Fire Detection and Fire Characterization Over Africa Using Meteosat SEVIRI

Gareth J. Roberts and Martin J. Wooster

Abstract—Africa is the single largest continental source of biomass burning emissions and one where emission source strengths are characterized by strong diurnal and seasonal cycles. This paper describes the development of a fire detection and characterization algorithm for generating high-temporal resolution African pyrogenic emission data sets using data from the geostationary Spinning Enhanced Visible and Infrared Imager (SEVIRI). The algorithm builds on a prototype approach tested previously with preoperational SEVIRI data and utilizes both spatial and spectral detection methods whose thresholds adapt contextually within and between imaging slots. Algorithm validation is carried out via comparison to data from ~800 temporally coincident Moderate Resolution Imaging Spectroradiometer (MODIS) scenes, and performance is significantly improved over the prior algorithm version, particularly in terms of detecting low fire radiative power (FRP) signals. On a per-fire basis, SEVIRI shows a good agreement with MODIS in terms of FRP measurement, with a small (3.7 MW) bias. In comparison to regional-scale total FRP derived from MODIS, SEVIRI underestimates this by, on average, 40% to 50% due to the nondetection of many low-intensity fire pixels (FRP < 50 MW). Frequency-magnitude analysis can be used to adjust fire radiative energy estimates for this effect, and taking this and other adjustments into account, SEVIRI-derived fuel consumption estimates for southern Africa from July to October 2004 are 259–339 Tg, with emission intensity peaking after midday and reducing by more than an order of magnitude each night.

Index Terms—Carbon, fires, remote sensing.

I. INTRODUCTION

BIOMASS burning is a key Earth system process, a major element of the terrestrial carbon cycle, and a globally significant source of atmospheric trace gases and aerosols [3]. Depending upon their size, location, and timing, fires can significantly modify land surface properties, influence atmospheric chemistry and air quality, and perturb the radiation budget (Intergovernmental Panel on Climate Change, 2001). Millions of square kilometers of the African landscape are burned each year, and fire in Africa is characterized by strong variability, particularly diurnally and seasonally [25]. African fires are responsible for an average of perhaps 30% to 50% of the total amount of biomass burned globally each year, making Africa, on average, the single largest biomass burning emission source [4], [65], [67].

The burning of biomass in wildland fires is accompanied by a wide variety of characteristic spectral signature changes that can be detected by remote sensing, including those related to the intense thermal emission from combustion [31], [43], to the albedo and spectral reflectance of newly burned surfaces, and to the presence of smoke plumes containing trace gas and aerosols in highly elevated concentrations [32], [66]. For these reasons and because of the widespread but highly variable nature of global biomass burning activity, observations from Earth-orbiting remote sensing satellites are considered the key to better characterizing the extent and influence of this phenomenon.

Observations of actively burning fires probably represent the earliest method that is used regularly to examine biomass burning from satellite Earth observation [13]. Most active-fire studies have relied on data from polar-orbiting satellites, but their restricted overpass frequency, coupled with fires that have typically strong diurnal cycle, means that the information they provide typically represents only a rather limited temporal sample. Such limited repetition rates may also not be fully consistent with the need to link emission estimates to models of atmospheric transport and chemistry [49], [68], and for these reasons, the use of geostationary systems for recording the signatures of biomass burning has received a significant amount of attention [26], [50], [51]. In particular, active-fire detections derived from Geostationary Operational Environmental Satellites (GOES) imagery have been used by Holben et al. [29] and Reid et al. [52] to parameterize the lower boundary condition of atmospheric process models in order to determine emission longevity, transport, effects, and fate. Despite the relative spatial coarseness of the geostationary observations, incorporation of the GOES-derived active-fire data has had a significant impact on the ability to correctly forecast atmospheric aerosol loading [52].

The launch of Meteosat-8 (formerly Meteosat Second Generation) in 2002 offered a new possibility to apply geostationary active-fire detection methods over Africa, Earth’s most fire-affected continent. Meteosat-8 carries the Spinning Enhanced Visible and Infrared Imager (SEVIRI) instrument, an imaging radiometer with a 15-min repeat cycle that can be used to detect pixels containing actively burning fires and measure their rate of radiative energy emission in a number of spectral bands [54]. Integrated across all wavelengths, the fire radiative power (FRP) describes the overall rate of radiative energy emission from the fire, which relates to the rate of combustion [73]. As detailed in [72], if we know a fire temperature distribution within a pixel, then the pixel’s true FRP can be calculated using

$$\text{FRP}_{\text{TRUE}} = A_{\text{samp}} \varepsilon \sigma \sum_{i=1}^{n} A_n T_n^4$$  \hspace{1cm} (1)

where for a fire made up of $n$ distinct temperature components, $\text{FRP}_{\text{TRUE}}$ is the FRP ($J/s$), $A_{\text{samp}}$ is the surface sampling area ($m^2$), $\sigma$ is Stefan–Boltzmann constant


