image (**Figure 7c**) best highlights the AF pixels, and this difference metric is the basis of most AF detection algorithms (Section 4).

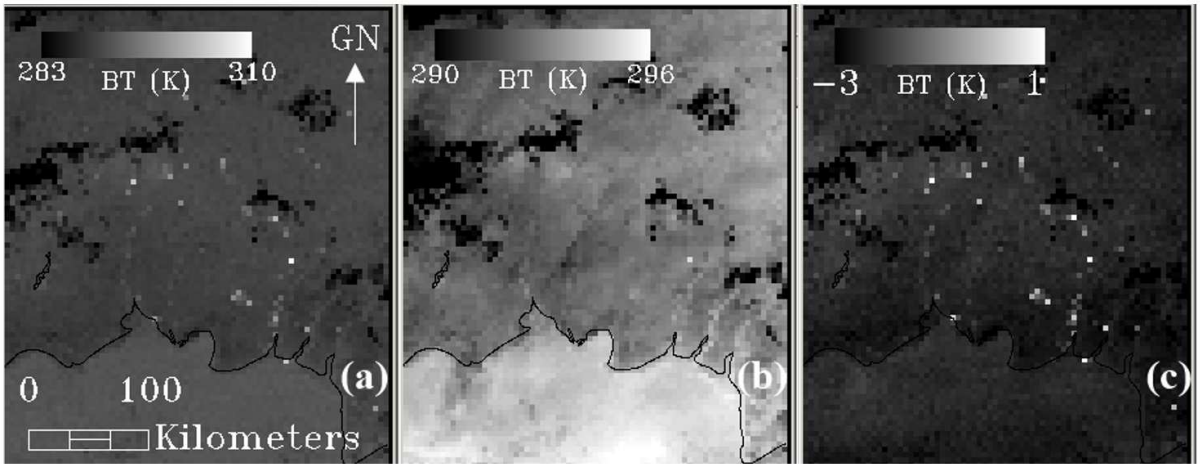


Figure 7. Night-time AVHRR local area coverage (LAC) ~ 1 km spatial resolution imagery of large-scale fires burning in primarily in peatlands across southern Kalimantan (Indonesia) on 24th August 1991. (a) MIR and (b) LWIR brightness

temperature (BT) data. The presence of a sub-pixel fire affects the BT more in the MIR than in the LWIR, and the MIR and LWIR BT difference shown in (c) most clearly highlights them.

Figure 7 shows a largely cloud free situation. Unlike smoke, meteorological clouds obscure active fires from view, and can also contribute to sunglint-induced false alarms. Cloud masking is thus an important component of EO-based AF detection. Information on cloud masked areas is also essential for AF product users to understand whether a location is considered free of detectable fires, or whether there is uncertainty due to cloud cover. Atwood *et al.* (2015) demonstrate that AF detection can occur through even very thick smoke, but that some satellite AF product cloud masking procedures inadvertently mask out heavily smoke affected areas as being affected by cloud. Conservative cloud masks can also result in higher rates of AF omission, and so underestimation of regional-scale FRP totals (Freeborn *et al.*, 2014; Hall *et al.*, 2019; Liu *et al.*, 2020). However, Wooster *et al.*, (2018) demonstrate that considerable spatio-temporal detail on fire activity in strongly smoke and cloud affected regions can still be gained with suitable tailoring of AF product cloud masking procedures.

To aid understanding of the exact source of the types of elevated spectral signals shown in **Figure 6** over fire affected pixels, Parent *et al.* (2010) made high spectral resolution laboratory measurements of fire emitted radiation. Planckian thermal emission was seen coming from both the hot fuel and from luminous hot soot particles in the flames, but whilst the fuel typically had a high emissivity across the IR region, that of the flames depended strongly on soot concentration and flame depth (Àgueda *et al.*, 2010; Johnston *et al.* 2014). However, even in low emissivity (e.g. thin, low soot concentration) flames showing low amounts of Planckian thermal emission, strong thermal emission in narrow spectral 'emission line' regions were seen from hot gases such as CO_2 and H_2O (Parent *et al.*, 2010). EO sensors prioritized for AF remote sensing generally avoid use of such spectral regions however, since ambient atmospheric CO_2 and H_2O absorb strongly at these same wavelengths and would tend to obscure the surface emitted signals when observing from space. Atmospheric transmittance is taken into account of during the generation of certain AF products, but typically only in terms

ambient atmospheric gaseous constituents (e.g. Wooster *et al.*, 2015; Section 5). In terms of aerosols, wildfire smoke is dominated by very small particles (i.e. PM2.5 and smaller) that are inefficient scatterers of MIR and LWIR radiation, and this is the reason that fires can be identified though even strongly smoke-affected regions as long as the data are not masked as cloudy (Atwood *et al.*, 2015). However, thick smoke is likely to have some impact on the retrieved FRP, including via any black carbon component absorbing some of the fire-emitted thermal radiance. This is yet to be accounted for in FRP retrieval algorithms.

4. Active Fire Detection Algorithms and Products

4.1. Active Fire Detection Algorithms

4.1.1 Early Work

Dozier (1981) and Matson and Dozier (1981) undertook some of the earliest satellite-based studies of sub-pixel 'thermal anomalies'. They explained the causes of the spectrally varying BTs seen in AVHRR data containing sub-pixel hot sources (e.g. Figure 7), and these characteristics still underly almost all AF detection methods used today. They proposed a so-called bi-spectral fire characterisation algorithm that used non-linear simultaneous equations to estimate the fires sub-pixel effective temperature and area (see Section 5.1). Prior to application of this bi-spectral, other approaches are often used to identify the pixels to which it should be applied.

4.1.2 Fixed threshold algorithms

Fixed threshold AF detection algorithms apply relational operators and fixed thresholds to the BT data captured in individual spectral bands (e.g., $T_{MIR} > 320K$) and/or to band differences (e.g., $T_{MIR} - T_{LWIR} > 10$ K). Their simplicity provides computational efficiency, but even carefully-tuned thresholds can in general only satisfy AF detection accuracy requirements under the specific regional/seasonal conditions for which they were derived (Kaufman *et al.*, 1990; Pereira and Setzer, 1993), or they must

be applied under relatively stable ambient background temperature conditions (e.g. at night; Wooster *et al.*, 2012b). Use of higher thresholds can help alleviate false alarms related to by ambient background temperature variations, as was the case with the ESA World Fire Atlas, but increase the chance of omitting smaller and/or cooler fires (Arino *et al.*, 1999).

4.1.3 Contextual algorithms

Contextual algorithms incorporate dynamic thresholds, which adapt to local conditions to aid detection of smaller and/or cooler fires whilst minimizing false alarms. In this approach, candidate AF pixels are first detected using liberal fixed thresholds - generally applied to the T_{MIR} and/or $T_{MIR} - T_{LWIR}$ data. False detections are then removed from this 'potential AF pixel' set by comparing the signal of each candidate AF pixel to that of neighboring non-fire pixels within a surrounding geographic window. Some of the first contextual AF detection algorithms were developed for use with AVHRR (e.g. Flasse and Cecatto (1996); Giglio *et al.*, 1999) as part of the IGBP-DIS global fire initiative (Section 2). Evolutions followed, including use of differently sized windows (e.g. Giglio *et al.*, 2003, 2016; Zhukov *et al.,* 2006), and spatial filters to improve rejection of non-fire pixels in the early stages and allow use of more liberal fixed thresholds able to better capture smaller/cooler fires (Roberts and Wooster, 2008).

Contextual algorithms still remain the most commonly used AF detection method. Since their initial development (Flasse and Ceccato, 1996; Giglio *et al.*, 1999; Kaufman *et al.,* 1998), they have been applied to data from numerous LEO sensors, including VIIRS (Schroeder *et al.,* 2014; Csiszar *et al.,* 2014; Zhang *et al.*, 2017), MODIS (Kaufman *et al.,*1998; Giglio *et al.,* 2016), the BIRD Hot Spot Recognition System (HSRS, Zhukov *et al.,* 2006), the TRMM Visible and Infrared Scanner (VIRS, Giglio *et al.,* 2000), SLSTR (Wooster *et al.,* 2012b; Xu *et al.*, 2020), and Landsat (Schroeder *et al.* 2016; Kumar and Roy, 2018), and also GEO sensors such as those carried by Meteosat (e.g. Wooster *et al.,* 2015; Amraoui *et al.,* 2010; Di Biase and Laneve, 2018), GOES (Prins *et al.*, 1998; Xu *et al.,* 2010; Schmidt *et al.*, 2017; Xu *et al.*, 2021), Himawari (Xu *et al.*, 2017; Wickramasinghe *et al.,* 2016), and FengYun (Xu *et al.,* 2011).