(5.67 \times 10^{-8} \text{Js}^{-1} \cdot \text{m}^{-2} \cdot \text{K}^{-4}), A_n$ is the fractional area of the $n$th thermal component within the sampling area, $T_n$ is the temperature (K) of the $n$th thermal component, and $\varepsilon$ is the emissivity. Most work to calculate the subpixel fire characteristics that are necessary for use (1) has been conducted with data from relatively high spatial resolution sensors. Recently, for example, Dennison et al. [12] used a multiple endmember spectral mixture analysis approach with hyperspectral Advanced Visible/Infrared Imaging Spectrometer (AVIRIS) imagery to derive subpixel fire temperature and fractional area from which FRP could be derived using (1). However, in the case of data from satellite Earth-observing (EO) sensors that measure infrared (IR) radiances in only a few discrete wavebands, such a spectral unmixing approach is inapplicable. The bispectral method [13] is, in theory, applicable to such data and requires observations in only two IR wavelengths, although it is demonstrated in [21] and [72] that the relatively weak contribution of many fires in the longer wavelength channels means that sensible retrievals of subpixel “effective” fire temperature and area are often only possible when using relatively high spatial resolution data, such as that from the Bispectral InfraRed Detection small satellite [72], [74], [75]. For lower spatial resolution sensors, alternative methods that do not rely on accurately quantifying the fire contribution to the longwave IR signal are more widely appropriate [34], [35], for example, the mid-infrared (MIR) radiance method in [72]. This approach uses a fourth-order power-law approximation to the Planck function, which is valid over a smoldering (~650 K) to flaming (~1350 K) fire temperature range, to provide FRP estimates from observations of only the fire-emitted MIR spectral radiance, thus avoiding the requirement to know the fire pixels’ subpixel temperature distribution

\[
FRP_{\text{MIR}} = \frac{A_{\text{samp}} \sigma \varepsilon L_{\text{MIR}}}{\alpha \varepsilon_{\text{MIR}}} \tag{2}
\]

where $L_{\text{MIR}}$ is the MIR spectral radiance of the fire within the pixel (i.e., with the contribution from the ambient background part of the pixel removed), $\varepsilon$ is the emissivity which is assumed to radiate as a gray body ($\varepsilon = \varepsilon_{\text{MIR}}$) [42], $A_{\text{samp}}$ is the pixel sampling area, and $\alpha$ is the power-law constant [watts per square meter per steradian per micrometer per fourth-order kelvin, (W \cdot \text{m}^{-2} \cdot \text{sr}^{-1} \cdot \mu \text{m}^{-1} \cdot \text{K}^{-4})]. Integrating the FRP over time provides a measure of the total amount of fire radiative energy (FRE) released, which, in turn, can be used to estimate the amount of fuel that was burned in order to produce this energy [54], [73]. The FRE approach to deriving fuel consumption estimates, in theory, provides a more direct measure of biomass consumption than the traditional bottom-up burned area-based approaches that require additional data on fuel load and combustion completeness [59], [65], and the ability to apply (2) to data from even coarse resolution sensors means that it is well suited for use with data from geostationary imagers. Further detailed reviews of the various other options for fire characterization, and more detail on the methods discussed here, can be found in [34], [43], [51], and [72].

Roberts et al. [54] and Wooster et al. [73] described the first prototype algorithm for the detection and FRP characterization of active fires from SEVIRI. This work was undertaken during instrument commissioning and, thus, was limited in spatial and temporal scales (southern Africa only, 4.5 days of data in September 2003). For these area and time period, the algorithm in [54] showed strong levels of performance for fires whose FRP exceeded ~100 MW, but the analysis of contemporaneous MODIS imagery indicated that, in many cases, there were very many fires present within a scene whose FRP was significantly lower than this and which usually remained undetected within the SEVIRI data. While, by definition, such fires will individually be burning less fuel per unit of time than will the larger more detectable events, their high frequency makes them potentially significant in terms of overall cumulative emissions. A key reason for enhancing the performance of the original geostationary fire detection algorithm described in [54] was therefore to improve the detection of low FRP fires and also to increase the ability of the algorithm to cope with inter- and intrascene illumination variations that can affect fire detection accuracy. By using the operational SEVIRI data, we now have modified and significantly extended the original algorithm presented in [54] in order to meet these aims. Here, we present this newly enhanced algorithm and include results of a full performance evaluation made against simultaneous observations by MODIS made over three full months of data covering the entire African continent. The new algorithm is generic in design and, in theory, applicable to data from other geostationary systems, such as those delivered by the GOES, Multifunctional Transport Satellite (MTSAT), Indian National Satellite (INSAT-3D), and Fengyun (FY2C) systems, subject of course to modifications expected to be required due to the particular individual characteristics of each multispectral imager [39].

II. SEVIRI Imaging Radiometer

The specifications of the SEVIRI instrument are detailed in [2] and [54], and only a brief summary is provided here. SEVIRI provides a 10-bit radiometric imagery of the Earth disk, which is centered on Africa and Europe, in 11 spectral channels located between 0.6 and 14 $\mu$m every 15 min. At the subsatellite point (SSP), the spatial sampling distance of these measurements is 3 km, and the instantaneous field of view (IFOV) is 4.8 km. A twelfth higher spatial resolution broadband high-resolution visible (HRV) channel operates at a spatial sampling distance of 1 km. SEVIRI delivers 96 images (~26 Gb of data) per day, equating to in excess of 35 000 images (9.5 Tb) per year. SEVIRI level-1.5 radiometrically calibrated and geometrically corrected imagery is the data product intended by EUMETSAT to be used for derivation of geophysical data, such as the fire product described herein. The level-1.5 10.8-thermal infrared (TIR) and 3.9-{$\mu$m} (MIR) channel data allow pixels containing actively burning fires to be detected with the type of dual-wavelength approaches first discussed by Dozier [13], and the FRP of these fire pixels can then be estimated using the MIR radiance method described previously in Section I.

III. Enhanced Geostationary Fire Detection Algorithm

A. Cloud Detection

Cloud detection is a critical component of any active-fire detection algorithm. By day, MIR reflections from clouds can
be mistakenly detected as active fires if they are not adequately masked out [45]. Procedures applied by the Meteorological Product Extraction Facility (MPEF) at EUMETSAT provide the primary means of detecting cloudy pixels in SEVIRI level-1.5 data. The cloud-masking procedure is part of a larger processing scheme, the scenes (SCE) and cloud analysis (CLA) algorithm, operated by the MPEF. The SCE algorithm derives a basic cloud mask, classifying each pixel as cloudy or clear sky using a large number of multispectral pixel-level thresholding tests, based upon procedures first developed by Saunders and Kriebel [57]. Full details of the SCE algorithm are presented in [46] and [64]. There remains a tendency for some small clouds and cloud edges to remain unmasked in the SCE product [46]. We therefore supplement this with a second cloud mask derived from thresholding the higher spatial resolution SEVIRI HRV channel data. We define cloud-contaminated pixels as those where the radiance exceeds a predefined HRV channel threshold, which varies in accordance with land cover and solar zenith angle, and which were derived and tested on multiple SEVIRI scenes covering the full diurnal cycle. We use four landcover classes (desert, arid, semiarid, and significantly vegetated) derived via merging of the 27 classes that were present in the Global Land Cover Map 2000 (GLC2000, [47]). This HRV-derived cloud mask is resampled to 3 km before being merged with the corresponding SCE mask. The merged mask is then used to exclude cloud-contaminated pixels from further analysis.

Fig. 1 shows an example of the SEVIRI cloud mask. In comparison to the raw SEVIRI radiance data shown in Fig. 1(c), many small clouds remain undetected by the SCE cloud mask [Fig. 1(a)], particularly along the eastern coast of southern Africa and southern Madagascar. However, many of these clouds are detected by the merged SCE and HRV-derived cloud mask [Fig. 1(b)] due to the higher spatial resolution of the HRV measurements. One artifact of using a static landcover map for parameterizing the thresholds used in the HRV channel mask is that sharp boundaries between different cover types can sometimes be erroneously flagged as cloud due to inaccuracies in the geolocation match between the SEVIRI data and the landcover map, or to incorrect landcover specification. This sometimes results in erroneous “cloud” edges at the boundary between different cover types and is evident, for example, in Fig. 1(b) at the boundary between the desert and sparse vegetation in Namibia. However, this is only of real importance if the mask incorrectly removes areas that are the sites of active fires (which are less likely in such sparsely vegetated areas), and in any case, this is deemed preferable to potentially having a large number of “false-alarm” fires caused by undetected cloud-contaminated pixels.

B. Active Fire Detection

The sensitivity of MIR channel to the intense fire thermal emissions is such that pixels containing fires filling only 0.01%–0.1% of the sensor IFOV are potentially discriminated by using simple thresholding techniques [55], [73]. However, relying on the MIR channel alone is problematic since daytime subpixel specular reflections from water bodies or clouds, or thermal emissions from uniformly heated warm surfaces such as bare rock, can result in large MIR signals that by themselves maybe indistinguishable from fires [74]. Therefore, additional tests using data from other spectral channels, for example, the MIR-TIR brightness temperature difference (BTD), must be used to screen out these possibilities and, thus, confirm whether each “potential” fire pixel does indeed contain an actively burning fire [54].