4.1.4 *Multi-temporal algorithms*

The majority of AF detection algorithms are applied to single date imagery, with some adding basic temporal constraints to remove possible false alarms (e.g., Prins *et al.*, 1998; Xu *et al.*, 2010; Kumar and Roy, 2018). Some multi-temporal AF detection algorithms have been developed however. These either identify fire-related pixel-level thermal variations via multi-temporal change detection (e.g. Filizzola *et al.,* 2017), or model the ambient pixel BT diurnal cycle and identify fire-related departures from this (e.g. Roberts and Wooster, 2014). Both approaches aim to identify an AF pixel via thermal differences compared to expectations, whilst accounting for temporal variability. In the multi-temporal change detection approach, statistical characterizations of a fire-relevant parameter (e.g., the MIR BT or MIR-LWIR BT difference) at each pixel location are calculated over a suitably long period; and such approaches have been applied to LEO (Marchese *et al.*, 2017) and GEO (Laneve *et al.* 2006; Filizzola *et al.,* 2017) data. Model-based approaches exploit the latter's higher temporal frequency to characterize the ambient BT diurnal cycle and then forecast this forward in time (Udahemuka *et al.,* 2007; Hally *et al.,* 2017). Optimal estimation techniques, such as Kalman filters, can build on this baseline to assimilate observed BTs and deploy statistical thresholds to confirm whether active fires are present based on departures from the modelled diurnal trend. Although computationally intensive, this approach has been applied to GEO data (van den Bergh and Frost, 2005; van den Bergh *et al.,* 2009; Roberts and Wooster, 2014; Hally *et al.,* 2016), and in some cases has been shown to detect fires unidentifiable using the more standard contextual approach (van den Bergh *et al.*, 2009; Roberts and Wooster, 2014).

4.1.5 Non-thermal infrared methods

AF detection methods using visible (VIS), NIR and SWIR band data have been developed for nighttime use. The VIS-NIR band (0.5 - 0.9 μm) on the 2.7-km U.S. Air Force DMSP-OLS sensor (Elvidge *et al.*, 1996) enabled nighttime detection of city lights, lightning flashes and active fires using a simple contextual algorithm that identified

pixels far brighter than its neighbors. Elvidge *et al.* (2013) extended the approach to 750 m VIIRS day-night band (0.5 - 0.9 μm) data, combining it with that from the SWIR-to-LWIR bands and using a Planck function fitting approach to more confidently discriminate fires from other visible light sources. Some nighttime AF detection algorithms also employ SWIR radiances measures where available. For example, Elvidge *et al.* (2015) combined Landsat-8 SWIR and LWIR data to discriminate flaming and smoldering peatland fires, whilst Fisher and Wooster (2019) used nighttime SLSTR SWIR and MIR data to discriminate gas flares from vegetation fires.

Daytime SWIR algorithms have also been developed for use with medium spatial resolution sensors having no MIR capability. The most common approaches, developed for ASTER (Giglio *et al.*, 2008) and then Landsat-8 (e.g., Schroeder *et al.*, 2016, Kumar and Roy, 2018) rely on a fire-sensitive SWIR band and a comparatively insensitive NIR band to identify the increased SWIR radiance associated with fires (Figure 6). Commission errors can result from some highly reflective non-burning surfaces (e.g., certain buildings), but the joint availability of Landsat-8 and Sentinel-2 imagery provides ~3-day median global coverage (Li and Roy, 2017) and the potential for relatively infrequent but spatially detailed global AF detection.

Finally, more experimental techniques requiring still novel sensors have been developed. For example, the identification of specific narrow-band NIR emission lines related to the thermal excitation of potassium (K) that occurs only in flaming fires has seen an early demonstration from space (Amici *et al.*, 2011).

5. Fire Radiative Power (FRP) and Fire Characterization

5.1 FRP Retrieval

Since the late 1990's, AF detections have been increasingly accompanied by efforts at fire characterization, mostly in terms of retrievals of fire radiative power (FRP; usually expressed in MW). FRP is the rate at which the fires within a pixel are emitting thermal energy, integrated over all angles and wavelengths. An empirically-derived algorithm for direct estimation of FRP was first proposed and demonstrated with MODIS airborne

simulator data by Kaufman *et al.* (1998) - Equation [1]. An underlying assumption is that, since heat yields are relatively constant among vegetation types (Stott, 2000), remotely sensed FRP retrievals provide data useful for estimating rates of fuel consumption and smoke emission, as first demonstrated by Wooster *et al.* (2005) and Kaufman *et al.* (1998), Freeborn *et al.*, (2008) and Ichoku *et al.* (2008) respectively. Equation [1] was used to retrieve FRP in the early (Collections 1 - 4) MODIS AF Products (Giglio *et al.*, 2003), in units of emitted power per unit area of the pixel:

$$FRP = 4.34 \times 10^{-19} \sum \quad T_{MIR,fire}^{8} - T_{MIR,bg}^{8}) \qquad [1]$$

where $T_{MIR,fire}$ and $T_{MIR,bg}$ are the MIR BT (K) of the AF pixel and the mean of the surrounding "background" pixels respectively.

Whilst Equation [1] performs well for MODIS, its empirical nature means it is specific to data from that sensor. It starts to underperform when applied to finer spatial resolution data that record higher BTs due fires covering a greater proportion of their pixel area (Section 3) (Wooster *et al.*, 2003). Wooster *et al.* (2003, 2005) derived a more physically based approach to FRP retrieval, based on a power-law approximation to the Planck function and which linearly related FRP (MW) to the AF pixels excess MIR spectral radiance above the background:

$$FRP = \frac{A_{sampl} \cdot \sigma \cdot \varepsilon}{\cdot \varepsilon_{MIR}} (L_{MIR,fire} - L_{MIR,bg}), \qquad [2]$$

where σ is the Stefan-Boltzmann constant (5.67x10^{-8} J s^{-1} m^{-2} K^{-4}) and ε and ε_{MIR} are the broadband and MIR spectral emissivities respectively (that cancel as the fire is generally considered a greybody or blackbody), L_{MIR} is the MIR spectral radiance of the AF pixel (W m^{-2} sr^{-1} μm^{-1}), and $L_{MIR,bg}$ is the estimate of what the AF pixel spectral radiance would be if it did not have a fire within it (typically taken as the mean or median MIR

spectral radiance of the surrounding background pixels), α (W m^{-2} sr^{-1} μm^{-1} K^{-4}) is a coefficient dependent upon the sensor's MIR channel spectral response (Wooster *et al.,* 2005), and A_{sampl} is pixel area (km^2).

Similar to its use in Equation [2], for MODIS Collection 5 an A_{sampl} multiplier was added to Equation [1] to provide MODIS FRP outputs directly in MW, and from Collection 6 onwards the FRP retrieval method was shifted to Equation [2] (Giglio *et al.,* 2016). Giglio *et al.* (2016) found an average 16% difference when comparing MODIS' FRP retrievals based on Equations [1] and [2], with greater differences at lower FRPs reflecting the fact that the MIR radiance method tends to underestimate FRP for emitters < 600K (a lower temperature than that of most active combustion zones; Wooster *et al.,* 2003; Dennison 2006). This underestimation is not necessarily disadvantageous, since it means that radiant heat from warm, recently burned areas not actively consuming fuel often do not contribute significantly to the total per-pixel FRP measure from which combustion rates are often derived (Wooster *et al.,* 2005). However, it may prove more problematic in peatland fires, where underground combustion can lead to rather low surface temperatures in the burning areas (e.g. Elvidge *et al.,* 2015; Fisher *et al.*, 2020).

Moving beyond the single-band FRP retrieval methods discussed above, another approach to FRP estimation is to exploit outputs of the 'bi-spectral' method introduced in Section 4.1.1, namely the effective fire temperature (T_f, K) and sub-pixel proportion (p_f) of the Matson (1981) and Matson and Dozier (1981) approach:

$$L_{MIR} = \tau_{MIR} p_f B_{MIR}(T_f) + (1 - p_f) L_{MIR,bg} \quad [3]$$

$$L_{LWIR} = \tau_{LWIR} B_{LWIR}(T_f) + (1 - p_f) L_{LWIR,bg} \quad [4]$$

$$FRP = \sigma(T_f^4 - T_{bg}^4) p_f A_f \quad [5]$$

where L_x is the AF pixel spectral radiance (W m^{-2} sr^{-1} μm^{-1}) observed in the denoted spectral band x, $B_x(T)$ is the Planck function (W m^{-2} sr^{-1} μm^{-1}), τ is the atmospheric transmittance, $L_{X,bg}$ is the ambient background spectral radiance (i.e. non-fire, W m^{-2} sr^{-1} μm^{-1}), σ is the Stefan-Boltzmann constant (5.67x10^{-8} J s^{-1} m^{-2} K^{-4}) and $T_{x,bg}$ is the brightness temperature (K) of the ambient background in band x.

Per-pixel errors of T_f and p_f can be large, especially for lower values of p_f, and errors of ~100 K and ± 50% respectively at one standard deviation (σ_η) were demonstrated for even easily detectable active fires (p_f >0.005; or 0.5% of the pixel area) by Giglio and Kendall (2001). This is mainly due to challenges in sufficiently precisely isolating the difference between the AF and ambient background pixel signals in the LWIR - where fire thermal emission is far less strong (Figures 5, 6 and 7), though errors in T_f and p_f may counteract each other somewhat when delivering FRP through Equation 5 (Wooster and Rothery, 1997). Inter-band spatial misregistration effects can also impact bi-spectral estimation of T_f and p_f (Shephard and Kennelly, 2003), though Briess *et al.* (2003) and Zhukov *et al. (*2006) tackled this by applying the approach at the fire cluster (rather than AF pixel) level. Overall, whilst the geostationary GOES WFABBA product (Prins *et al.,* 1998) applied this approach for FRP estimation, it is not particularly recommended for use with moderate to low spatial resolution data (Giglio and Schroeder, 2014; Giglio and Kendall, 2001). Most LEO and GEO AF products now base their per-pixel FRP retrievals on the MIR radiance method of Equation 2 (Wooster *et al.,* 2003; 2005). This includes those from VIIRS (Csiszar *et al.*, 2014), Meteosat (Wooster *et al.,* 2015), Himawari (Xu *et al.,* 2017), GOES (Xu *et al.*, 2010; 2021), SLSTR (Xu *et al.,* 2021) and MODIS (Giglio *et al.*, 2016).

In 2020, the Committee on Earth Observation Satellites (CEOS) Land Product Validation (LPV) Subgroup indicated that the current validation level of satellite FRP products is less advanced than for burned area, partly due to the ephemeral nature of active fires and the logistical and technical difficulties posed when trying to get independent, simultaneous FRP observations to match satellite estimates. However, by exploiting repeated observations occurring near the MODIS swath edge, Freeborn *et al.* (2014a) showed that variations in the exact sub-pixel placement of the fire contribute

per-pixel MODIS FRP uncertainties that are normally distributed with σ_η = 26.6%, with simulations demonstrating that at the scale of fire clusters this reduces to less than ~5% for fires containing in excess of ~ 50 MODIS AF pixels. Such size-dependent FRP uncertainties should be considered during any intercomparion and/or validation of satellite-based FRP data.

5.2 Fire Radiative Energy (FRE) Estimation

Fire radiative energy (FRE, MJ) is the temporal integral of FRP between two points in time (t_0 and t_n) (Wooster *et al.*, 2005), defined for discrete, evenly spaced, temporal sampling as:

$$FRE = \sum_{t_0}^{t_n} FRP_t \Delta t \qquad [6]$$

where FRP is the fire radiative power (MW) at time t and Δt is the time (secs) between FRP retrievals. In fire ecology, the term fire radiative energy [or flux] density (J m^{-2}) is sometimes used (e.g. Kremens *et al.*, 2010; Sparks *et al.* 2017), but should be limited to situations where estimates of radiant energy release at a point are required.

FRE estimates are best achieved from GEO data, because high imaging frequencies provide the best temporal sampling (Freeborn *et al.,* 2009; Roberts and Wooster, 2008; Li *et al.,* 2018; Ellicott *et al.,* 2009; Roberts *et al.*, 2018a). However, the typically coarser pixel areas of GEO sensors mean they often fail to detect the lower FRP component of a region's fire regime, and a single GEO imager provides neither global coverage nor high-quality observations at very high latitudes (Figure 4). Numerous methods have attempted to estimate FRE from more infrequent LEO-derived FRP data, for example from the ~ four daily observations provided by MODIS that broadly sample the diurnal fire cycle (e.g. Boschetti and Roy, 2009; Freeborn *et al.*, 2011). The most widely applied method represents the FRP diurnal cycle using a modified Gaussian (perhaps informed by past GEO-FRP data), tailoring its characteristics via MODIS observations when available (Ellicott *et al.,* 2009, Vermote *et al.,* 2009; Andela *et al.,* 2015; Yin *et al.*, 2019). To counteract effects coming from the relatively small number of

daily MODIS observations, and the fact fires are differently detected depending on their position in the MODIS swath which has a 16-day repeat cycle (Freeborn *et al.,* 2009), most LEO-derived FRE estimates are delivered at lower spatio-temporal resolutions (e.g., 0.25°; 8 days).

6. Satellite Active Fire and FRP Products

The number of routinely available GEO and LEO AF products has grown substantially over the last two decades (Table 1), with several LEO products having global and/or multi-decade coverage (Arino *et al.,* 2012; Csiszar *et al.,* 2014; Giglio *et al.,* 2016; Xu *et al.*, 2020). Most use contextual AF detection methods (Section 4.1.3), with the NASA MODIS AF products demonstrating an excellent approach where re-processed Collections are periodically released based on algorithm refinements and updated calibration/geolocation information (Giglio *et al.,* 2003; 2016). Such updates are mostly driven by routine product quality and validation assessments, along with science developments (Justice *et al.*, 2002a; 2002b).

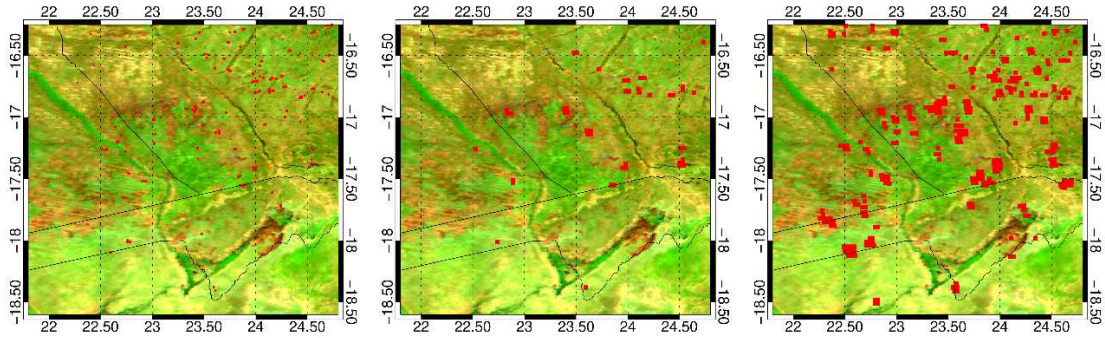
Assessing the absolute accuracy and precision of AF products is difficult for reasons discussed in Section 5. In addition to daytime sunglints, non-burning hot areas and regions of high local thermal contrast can result in AF detection errors of commission in places such as deserts, urban areas, and forest clear cuts (e.g. Schroeder *et al.* 2008; Kumar and Roy, 2018). Such effects are potentially magnified in higher spatial resolution products (e.g. Schroeder *et al.*, 2014; Zhang *et al.*, 2017). AF detection errors of omission are generally related to surface obscuration by cloud (or thick smoke removed incorrectly during cloud masking), fires not burning at the observation time, or small and/or too cool fires having an FRP below the products minimum detection limit (Giglio 2007; Roy *et al.*, 2008; Roberts *et al.*, 2015; Hall *et al.*, 2019). Commission errors for the best performing products range from a few percent to about 10%, depending on sensor and algorithm specifics. Some of the most mature (e.g., the NASA MODIS products) claim mean global commission errors of around 3% (Giglio *et al.*, 2016). Mature geostationary AF products typically have similar commission errors to LEO products, but higher omission errors due to their larger area pixels and thus higher

763 minimum FRP detection limit (as is apparent in **Figures 5** and **8**). Conversely, the
764 higher temporal frequency GEO AF products can sometimes identify fires that are not
765 detected by LEO products, such as those ignited and burned out between LEO
766 overpasses or in cloudy regions where the land surface is viewed briefly by the GEO data
767 as the clouds move (Roberts and Wooster, 2008; Roberts *et al.*, 2015; Hally *et al.*, 2017).
768
769 **Table 1.** LEO and geostationary orbit systems used to generate Active Fire (and for
770 some also FRP) products.
771

Instrument	**Spatial resolution of active fire data**	**Geographic coverage**	**Satellite Orbit**	**Satellite / Agency**
MODIS	1 km	Global	LEO	Terra, Aqua/ NASA
GOES ABI	2 km	75.2 ° W: North and South America 135 ° W: Pacific Ocean, Hawaii, North and South America	Geostationary	GOES-E and -W /NOAA
Himawari AHI	2 km	140.7 ° E: East Asia, Australia, Pacific Ocean	Geostationary	Advanced Himawari Imager (AHI), JAXA and JMA
Meteosat SEVIRI	3 km	0 °: Europe, Africa, 41.5 E	Geostationary	Eumetsat
VIIRS	375 m, 750 m	Global	LEO	S-NPP, JPSS1/NOAA 20 NASA/NOAA
NOAA AVHRR	1 km	Global	LEO	POES / NOAA METOP / Eumetsat

(A)ATSR	1 km	Global (but only nighttime AF product)	LEO	ERS-2* and ENVISAT
SLSTR	1 km	Global	LEO	Sentinel-3/ Eumetsat and ESA
HSRS	350 m	Global (but on-demand products)	LEO	Firebird Constellation / DLR

*ERS-1 also carried an ATSR sensor, but its MIR channel failed soon after launch.



(a) (b) (c)

Figure 8. Active fire detections made on 31st August 2017 (red) in a region of southern Africa using (a) Terra MODIS and Aqua MODIS, (b) Meteosat SEVIRI observations made near-simultaneously with MODIS, and (c) all SEVIRI data collected over that day (24-hrs). Background is a MODIS surface reflectance image (RGB: 2.1 μm, 0.8 μm and 0.6 μm).