Geostationary active-fire detection algorithms must be able to operate under the wide range of illumination and landcover conditions encountered over the full Earth disk during any particular imaging slot (Fig. 2). The so-called “contextual” algorithms, whose thresholds and tests vary over space and time, are therefore most appropriate. The original algorithm in [54] was based on the contextual fire detection approach used
The enhanced fire detection algorithm was increased sensitivity to low FRP fire pixels, rather liberal spectral thresholds were required to be used in Stage 1a such that only pixels that were believed definitely not to contain active fires were removed (for example, pixels that are believed to be cloud contaminated but which were not flagged as such by the SCE + HRV cloud mask). Potential fire pixels are selected in Stage 1a using

\[
\text{MIR}_{\text{thresh}} = 310.5 - 0.3 \times \vartheta_s
\]

\[
\text{BTD}_{\text{thresh}} = 1.75 - 0.0049 \times \vartheta_s
\]

where \(\text{MIR}_{\text{thresh}}\) is the MIR threshold (in kelvin), \(\text{BTD}_{\text{thresh}}\) is the 3.9–10.8 BTD threshold (in kelvin), and \(\vartheta_s\) is the solar zenith angle (in degrees). At night, constant 280- and 1-K BTD thresholds are used.

One potential source of false detections is large areas of solar-heated bare ground or other “warm” surfaces. In order not to unduly increase commission errors and computational cost, a series of spatial thresholds is now employed in Stage 1b, which attempts to avoid pixels within large homogeneously radiant areas of warm land being passed to Stage 2. A high-pass filter is applied to the BTD imagery since the contrast between fire- and nonfire pixels is greater here than in the MIR channel alone [55]. The theory is that, since each SEVIRI pixel measures the spatially averaged radiance signal over many square kilometers, the BTD recorded at nonfire “background” pixels generally changes rather gradually from pixel to pixel. However, a pixel containing an active fire represents a high spatial frequency BTD change, which can be isolated via the high-pass spatial filter [63]. Filter kernels of sizes \(3 \times 3\), \(5 \times 5\), and \(7 \times 7\) pixels are used in order to try to ensure that both single- and multiple-pixel fires are appropriately detected by this filtering process. Pixels passing Stage 1b are those where the filter output exceeds a threshold \((P)\), which is defined in relation to the filter output standard deviation calculated for the entire image (again adjusted by the per-pixel solar zenith angle)

\[
P = \text{HP}_{\text{filter}} \geq \text{DT} \times \delta_{\text{filter}}
\]

where

\[
\text{DT} = 2.5 - 0.012 \times \vartheta_s
\]

Stage 1c selects the potential fire-pixel set as those pixels passing both Stages 1a and 1b. The larger set of potential fire pixels generated by this three-stage process contains many more low FRP fire pixels than does that generated by the application of the algorithm in [54]. This is due to the lower spectral thresholds applied during the selection of the potential fire-pixel set, which are possible to apply because of the inclusion of the additional spatial filter test that correctly prevents large areas of homogeneously warm soil (and, thus, very large numbers of ambient “homogenous” pixels) being included in the potential fire-pixel set. Many of the potential fire pixels are ultimately confirmed as true fire pixels, as will be seen in the results of the performance evaluation (Section VI-A).
Two further tests are conducted before contextual tests commence at Stage 3. These Stage 2 tests are designed to eliminate potential fire pixels caused by sunglint from water bodies or undetected subpixel clouds. For pixels whose solar zenith angle is less than 90°, the MIR/RED (3.9 μm/0.6 μm) radiance-ratio approach in [74] and [75] is used to discriminate sunglint-affected pixels. Fire-emitted spectral radiance is maximum in the MIR, whereas solar-reflected signals are maximum in the RED; therefore, the MIR/RED ratio can be used to discriminate these cases more effectively than can the BTD measure alone (Fig. 4). The thresholds applied in this test are listed together with the other test thresholds in Table I, and their application depends on whether any cloudy pixels are present in a 15 × 15 pixel window centered on each potential fire pixel. If so, the spectral radiance ratio test is applied in conjunction with a MIR/TIR spectral radiance ratio test that can supersede the results of a pixel failing the MIR/RED radiance ratio test and, thus, still allow the pixel to be detected as a fire pixel. This strategy attempts to limit cases where heavy aerosol or thin cloud overlies a fire and causes the MIR/TIR spectral radiance ratio test to result in a nondetection [74], [75]. The MIR/TIR radiance ratio threshold is set comparatively high to ensure that, should a pixel fail the MIR/RED radiance ratio test, only pixels that are believed very likely to be fires are passed on (i.e., the more intense/larger events that have greater MIR/TIR radiance ratios).