7. AF Relationships to Fuel Consumption and Atmospheric Variables

7.1 Fuel Consumption Estimation

One of the earliest applications of satellite data related to landscape fires was to estimate amounts of dry biomass consumed ($M_{consumed}$) (Seiler and Crutzen, 1980). The standard methodology is to combine satellite-derived burned area (BA) data with biome- and date-dependent fuel consumption per unit area (F_c) estimates, and this is the basis of the widely-used Global Fire Emission Database (GFED, van der Werf *et al.*, 2017). However, the method is unable to operate close to real time since BA data are typically only available after the fire event, and the F_c estimates rely on environmental models driven by meteorological and other data only available with a time delay. As detailed in Section 5 however, FRP measures can provide almost real-time information directly proportional to rates of fuel consumption and smoke emission. FRE (MJ) estimates derived from laboratory-scale 1 Hz FRP measures of mainly cured dry grass fires were shown to be linked to dry biomass consumed via an 'FRE combustion coefficient' (F_c) of 0.37±0.02 kg MJ^{-1} (Wooster *et al.*, 2005):

$$M_{consumed}\ (kg) = 0.37 \times FRE\ (MJ) \qquad [7]$$

Confirmation of similar 'combustion coefficient' values for other fuels was subsequently demonstrated in further small-scale fire experiments (e.g. Freeborn *et al.,* 2008; Kremens *et al.,* 2012), and the FRE approach to fuel consumption estimation been applied to landscape-scale fires using EO data from e.g. Meteosat SEVIRI (Roberts *et al.* 2005; 2011; 2018a), GOES (Li *et al.,* 2018) and MODIS (Ellicott *et al.,* 2009; Vermote *et al.,* 2009; Kaiser *et al.,* 2012; Andela *et al.,* 2015; Yin *et al.*, 2019; McCarley *et al.*, 2020). However, spaceborne FRP retrievals are subject to perturbations beyond those affecting small-scale field or laboratory studies, potentially altering the effective value of the FRE combustion coefficient. Mota and Wooster (2018) summarize such effects as coming from AF omission errors (Section 4.2), interception of surface-emitted radiation by overlying tree canopies (Roberts *et al.,* 2018b, Mathews *et al.*, 2016; Johnston *et al.,* 2018), atmospheric effects (Wooster *et al.*, 2015), fuel moisture variations (Smith *et al.,* 2013), and potentially fire size-dependent variations in the radiative fraction of the fuel heat yield (Freeborn *et al.*, 2008). Such effects may be responsible for the generally larger and biome-dependent FRE combustion coefficients

derived by Kaiser *et al.* (2012) derived from Global Fire Assimilation System (GFAS)-based FRE estimates and GFED (burned area)-based fuel consumption totals. Despite remaining uncertainties, the FRP and FRE approach provides the only direct route to, respectively, rapidly estimating fuel consumption and smoke emission rates whilst a fire is burning, and the totals of these immediately after a fire has ceased. Further benefits may stem from removing the use of models that are sometimes difficult to parameterize, for example Nguyen and Wooster (2020) demonstrated one of the first EO-based mappings of fuel consumption per unit (F_c) area across Africa, based solely on Meteosat FRE data and 20 m spatial resolution BA mapping.

7.2 Smoke Emissions Estimation from Active Fire Data

Fire emissions estimation is one of the main applications for EO-derived data on active fires. Johnston *et al.* (2012) used GFED data and a global atmospheric model to estimate that hundreds of thousands of excess deaths annually are related to exposure to smoke from landscape fires, and Roberts and Wooster (2021) recently revised this estimate upwards based on the FRP-based smoke emissions estimates provided by GFAS. Emissions of a particular smoke species are typically estimated using:

$$M_x = EF_x \times M_{consumed} \quad [8]$$

where M_x is the mass of the emitted species x (g) and EF_x its emission factor (g.kg^{-1}).

However, in part due uncertainties in the 'combustion coefficient' values of Equation 7 associated with different satellite datasets and/or biomes (see Section 6.1) there is an interest in relating spaceborne FRP estimates directly to rates of smoke emission (R_x), first demonstrated by Ichoku and Kaufman (2005):

$$R_x = C_e^x \times FRP \quad [9]$$

where, R_x is the rate of emission of species x (expressed in kg.s^{-1}) and C_e^x is the emission coefficient for species x (kg.MJ^{-1}).

Values of C_e^x are typically derived from comparisons between satellite-derived FRP datasets and the emitted species in question, primarily at present particulate matter (PM) amounts estimated via aerosol optical depth (AOD) measures (Ichoku and Kaufman, 2005; Mota and Wooster, 2018; Nguyen and Wooster, 2020). The approach has been successfully demonstrated for near real-time PM emissions estimation in the U.S. (e.g. Jordan *et al.*, 2008), Canada (e.g. Henderson *et al.*, 2008), and Europe (e.g. Sofiev *et al.*, 2009), and for global-to-continental scale emissions estimation to support science studies (e.g. Vermote *et al.*, 2009; Ichoku and Ellison, 2014; Mota and Wooster, 2018; Nguyen and Wooster, 2020). Table 3 lists the major global fire emissions datasets derived from satellite AF datasets, including GFED since whilst it primarily uses burned area data it uses AF detections to aid BA estimation in certain circumstances (see Section 8).

Table 3: Global fire emissions inventories and real-time monitoring systems based in part on satellite AF data. Note that those not updated in near real time are less appropriate for use in e.g. atmospheric monitoring and forecasting systems. Note that FREMv2 is based on FRP measures derived from GEO systems and so is not global. We focus on here on that derived from Meteosat over Africa.

Emission Dataset Name, version, and access*	***Spatial Resolution***	***Highest Temporal Frequency***	***Satellite Active Fire Obs Used#***	***Emission Factor / Coefficient***	***Data Availability period***	***Example Reference@***
FINN_v1.5	1 km	Daily	N_{pix}	EF_x	2002–Present	*Wiedinmyer et al., 2011*
FLAMBE-ARCTAS	1-4 km	Hourly	N_{pix}	EF_x	2000–Present	*Reid et al., 2009*

GBBEPx_v2	0.25 deg	Daily	FRP	EF_x	2017–Present	*Zhang et al., 2012* *Zhang et al., 2017*
GFAS_v1.2	0.1 deg	Daily	FRP	EF_x	2001–Present	*Kaiser et al., 2017*
GFED_v3.1	0.5 deg	3-hourly	BA, N_{pix}	EF_x	1997–2011	*van der Werf et al., 2010*
GFED_v4.1s	0.25 deg	3-hourly	BA, N_{pix}	EF_x	1995–Present	*van der Werf et al., 2017*
FEER_v1.0-G1.2	0.1 deg	Daily	FRP	C_e^x	2003–Present	*Ichoku and Ellison, 2014*
IS4Fires_v2.0	0.1 deg	3-hourly	FRP	C_e^x	2000–Present	*Sofiev et al., 2009*
QFED_v2.5	0.1 deg	Daily	FRP	C_e^x	2000–Present	*Darmenov and da Silva, 2015*
FREMv2	Per-Pixel & 0.1 deg	15 mins	FRP	C_e^x	2004-Present	*Nguyen and Wooster, 2020*

*Dataset websites as of March 2021:

FINN (https://www2.acom.ucar.edu/modeling/finn-fire-inventory-ncar);

FLAMBE (not available);

GFAS (https://www.ecmwf.int/en/forecasts/dataset/global-fire-assimilation-system);

GFED (http://www.globalfiredata.org/);

FEER (https://feer.gsfc.nasa.gov/data/emissions/);

IS4Fires (http://is4fires.fmi.fi);

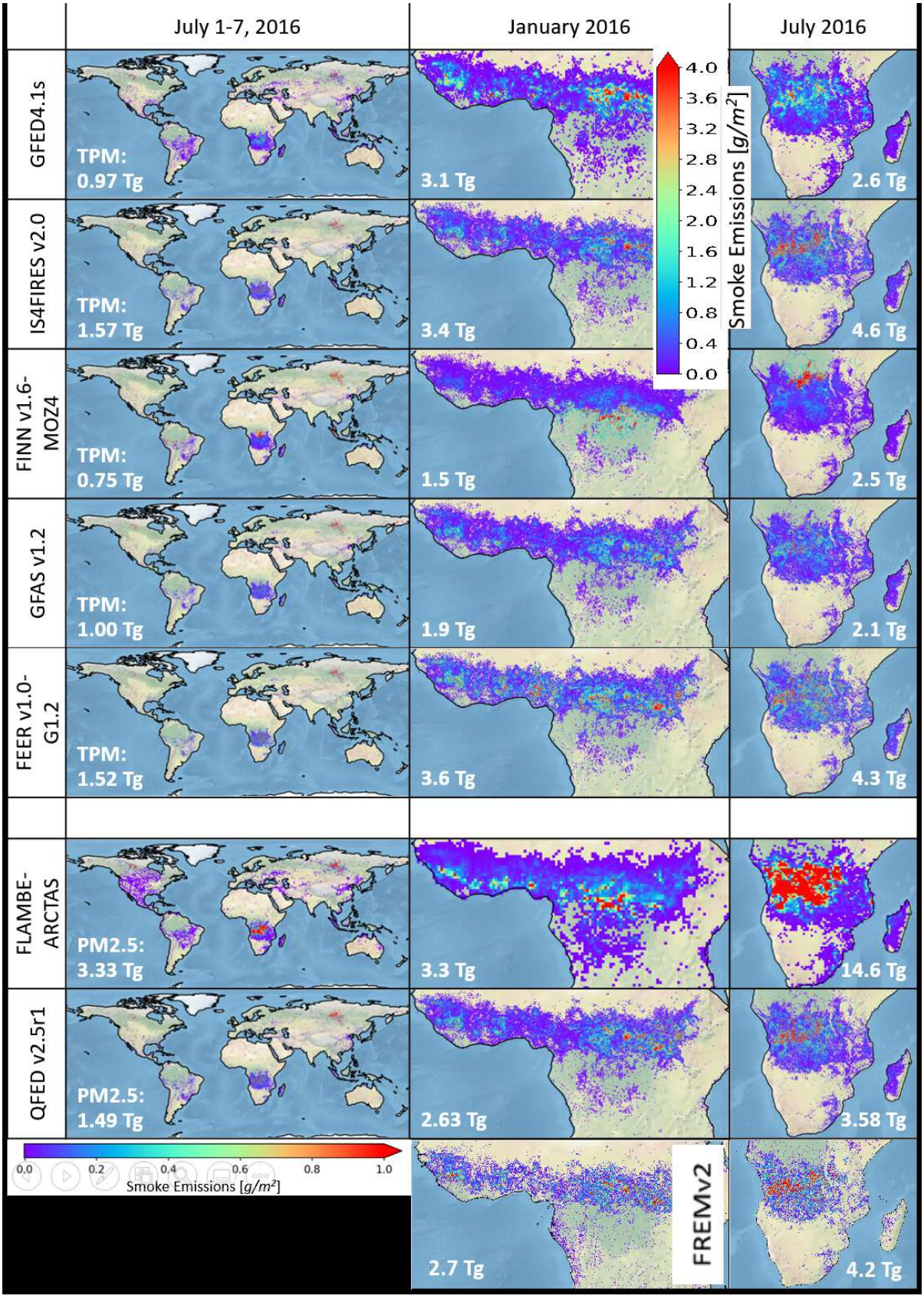
QFED (http://wiki.seas.harvard.edu/geos-chem/index.php/QFED_biomass_burning_emissions);

GBBEP (http://www.ospo.noaa.gov/Products/land/gbbepx/)

#This includes the parameter type used in generating the emission dataset (and the sensor/satellite that acquired such observations enclosed in parenthesis): N_{pix}=fire-pixel count; FRP=fire radiative power

@The indicated references are respective representative examples but may not be the most relevant reference for each dataset.

Figure 9 shows an emissions inventory intercomparison for seven of the datasets detailed in Table 3 (1-7 July 2016) available globally, both worldwide and for the peak fire month in northern and southern hemisphere Africa. Although it would have been best to show the same smoke aerosol species (in this case, total particulate matter; TPM) for all products, FLAMBE and QFED only provide $PM_{2.5}$ so this is shown instead. Continued uncertainty in fire emissions estimates is evidenced by the more than two times difference among the TPM emissions estimates, and the larger differences when considering $PM_{2.5}$. Other estimates, conducted as yet only for Africa, show similar ranges of estimation (Nguyen and Wooster, 2020). Nevertheless, there appears to be some improvement compared to the factor of 12 difference found even relatively recently (Zhang *et al.,* 2014). Uncertainties stem from a combination of and/or propagation of errors that, depending on the exact method and calculations employed, come from the satellite-derived variables (e.g. AF pixel counts, FRP, and AOD), the aforementioned 'combustion coefficient' conversion factor, the representativeness of the emission factors (EF_x), any required smoke injection height and velocity estimates, and the host of applicable model parameterizations/assumptions. Further research is needed to quantify the absolute magnitudes and sources of these uncertainties, and thus improve our current quantification of continental-to-global fire emissions.


July 1-7, 2016
January 2016
July 2016
GFED4.1s
TPM: 0.97 Tg
3.1 Tg
2.6 Tg
IS4FIRES v2.0
TPM: 1.57 Tg
3.4 Tg
4.6 Tg
FINN v1.6-MOZ4
TPM: 0.75 Tg
1.5 Tg
2.5 Tg
GFAS v1.2
TPM: 1.00 Tg
1.9 Tg
2.1 Tg
FEER v1.0-G1.2
TPM: 1.52 Tg
3.6 Tg
4.3 Tg
FLAMBE-ARCTAS
PM2.5: 3.33 Tg
3.3 Tg
14.6 Tg
QFED v2.5r1
PM2.5: 1.49 Tg
2.63 Tg
3.58 Tg
FREMv2
2.7 Tg
4.2 Tg
Smoke Emissions [g/m²]
0.0
0.4
0.8
1.2
1.6
2.0
2.4
2.8
3.2
3.6
4.0
Smoke Emissions [g/m²]
0.0
0.2
0.4
0.6
0.8
1.0

907

Figure 9: Landscape fire emissions estimates of total particulate matter (TPM) or particulate matter of 2.5 μm or less aerodynamic diameter ($PM_{2.5}$), as contained within different fire emissions databases (Table 3). Left column: July 1-7, 2016 global distribution; Middle column: January 2016 northern sub-Saharan Africa distribution; Right column: July 2016 southern sub-Saharan Africa distribution. Total emission of the respective smoke species for the respective time periods is indicated on each panel. FREMv2 is based on geostationary data and so is not global.

8. Relationships to Fire Regimes and Ecosystem Variables

AF detections and FRP data are most commonly used to identify fire timing, location, intensity, and smoke emissions source strength. However, they have also been used to infer burned area, fire behavior and fire impacts on the terrestrial environment, both during and after fire events, and to help define areas characterized by different fire regimes.

8.1 Burned Area

Satellite data have been used for nearly 40 years to directly map burned area via a fires impact on surface reflectance (Chuveico *et al.*, 2019). However, in the 1980's and 1990's BA estimates were often calculated using AVHRR-derived AF pixel counts (e.g. Matson *et al.* 1987; Matson and Holben 1987) – mainly because AVHRR data are sub-optimal for direct BA mapping (Giglio and Roy, 2020). However, AF errors of omission related to e.g. cloud cover or to fires that were not burning at the satellite observation time mean that AF pixel counts often provide an imperfect proxy for area burned. **Figure 10** shows an area of burned savanna imaged by 30 m Landsat data and overlain with contemporaneous MODIS AF detections. The latter document the spread of the fire but contain extensive spatial gaps, and even interpolation of the AF detections would not fully reconstruct the full BA extent.

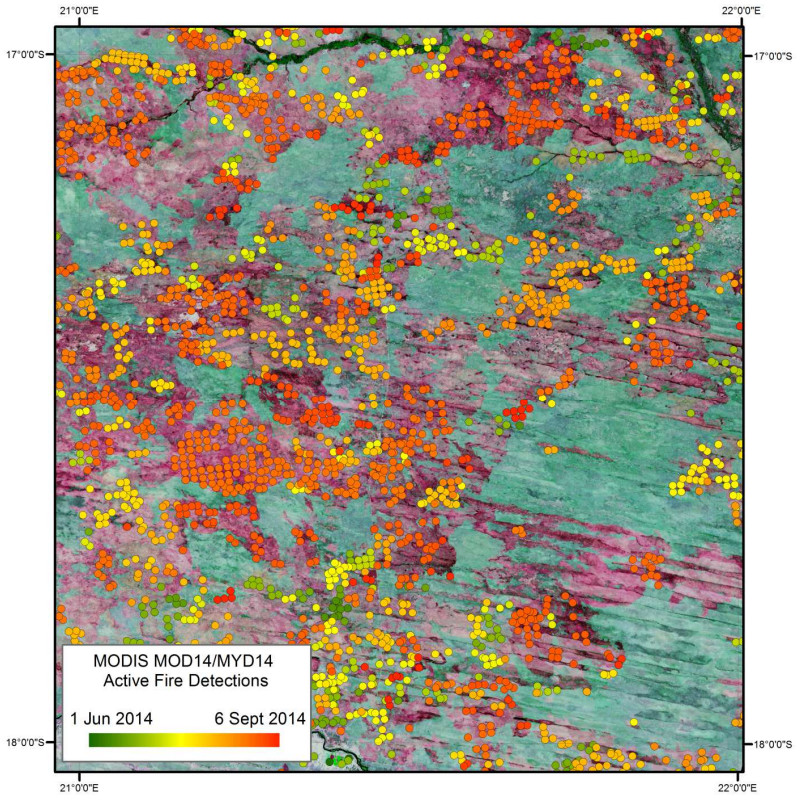


Figure 10: MODIS 1 km active fire pixel detections (shown with a rainbow color scale indicating the day of detection over a three month period) superimposed on a Landsat 8 OLI image (R: 2.2 µm, G: 0.86 µm, B: 1.6 µm, burned areas are apparent in magenta tones) acquired on the last day of the MODIS active fire detections (6th September, 2014) for 100 km × 100 km over the Caprivi Strip on the border between Angola and Namibia.

Whilst **Figure 10** shows a clear pattern between BA extent and matching AF pixel count, several studies (e.g. Giglio *et al.,* 2013; Hantson *et al.,* 2013) demonstrate the ratio to be biome-dependent. These include Roy *et al.* (2008) who found that for low percent tree cover and leaf area index (LAI) landscapes, the MODIS 500 m BA product defined a greater proportion of the landscape as burned than did the MODIS AF product; yet with increasing tree cover (>60%) and LAI (>5) the reverse was often true. Biome-specific calibrations have been undertaken to estimate BA from AF pixel counts

(Scholes *et al.,* 1996; Giglio *et al.,* 2013), with for example GFED using nighttime ATSR AF detections (Arino *et al.*, 1999) to estimate BA for the pre-MODIS 1997-2000 period via:

$$BA_{i,t} = \propto_i AF_{i,t}^{\beta_i} \quad [12]$$

where $BA_{i,t}$ is the burned area in grid cell i and month t (0.25° grid cells), $AF_{i,t}$ is the AF detection for the same cell and time, and $\propto_i$ and β_i are dimensionless and spatially-varying parameters estimated independently using regression of post-2000 ATSR AF pixel counts (Arino *et al.*, 1999) with the 500 m MODIS BA product (Giglio *et al.* 2013).