The final Stage 2 test determines if a potential fire pixel is immediately neighbor by cloud-contaminated pixels or is within a two-pixel radius of a water body (as identified via the GLC2000 map). These potential fire pixels are discounted if their MIR brightness temperature is lower than 320 K, since experience shows that a very large proportion of these are false detections caused by the spectrally varying signatures of undetected cloud or land–water boundaries. While the Global Lakes and Wetlands database [44] provides a more complete source of information on water bodies, the GLC2000 landcover map is sufficient to mask the permanent water bodies within which fires are not expected to occur. Although it is also important to attempt to limit the effects of sunglint-induced false alarms at seasonal or occasionally flooded areas, true active fires can also be very common over such regions in the dry season. For this reason, such occasionally flooded areas are not masked out, and instead, the aforementioned MIR/RED radiance ratio provides the primary method to limit false alarms in such regions.

Stage 3 of the algorithm represents the collection of background statistics for each potential fire-pixel output from Stage 2. The function of this “background characterization” is to estimate what the signal of the potential fire pixel would have been in the absence of a fire and, therefore, to determine whether the actually observed signal is sufficiently elevated above this to be considered as a true fire pixel (and if it is so, then by how much, since the calculation of FRP is a function of this parameter [73]). Implicit is the assumption that neighboring pixels have the same background surface characteristics as the potential fire pixel itself, and the extent to which this is true depends on the surface spatial homogeneity and the sensor spatial resolution. This assumption is inherent in almost all contextual algorithms, including that used for the MODIS fire products, and algorithm sensitivity to this assumption was analyzed in detail by Wooster et al. [73]. The standard deviation of the background pixel signal is also used to provide a measure of uncertainty on the calculation of FRP [73]. The region from which representative background pixels are selected commences as a 5 × 5 pixel window around each potential fire pixel and is expanded up to a maximum of 15 × 15 pixels until more than 65% of the window pixels are classed as valid background pixels using the following criteria: 1) They are cloud-free land pixels; 2) they have BTD and MIR brightness temperature signals that are less than those of the potential fire pixel; 3) they are not in the potentially sunglint-affected region (i.e., they have a viewing zenith angle that is more than 2° larger than the sunglint angle); 4) they have a MIR/TIR spectral radiance ratio that is less than 0.018; 5) they have a MIR brightness temperature exceeding 270 K; and 6) they have a MIR brightness temperature that is less than 330 K and a BTD that is less than 8 K. These latter thresholds are set high since the MIR brightness temperatures of many large sparsely vegetated areas of Africa regularly exceed 328 K. A point to note is the inclusion of test 5 which is used to prevent pixels with anomalously low brightness temperatures being incorporated into the background pixel set. Such pixels are sometimes observed in SEVIRI data neighboring of active fires, and a similar image processing artifact has been noted in data from other sensors (see, e.g., [1]). A related point is that SEVIRI pixels immediately neighboring any potential fire pixel are not included in the background pixel set since point spread function effects in the level-1.5 data often result in these pixels being significantly affected by the fire thermal emission. As a result, the maximum number of valid background window pixels that can be selected using, for example, the 5 × 5 pixel window is 16. If none of the background window sizes has more than 65% of the background pixels passing tests 1) to 6), then the potential fire pixel cannot be confirmed as a true fire pixel.

For each potential fire pixel, the mean and mean absolute deviation of the MIR brightness temperature and BTD are
TABLE I


<table>
<thead>
<tr>
<th>ALGORITHM STAGE</th>
<th>WAVEBANDS/PRODUCTS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>3.9 μm Brightness Temperature</td>
</tr>
<tr>
<td>Stage 1: PFP test (day)</td>
<td>310.5 to 280 K</td>
</tr>
<tr>
<td>Stage 1: PFP test (night)</td>
<td>283 K</td>
</tr>
<tr>
<td>Stage 2: Sunglint Test</td>
<td>-</td>
</tr>
<tr>
<td>Stage 2: Sunglint Test</td>
<td>-</td>
</tr>
<tr>
<td>Stage 5: PPF 1</td>
<td>-</td>
</tr>
<tr>
<td>Stage 5: PPF 2</td>
<td>-</td>
</tr>
<tr>
<td>Stage 5: PPF 3</td>
<td>-</td>
</tr>
<tr>
<td>Stage 5: PPF 4</td>
<td>-</td>
</tr>
<tr>
<td>Stage 5: PPF (swamp/desert only)</td>
<td>-</td>
</tr>
</tbody>
</table>

Calculated from the background window pixel set. The mean absolute deviation is used since it is more robust to outliers than is the standard deviation, and this reduces statistical contamination by any unflagged cloud-contaminated pixels or other anomalies [24]. These background window statistics are used in Stage 4 to define the set of contextually varying thresholds against which each potential fire pixel is evaluated for confirmation as a true fire pixel. The tests used are

\[
\begin{align*}
T_4 & > T_4 + 2\delta T_4 \\
\Delta T & > \Delta T + 2.5 \\
\Delta T & > \Delta T + 2\delta \Delta T
\end{align*}
\]  