Some of the most recent iterations of GFED (e.g. v4.1s; van der Werf *et al.*, 2017) also use satellite AF detections to estimate the additional BA associated with fires too small to be mapped with the MODIS 500 m BA product. Whilst this 'small fire boost' successfully increases BA in many regions, it can also lead to significant errors in locations subject to many AF detection errors of commission (Zhang *et al.*, 2018). This points to the importance of understanding the regional and seasonal dependencies of AF detection errors.

8.2 *Rate of Spread and Intensity and Relationships to Fire Effects*

Some of the most ecologically important characteristics of an actively spreading landscape fire are the fire front rate of spread (ROS) and fireline intensity (FLI; Byram, 1959) (Bond and Keeley, 2005). AF data have been related to both – though primarily those based on airborne rather than satellite observations (e.g. Pastor *et al.,* 2006; Paugam *et al.,* 2013). Most satellite AF data use has been limited to mapping wildfire progression across the landscape (e.g. Veraverbeke and Hook, 2013), and whilst ROS estimation has been attempted from LEO (Andela *et al.*, 2019) and occasionally GEO (Liu *et al.*, 2020) AF data, the low spatial and/or temporal resolution of the source data provides limitations. FLI represents the rate of heat release per unit time per unit length of the fire front (kW m^{-1}; Alexander, 1982), and unlike FRP it includes the all heat transfer mechanisms. Thus any FRP-based FLI calculations need to assume a radiant

fraction, or simply provide the FLI radiative component only (e.g. Wooster *et al.*, 2004; Riggan *et al.*, 2004; Smith and Wooster, 2005). FRP-derived values of fire heat release may provide links to the effects on plant physiology, such as pre-and post-fire change in net photosynthesis, tree radial growth, or landscape-scale forest net primary production (NPP) change (e.g. Sparks *et al.,* 2017; 2018; **Figure 11**).

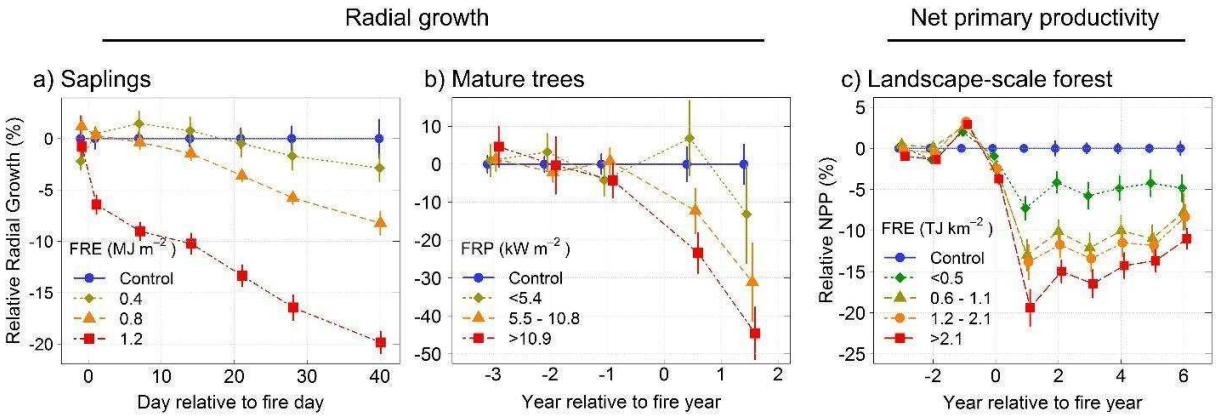


Figure 11. Radial tree growth and NPP patterns seen across different temporal and spatial scales in areas subject to varying levels of fire activity (as expressed by FRP and FRE per unit area values at (a) 2 yr old Pinus contorta saplings in laboratory experiments and (b) mature (>35 years old) Pinus ponderosa trees burned in stand-scale prescribed fires respectively. Similar patterns were observed in (c) at the regional scale using net FRE per unit area and NPP measures derived from MODIS. See Sparks *et al.* (2017; 2018).

8.3. Fire regime characterization

A fire regime describes the prevailing, long-term fire patterns and characteristics of an area, emerging from feedback interactions between climate, vegetation, and the regions natural and anthropogenically driven fires (Whitlock *et al.*, 2010). A fire regimes principle characteristics are fire *frequency, seasonality, spread patterns, intensity* and *fuel consumption* (Bond and Keeley 2005; Gill 1975). Satellite AF data have been used to provide contemporary views of landscape fire regimes and to distinguish parameters

related to fire size, intensity, severity, and most commonly fire seasonality, frequency and diurnal cycle. Each LEO sensor such as AVHRR, MODIS, and VIIRS typically image areas a few times daily per satellite, enabling fire diurnal cycles to be roughly characterized using either day/night ratios (Giglio *et al.* 2006; Langaas 1992) or interpolation between observations (Andela *et al.* 2015; Ellicott *et al.* 2009). The TRMM low-inclination, drifting orbit enabled fire diurnal cycles to be characterized from 8-yrs of VIRS data (Giglio 2007), but the high temporal resolution (and constant ground footprint areas) provided by geostationary sensors are optimum for diurnal cycle characterization. GEO data have been applied for this purpose across the Americas (e.g. Prins *et al.,* 1998; Xu *et al.,* 2010; Zhang *et al.,* 2012), east and south-east Asia (e.g. Hyer *et al.,* 2013; Xu *et al.,* 2017) and Africa (e.g. Roberts *et al.,* 2009; 2018a) (**Figure 12**).

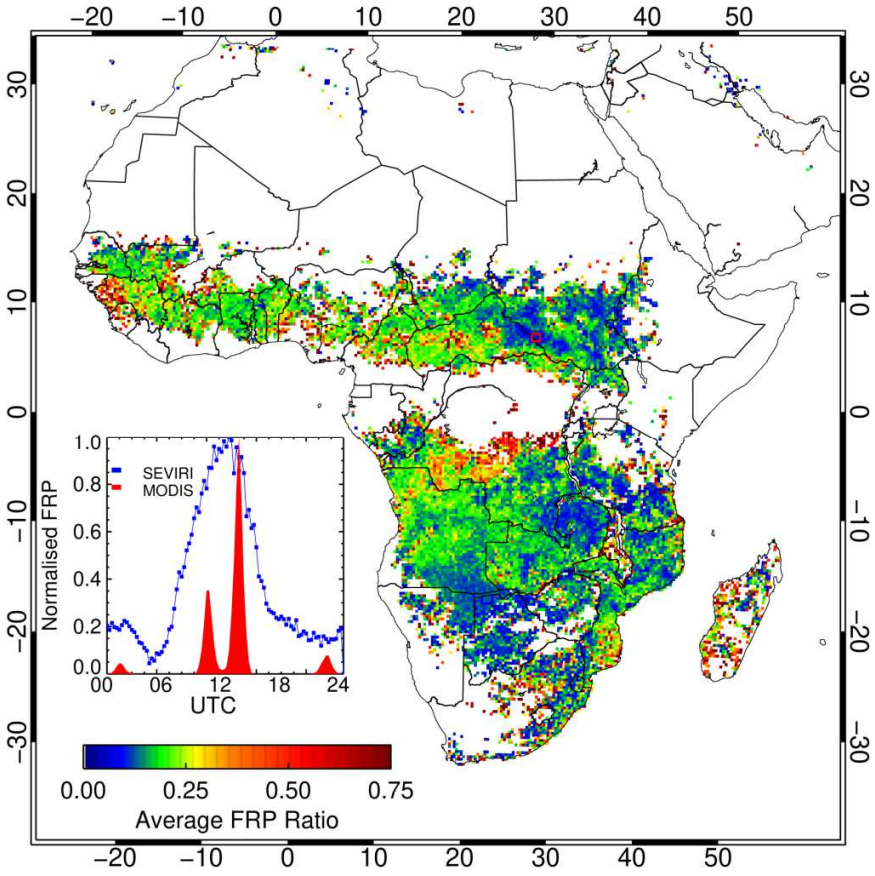


Figure 12. Fire radiative power (FRP) diurnal cycle variability across Africa, as derived from a year of the 96 daily FRP datasets provided by the geostationary Meteosat FRP-PIXEL product available from the EUMETSAT LSA-SAF (Wooster *et al.,* 2015; Roberts *et al.*, 2015). Generally, the fire diurnal cycle is semi-Gaussian, with a day-time peak and nighttime minima (see inset that shows normalized FRP values from SEVIRI and MODIS), but the timing of the peak spatially varies. The metric shown is the ratio between the summed FRP measured by SEVIRI at only the times of MODIS overpasses, and that measured over the full 24-hr cycle. Changes in the timing of the diurnal cycle peak are reflected in changes to this ratio.

Satellite AF data indicate that fire diurnal cycles are mostly characterized by mid-afternoon (local solar time) peaks, with less activity (and with generally lower intensities) between late evening and early morning (Giglio, 2007; Hyer *et al.,* 2013; Roberts *et al.,* 2009). During droughts, increased combustion of deep organic soils sometimes results in a less pronounced and/or temporally extended diurnal cycle (e.g. Kaiser *et al.,* 2012; Wooster *et al.,* 2012a; 2018), whereas in agricultural regions a bi-modal diurnal cycle may be driven by local burning practices (Xu *et al.,* 2017). New fire seasons can also sometimes rapidly arise, driven by changes in fire policy and/or enforcement (e.g. Zhang *et al.*, 2020). Further fire regime characteristics derivable from satellite AF data include size distributions, sometimes derived from FRP (e.g. Wooster and Zhang, 2004) though more commonly from BA (e.g. Archibald *et al.,* 2010). Fire type can sometimes be elucidated, with clusters of adjacent AF pixels deployed to identify spatially contiguous flaming and smoldering areas (Langaas, 1992), and on an instantaneous basis large AF pixel clusters can either be associated with long and narrow fire lines such as found in savannas (e.g. Dwyer *et al.,* 2000), or deep flaming fronts with residual combustion behind, typical of Canadian forest fires (Cahoon *et al.,* 2000). Fire regimes in areas with higher fuel loads and which burn under hotter, drier, and windier conditions generally exhibit higher upper limits of FLI ($W.m^{-1}$), reaction intensity ($W.m^{-2}$), and heat release per unit area ($J.m^{-2}$). These are key fire behavior attributes influencing fires' short- and long-term ecological impact, though thus far their estimation is only rarely attempted from AF data (see Section 7). More commonly, FRE-

derived fuel consumption totals (Section 7) have been ratioed against BA data to derive fuel consumption per unit area measures (e.g. Roberts *et al.*, 2011; Mota and Wooster, 2018; Nguyen and Wooster, 2020), and have been used to help discriminate identical fire regimes happening at different times of the year under variable meteorological conditions (e.g., Andela *et al.*, 2015; Boschetti and Roy 2009; Freeborn *et al.,* 2016). FRP distributions themselves have revealed regional as well as intra-biome fire regime variations (Wooster and Zhang 2004; Ichoku *et al.,* 2008; Giglio *et al.*, 2006; Laurent *et al.,* 2019), though such differences may be due to variations in an unknown combination of fire behavior attributes (e.g. radiant fraction, sub-pixel active fire area, fire intensity) coupled with influences such as canopy overstory effects (Roberts *et al.,* 2018b).

AF products are particularly well suited for characterizing fire seasons, or the times of the year when large and intense fires are most prevalent. A variety of temporal metrics (e.g., start and end dates, peak month, and fire season duration etc.) have been derived from both AF pixel counts and FRP data, and used to map regional to global variations in fire seasonality (e.g. Dwyer *et al.,* 2000; Giglio *et al.,* 2006). Locations where the fire season leads or lags seasonal weather may indicate the degree of control that humans exert on a regions fire regime (Le Page *et al.,* 2010). For example, across much of northern Africa, rural communities purposely ignite early season fires under mild weather conditions to create a patchwork of fuel breaks in an attempt to limit the uncontrolled spread of more intense and more ecologically damaging late season fires (Laris, 2002). Agricultural residue burning periods similarly closely coincide with the timing of crop-specific planting and harvesting (Korontzi *et al.,* 2006; McCarty *et al.,* 2009; Zhang *et al.,* 2018; 2020)

Accumulating many years of AF observations allows retrieval of long-term attributes, such as fire return interval (average number of years between successive fires), fire frequency (the inverse of fire return interval), and measures of interannual fire variability and trend. However, derived chronologies of annual fire occurrence have been more commonly extracted from BA time-series (Devineau *et al.*, 2010; Freeborn *et al.,* 2014b). Instead, the simplest and most common AF analog has probably been the count of AF pixels detected per unit time and per unit area, referred to as both fire frequency and fire density (Chuvieco *et al.,* 2008; Csiszar *et al.,* 2005; Di Bella *et al.,* 2006; Soja *et al.,* 2004). Temporal trends in AF pixel counts are most often used to infer

changes in fire occurrence and when associated with time-series of climate, land cover, and anthropogenic variables have been used to identify locations of shifting fire regimes potentially associated with anthropogenic or climatic trends (Aragao and Shimabukuro, 2010; Arino *et al.* 2012; Gregoire and Simonetti, 2010; Pricope and Binford, 2012).

9. Online AF Data Delivery and Mapping Systems

Whilst certain of the AF products outlined in Section 6 have been available for several decades, widespread product delivery in easily accessible formats has been available for only around half this time. The MODIS Rapid Response System was the first attempt to provide near real-time global AF data (Justice *et al.,* 2002a), subsequently evolving into the NASA Fire Information for Resource Management System (FIRMS) (Davies *et al.,* 2014). These developments are part of a growing trend of "analysis ready data" (ARD), which aims to reduce the EO data pre-processing burden on users and enable easier and more immediate analyses. AF data are made available typically with very low data latency rates via these and other systems, generally within a few hours or less of the observation time.

AF detections have been available in analysis ready form for more than two decades, and this has helped spread their use in multiple applications. Many of these need not expose the user to detailed knowledge of the methods and algorithms (outlined in earlier Sections) that have been used to produce the AF data. Applications include strategic land and fire management, no-burning compliance monitoring, wildlife conservation, detection of illegal logging and/or poaching within protected areas, monitoring air pollution and improved understanding of fire regimes. As applications for AF data have evolved and matured, users have further articulated their information requirements (e.g., Trigg and Roy, 2007; Mouillot *et al.* 2014; Davies *et al.,* 2014), which in turn has led to more customized data products, more functional and accessible online data mapping and delivery systems including a wider variety of variables, and most recently also mobile accessible applications. Whilst some users simply wish to visualize AF data on a map, and others want to download it for their own analyses, increasingly there is a move to also provide broader contextual information in a single online application (e.g. land cover; atmospheric composition; fire risk, BA).

AF fire data delivery systems can be classified into three groups: 1) direct providers, who process and distribute their own AF data; 2) brokers, who take AF data from a direct provider and add value by customizing the information to serve specific user communities; and 3) those that are both direct providers and brokers. The latter often process data collected 'locally' in real-time via a so-called satellite direct reception (DR) or direct broadcast (DB) station, but also acquire additional AF data from others to provide broader geographic coverage. AF data users are now faced with a huge choice of data portals, and Appendix 2 provides detail on four key examples currently operating. We also include therein an example of how such data are used, in this case in support of national park fire management. Users select their most appropriate information delivery system based on data type and coverage, latency (time from satellite overpass to user availability), ease of use, and how the AF data can be viewed and queried alongside other types of information. GEO or DR-based LEO data feeds generally have some of the lowest data latency times, but more recently even non-DR equipped data portals for MODIS and VIIRS AF data, such as NASA FIRMS (part of NASA's Land, Atmosphere Near real-time Capability for EOS (LANCE)) offer AF data updates usually within 2.5 hours of the observation time, though some specifics of the near real-time (NRT) AF products served may differ from those of the "standard" data products. New data feeds are following this trend, with AF detections and FRP data Sentinel-3 (Wooster *et al.,* 2012b; Xu *et al.,* 2020) produced in two versions, NRT within a few hours of data capture (https://metis.eumetsat.int/frp/), and non-time critical (NTC) a few days later (https://scihub.copernicus.eu/dhus/#/home) .

10. Future Priorities in Active Fire Remote Sensing

10.1 Dataset Priorities

NRT and higher spatial and temporal resolution satellite AF and FRP products are a priority for the applications and science communities. Errors of AF commission and in particular omission should continue to be reduced, through sensor and algorithm development, robust validation, and provision of improved ancillary datasets such as masks optimized for the AF-application, e.g. cloud masks which do not mask out smoke contaminated areas, appropriate land/water maps, and maps of static IR emitters (e.g.

gas flares/volcanoes and potentially persistent false alarms due to e.g. specific industry or building types). Such developments are required to meet the temporal (1-6 hours) and spatial (0.25-3 km) resolution and FRP retrieval uncertainty (10% integrated over a pixel) target specifications outlined by the Global Climate Observing System (GCOS) Essential Climate Variable (ECV) programme (GCOS-200; 2016) and proposed by GOFC/GOLD and the Committee on EO Satellites (CEOS) Land Product Validation (LPV) working groups (Boschetti *et al.*, 2009). The need for long-term, climate quality, AF products offering global coverage remains paramount, and this entails systematic product generation, quality control, algorithm maintenance and when necessary reprocessing. Without reprocessing using updated calibration and geolocation information, and improved algorithms refined in response to routine product quality assessment periodic validations (Section 6), AF products become less suitable for addressing climate science questions.