(5)

where \( T_4 \) and \( \Delta T \) are, respectively, the MIR brightness temperature and BTD of the potential fire pixel, \( T_4 \) and \( \Delta T \) are, respectively, the mean MIR brightness temperature and mean BTD of the background pixel set, and \( \delta T_4 \) and \( \delta \Delta T \) are, respectively, the mean absolute deviation of the MIR brightness temperature and BTD of the background pixel set. All are in units of kelvin, and only potential fire pixels passing all three tests are classed as true fire pixels.

Stage 5 calculates a confidence statistic for each confirmed fire pixel based on the approach of Giglio et al. [23, 24]. Detection confidence is defined according to the absolute and relative fire-pixel signal and to the number of near-neighboring cloud and water pixels (the idea being that the fire pixels detected close to such features are more likely to be false detections due to sunglint or other nonfire effects). Two additional measures are utilized, which represent the number of absolute deviations that the fire-pixel MIR brightness temperature and BTD lie above the background [23, 24]

\[
\begin{align*}
z_4 &= \frac{T_4 - T_{\text{BG}}}{\delta T_4} \\
z_{\Delta T} &= \frac{T_{\Delta T} - T_{\Delta T_{\text{BG}}}}{\delta \Delta T}
\end{align*}
\]  

(6)

(7)

where \( T_4 \) is the MIR brightness temperature of the fire pixel, \( T_{\text{BG}} \) is the mean MIR brightness temperature of the background pixel set, \( \delta T_4 \) is the mean absolute deviation of the background pixel set MIR brightness temperature, \( T_{\Delta T} \) is the BTD of the fire pixel, \( T_{\Delta T_{\text{BG}}} \) is the BTD of the background pixel set, and \( \delta \Delta T \) is the mean absolute deviation of the background BTD pixel set. All units are in kelvin.

Fig. 5 shows the percentage of the potential fire pixels typically eliminated by each stage of the fire detection algorithm. The relative importance of each test varies markedly over the diurnal cycle. For example, the Stage 2 sunglint test is most important between 3 A.M. and 9 A.M. and between 1 P.M. and 5 P.M. times when sunglint from clouds is greatest. At night, only the cloud proximity test, valid background window test, and the contextual tests are applied; therefore, the percentage of the potential fire pixels removed by certain of these increases when compared to daytime conditions.
C1−C3 confidence functions represent the probable range of values that expected true fire pixels can exhibit. The confidence functions C4 and C5 account for the proximity of cloud and water pixels to the detected fire pixel. These latter functions are less influential for small background windows since the earlier Stage 2 test omitted the potential fire pixels having MIR brightness temperatures of < 320 K if they are adjacent to cloud or water pixels.

The final confidence value C, varying from zero (no confidence) to one (high confidence), is derived from the geometric mean of the five subconfidence functions

\[ C = \sqrt[3]{C_1C_2C_3C_4C_5}. \] (10)

Once all the potential fire pixels in an image have been assessed and their confidence statistic is calculated, Stage 6 applies a postprocessing filter to attempt to remove any remaining false detections. The fire-pixel confidence statistic, coupled with various other spectral thresholding tests, provides the mechanism for removing pixels that are thought likely to be false detections. The spectral thresholding tests use various combinations of solar zenith angle, BTD, MIR/RED, and MIR/TIR spectral radiance ratios, and at night, the 1.6-µm spectral radiance signal (since flaming fires emit significantly at this wavelength), and some are constrained via the solar zenith angle of the pixel (for example, certain of the optical channel tests are applied in regions of high solar zenith angles only). As an example, a 1.6-µm spectral radiance threshold is applied at night (in addition to the BTD and confidence parameter) to remove false detections which can occur due to undetected cloud (since the HRV cloud mask is unavailable at night and there are fewer thresholding tests applied when constraining the potential fire-pixel set). Table I details the full range of tests and thresholds applied during this postprocessing filter stage.

Finally, each confirmed fire pixel has its FRP calculated via the MIR radiance method in [72]. Regional-scale FRP measurements made over multiple SEVIRI imaging slots are then integrated over time to calculate the FRE (following the study in [54]), and through the calibration relationships in [73], the amount of biomass consumed is estimated.

Roberts et al. [54] carried out a theoretical assessment of SEVIRI’s capabilities to detect active fires using the algorithm as it existed at that time. By using the same methods, the absolute minimum fire size that is detectable by the newly enhanced algorithm is, in theory, 0.4–0.02 ha, given fire temperatures of 650 K (smoldering) to 1350 K (flaming), respectively, and assuming a minimum detectable (~2 K) increase in fire-pixel MIR brightness temperature compared to the background pixels. This also assumes nadir-viewing daytime conditions (20° solar zenith angle), with a midlatitude summer atmosphere (rural aerosol, 23-km visibility), a surface reflectance of 0.15, emissivity of 0.85, and kinetic temperature of 300 K. Such fires represent FRPs in the range of 30–45 MW. Such low FRP values are indeed present in the data set retrieved via SEVIRI, although such sensitive detections (at the 2-K MIR BT increase level) require a rather homogeneous background temperature regime that is certainly not found everywhere within an image. Actual FRP retrievals from SEVIRI (Section VI-E) indicate that algorithm sensitivity to fires with FRP < ~50 MW is, in
fact, limited since the spatial variability in the background tem- temperatures often puts the minimum detectable MIR BT increase somewhat above the 2-K level.

IV. ALGORITHM ACCURACY ASSESSMENT

An assessment of the relative performance of the current geostationary fire detection and characterization algorithm was conducted via a comparison of its results to those produced by the prior version described in [54]. Assessment of the algorithm accuracy, in terms of errors of omission, commission, and the degree to which SEVIRI captures the true regional-scale FRP signal, was performed via comparison to MODIS active-fire observations. MODIS is the sensor for which the measurement of FRP was first proposed as a means of classifying a fire emission source strength [35].

V. GEOSTATIONARY ALGORITHM COMPARISON

Fig. 6(a) indicates that the current enhanced algorithm described herein detects significantly more fire pixels than does the prior algorithm in [54], particularly during peak fire activity where fire-pixel number is increased approximately threefold. Over the day, the total number of confirmed fire-pixel detections is 128% greater for the current algorithm. Also highlighted are some of the difficulties encountered when using nondynamic thresholds, where, in the results produced by the algorithm in [54], two prominent detection “peaks” occur between 5 A.M. and 6 A.M. and 3 P.M. and 4 P.M. The earlier peak is due to undetected cloudy pixels being falsely classed as fire pixels. Reliable cloud detection is sometimes problematic at high solar zenith angles [45], and the algorithm in [54] incorporated only basic cloud-detection tests since the SCE and HRV cloud masks were not fully developed at that time. The latter peak is caused by the step change in the thresholds applied to detect fires within the algorithm in [54], which varied thresholds three times per day (6 A.M., 9 A.M., and 3 P.M.). In the current algorithm, the use of dynamic thresholds varying with solar zenith angle removes the need for such step changes, and the resulting fire-pixel count varies smoothly and more realistically over the diurnal cycle.

Fig. 6(b) shows the FRP temporal trajectory, an important feature of which is the reduced difference between the FRP magnitudes determined with the current algorithm and the algorithm in [54] when compared to the larger differences in the number of fire-pixel detections [Fig. 6(a)]. Nevertheless, at the peak, the FRP is almost double that observed with the algorithm in [54], and over the day, the FRE is 64% greater. Integrating the FRP over time to retrieve FRE, and converting this to the amount of biomass combusted, indicates that the current algorithm estimates fuel consumption to be 2.8 Tg, whereas the algorithm in [54] estimates fuel consumption to be 1.7 Tg. These FRP and FRE differences are smaller than for the number of detected fire pixels because the additional fire pixels detected by the current algorithm are typically those with low FRP values. This also results in a lower per-pixel mean FRP retrieval for the current algorithm [Fig. 6(c)].

The results of this comparison indicate that the current “enhanced” fire detection algorithm significantly improves the
A. Comparison to MODIS Fire Detections

It is important to assess the performance of the fire detection and characterization algorithm over a range of conditions and times since burning regimes and environmental conditions may vary both spatially and temporally [22]. For the purpose of this intercomparison, we selected all the MODIS active-fire-pixel detections from over 800 individual “MOD14” active-fire products [24], [36]. This represents all the active-fire-pixel detections made by MODIS over Africa in February, May, and August 2004, during which time, continental-scale fire activity shifted southward from Senegal and Ethiopia (February) to southern Africa (August). Matching SEVIRI data were selected as those taken within ±6 min of the MODIS overpass, and all such matchups were used in the comparison process.

Prior to the intercomparison, MOD14 fire detections were postprocessed to remove the influence of the “bow-tie” effect, an artifact of the MODIS design that results in off-nadir areas being imaged more than once in successive scans [69]. Double-counted off-nadir fire pixels were identified using their recorded latitudes and longitudes, and the duplicates were removed. The FRP for each remaining fire pixel was then calculated using the MIR radiance method in [72], applying the MIR radiance method algorithm coefficients presented in [73] for use with the MODIS data and taking into account the changing MODIS pixel area across the swath.