In addition to improving AF detection algorithms, efforts should focus on developing AF products maximizing use of currently available data, such as through blending GEO and LEO observations (e.g. Zhang et al., 2020). A long-standing GOFC/GOLD goal is the development of a global geostationary AF system, which is increasingly relevant given the improved AF fire detection apability of the new generation of GEO satellites. AF detection and FRP data have recently become available in NRT from Meteosat, Meteosat Indian Ocean, Himawari and GOES-E and -W using the same FTA algorithm originally developed for Meteosat SEVIRI (Roberts and Wooster, 2008; Wooster *et al.*, 2015; Xu *et al.*; 2017; 2021a). Similarly, the availability of Landsat and Sentinel-2 imagery having pixel sizes in the tens of meters provides detailed SWIR-based AF detection that may complement coarser spatial resolution but more frequently available AF products, if only initially for validation of the latter. The increasing number of very high spatial resolution (1-3 m) sensors should also be evaluated for their potential use in AF detection. Development of additional ancillary datasets, such as those related to fuel load per unit area, and biome, season and fuel-moisture dependent trace gas and aerosol emissions factors (EFs), is required to further improve fire emissions estimation.

10.2 EO Sensor and Mission Priorities

This review has reiterated that to provide optimum data for AF remote sensing, a typical sensor requires co-registered channels in the MIR (3 – 5 μm) and LWIR (8 – 14 μm), a co-located VIS or NIR channel to aid daytime masking of false alarms and cloud. The exact spectral placement of each channel is less prescriptive, but for example the 3.959 μm "fire channel" of MODIS was selected due to its relative insensitivity to atmospheric water vapor absorption and avoidance of the CO_2 absorption window beyond ~ 4 μm (Kaufman *et al.*, 1998). Of key importance for FRP retrieval are MIR measurements across a sufficient dynamic range to provide good quality, unsaturated data over the highest intensity and/or largest fires, as well as over the ambient temperature background. Without the former, the FRP of the most strongly emitting fires cannot be gauged, and without the latter the AF pixels themselves may not even be reliably detected. The required upper end of the MIR channel dynamic range needs to be set according to the sensors ground pixel footprint area, since the same fire will form a greater proportion of a smaller rather than larger pixel (MODIS 1 km² pixels have ~ 500 K saturation temperature *vs.* ABI 4 km² pixels have ~ 400 K). For the 60 m spatial resolution MIR band of the proposed Hyperspectral Infrared Imager (HyspIRI) payload, Realmuto *et al.* (2015) specified a 1200 K saturation temperature. As with MODIS and SLSTR, such wide dynamic ranges sometimes require two MIR detectors, or one detector operating with dual integration times or gain settings (e.g. BIRD HSRS and VIIRS). Other beneficial sensor attributes include limiting pixel area growth across the swath (as done with VIIRS and SLSTR; Schroeder *et al.*, 2014; Xu *et al.*, 2021b), a SWIR channel operating at night to aid hotspot detection, discrimination of fires from higher temperature targets such as gas-flares, and FRP estimation from the latter (Fisher and Wooster, 2018; 2019). SWIR wavebands centered around 2.2 μm appear most effective, and night-time use of a broad day-night (low light level) band (0.5 - 0.9 μm) similar to that of VIIRS can also be considered. SWIR-based AF detection is also possible by day if ground pixel footprints are small enough.

High temporal resolution AF data is required for operational fire monitoring, warning and fire-fighting applications, and to provide the most reliable estimation of FRE via FRP temporal integration. GEO systems meet this goal, with the newest such as Himawari (Bessho *et al.* 2016, Xu *et al.* 2017), Meteosat Second Generation (soon to be

superseded by Meteosat Third Generation [MTG]; Roberts and Wooster, 2008), GEO-KOMPSAT-2A and Feng-Yun 4A (Yang *et al.* 2017), and GOES-R (Schmit *et al.* 2017; Xu *et al.* 2017; 2021) including MIR bands having suitably extended dynamic ranges, and offering full-disk temporal resolutions as high as 10 minutes. However, their larger pixel areas result in minimum FRP detection limits typically at least 4× higher than from the nadir views of LEO sensors – so they generally cannot detect a substantial number of fires that MODIS type sensors would identify if they viewed the same location at the same time. MTG will offer 1 km data every 2.5 minutes over some areas, a first for the AF application, and even in densely populated Europe this may provide sufficient capability to usefully detect a significant number of newly ignited fires in advance of public call ins. Use of highly elliptical orbits could be explored to provide a high latitude, high temporal resolution AF capability. An achievable future GEO goal that would cover many of the applications supported by current LEO systems would be 500 m spatial resolution geostationary-based AF detection, and the Chinese Meteorological Agency (CMA) GF4 GEO satellite already includes a 400m MIR channel that demonstrates this is possible (Lu *et al.*, 2020).

An option to provide high spatial detail, low commission error AF data at increased temporal resolutions is via constellations of LEO systems placed to cover different overpass times. LEO capabilities continue to improve, and compared to MODIS Sentinel-3 SLSTR offers a somewhat improved AF detection sensitivity due to its on average smaller pixel footprint area (Xu *et al.*, 2020; 2021; **Figure 3**), whilst VIIRS' 375 m data offers a sensitivity around 10× better (Schroeder *et al.,* 2014; Zhang *et al.,* 2017). Going beyond the spatial resolution of VIIRS may provide diminishing returns, since the latter can already identify active areas of combustion of < 20 m^2, and over some landscapes high AF errors of commission can result from the IR clutter present in very finely detailed thermal imagery (Schroeder *et al.,* 2014; Zhang *et al.,* 2017). Performance trade-offs between the existing style of often larger satellites using cooled sensor technology and lower cost smaller missions that might enable lower-cost constellation development, possibly using uncooled detectors if their performance can be demonstrated (e.g. WildFireSat; Johnston *et al.* 2020), should be examined.

10.3 Other Research Priorities

Beyond datasets and sensors, there remain several primacies for ongoing research in AF remote sensing. These include a better understanding of errors and uncertainties in AF detection, FRP retrieval and fire emissions estimation, both spatially (e.g. by biome, temporally (e.g. diurnally, seasonally) and with respect to different sensors, products and observational (e.g. atmospheric and view angle) effects. Validation of AF products remains challenging, due to the ephemeral and dynamic nature of fire and to difficulties in obtaining co-located simultaneous and independent reference observations. On a global scale this has been limited to joint use of ASTER and Terra MODIS (see Section 1), and with Terra nearing its end of life there is a need to develop a validation strategy covering a wider array of instruments and times of day. Similarly, a uniform protocol to validate spaceborne FRP retrievals is required, particularly as it is a designated GCOS ECV and one which is still at the lowest validation stage according to the CEOS LPV validation hierarchy. Understanding the lower FRP components of a regions fire regime and how this is included or excluded by different AF data products remains important, as are ways to adjust for this when necessary. The ability to map fireline rates of spread remains a goal for many fire management applications, as is the need to further promote assimilation of NRT AF data into time-coupled weather-fire behavior modelling frameworks (Cohen and Schroeder, 2013). Research on the conversion between FRP, FRE and fuel consumption, trace gas and aerosol emissions continues to be a priority, as does the reconciling of such estimates with those from alternative (e.g. burned area) based approaches. Finally, the accuracy and usefulness of EO methods for flaming/smouldering fire discrimination - including via use of phenomena such as detection of landscape fire potassium emission lines - needs to be further examined, as does the need and ability to optimize any applied emissions factors used in subsequent smoke emissions calculations.

11. Summary and Conclusion

Observing landscape fires from space has a strong heritage, stretching back to the 1980's with NOAA AVHRR. Since then, satellite active fire (AF) data have become very

widely used by scientists and government agencies, and the number of spaceborne sensors equipped with measurement capabilities relevant to the AF application, including with 'fire-optimized' thermal channel dynamic ranges, has greatly increased. The NASA MODIS AF product suite is the most widely utilized, and the ease of access to these and other AF data through numerous data portals has proliferated beyond science to allow routine monitoring and reporting - as evidenced by their deployment by the media during the recent [2019] Amazonian fire activity increase (Kelley *et al.*, 2021) and during the 2019/2020 Australian black Summer bushfires (Abram *et al.*, 2021). Although these recent events have highlighted the relevance and importance of satellite AF products (e.g. Escobar, 2019), they have also reinforced the need for the community of data producers to more clearly communicate the limitations as well as benefits of each AF product, so as to reduce interpretation inaccuracies.

AF products have evolved from reporting the timing and location of actively burning fires to now include measures such as fire effective temperature, area and fire radiative power (FRP). Near real-time (NRT) EO data streams have allowed the FRP method to be used to deliver smoke emissions source strength information to a variety of atmospheric modelling systems, for example in support air quality forecasting. Future satellite missions, including higher spatial resolution GEO systems and increased numbers of AF-capable LEO systems, including the future possibly of small-satellite constellations, provide further opportunities for advancing both science and operational applications as their performance evolves. A key constraint remains the scarcity of reference data suitable for validating contemporaneous AF detections and FRP retrievals. Communities such as GOFC/GOLD and CEOS LPV are encouraged to continue to lobby space agencies to develop and launch missions that include sensors whose characteristics are optimized for the AF application, and often only relatively small adjustments to the initially planned characteristics are required – as was the case for example with Sentinel-3 SLSTR and Meteosat Third Generation. Looking forward, continuing climate and environmental change may potentially shift certain drivers of landscape fire (Rogers et al., 2020). Apparent policy or policy enforcement shifts appear able to rapidly alter fire characteristics over large regions (Sembhi et al., 2020), and the health impacts of the poor air quality that can come with landscape burning is a growing

concern. We can therefore expect the relevance and importance of satellite AF remote sensing to continue to grow.

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