Regional-scale FRP comparisons were carried out by comparing the cumulative interscene FRP that was simultaneously observed by each sensor over the area equivalent to the full MODIS image (from nadir to a scan angle of 55°) and to the area covering from nadir to 45° and nadir to 35°, respectively, in order to determine whether the level of agreement is influenced by MODIS viewing geometry (and thus, for example, the MODIS ground pixel area). A more localized accuracy assessment, which is useful if the fire regime changes at subregional scales, was performed by comparing cumulative MODIS- and SEVIRI-derived FRPs within the thirty 2.5° × 2.5° grid cells covering each individual MODIS image.

The wide-area comparisons discussed previously were complemented by an analysis made at the scale of individual fires (i.e., clusters of fire pixels). The approach adopted followed that first used by Roberts et al. [54] and Wooster et al. [72], clustering groups of spatially contiguous fire pixels in the primary data set into single “fires” and using the latitude and longitude ranges of that fire-pixel cluster (expanded by the equivalent of two SEVIRI pixels to account for any geocliotional offsets) to check for the presence of the same cluster in the matching data set. Errors of commission (false alarms) in the SEVIRI data set were assessed using that as the primary data set, whereas errors of omission (missed fires) were assessed using MODIS as the primary data set.

VI. RESULTS

A. Regional-Scale Comparisons

Fig. 7 shows the results of the regional-scale cumulative FRP comparisons. Although the current algorithm’s improved sensitivity to low FRP fire pixels means that the SEVIRI-derived regional FRP values are closer to those of MODIS than is the case with results found with the prior algorithm (which were shown in [54]), the regional-scale per-slot FRP is still clearly underestimated by SEVIRI with respect to MODIS (i.e., the gradient of the lines of best fit is \( \ll 1.0 \)). This underestimation is due to SEVIRI’s inability to detect the lowest FRP fire pixels, many of which MODIS can detect due to its significantly higher spatial resolution. Since the proportion of low-to-high FRP fire pixels varies between each MODIS image, the level of agreement between the cumulative interscene FRP recorded by SEVIRI and MODIS also varies, resulting in a significant scatter (as indicated by \( r^2 < 1.0 \)). Nevertheless, the relationship between SEVIRI- and MODIS-derived FRPs is strong in each case, and the relatively high degree of similarity in the results from the different months and areas (e.g., in terms of the slope of the operational linescan system (OLS) line of best fit, the rmse, and \( r^2 \) coefficient) indicates a degree of consistency in the fire regime and algorithm performance across Africa. The total FRP measures obtained by accumulating data from the entire month of matched SEVIRI and whole-swath MODIS imagery indicate SEVIRI-to-MODIS monthly cumulative FRP ratios of 0.57 (February), 0.60 (May), and 0.55 (August), again indicating a high degree of consistency between months. There are only relatively small changes when considering only the nadir-to-35° portion of the MODIS swath rather than the entire width (< 8% difference in the SEVIRI-to-MODIS FRP ratio).

Looking in detail, we see that in some cases, SEVIRI underestimates regional FRP by more than 50% compared to MODIS. The most significant cases turn out to be a consequence of small scattered clouds and the fact that the cloud mask used in the production of the MOD14 fire product is of a higher spatial resolution than that of SEVIRI and also appears less conservative in that it sometimes fails to mask smaller clouds and cloud edges [24]. This typically results in a greater proportion of pixels being flagged as cloud contaminated by SEVIRI than by MODIS, and this also allows MODIS to correctly identify active-fire pixels occurring between closely spaced clouds in a higher proportion of cases. In the remaining examples, thin clouds and/or heavy aerosols covered large areas, and the Stage 2 SEVIRI MIR/RED radiance ratio test caused a number of low FRP fire pixels to remain undetected in these cases.

B. Grid-Cell Scale Comparison

Fig. 8 shows the results of the SEVIRI- and MODIS-derived FRP comparison made at a 2.5° grid-cell resolution. As with the regional-scale comparisons (Section VI-A), a strong relationship is seen between the data from the two sensors, and the points where underestimation is most severe result from the same kinds of cloud and aerosol phenomena discussed in the previous section. Again, a relatively high degree of consistency
Fig. 7. Relationship between regional-scale interscene FRPs derived from all spatially matched contemporaneous SEVIRI and MODIS observations for (a) February, (b) May, and (c) August 2004 over the African continent. The data were taken from the entire MODIS swath, between nadir and 55° scan angle, and the area of the relevant contemporaneous SEVIRI image was spatially subset to reflect the same geographic coverage. The OLS linear best fit passing through the origin is shown (bold line), along with the 95% confidence intervals on the mean (dotted line) and on the prediction of $y$ from $x$ (outermost lines).

In each case, SEVIRI generally underestimates regional-scale FRP, primarily due to the nondetection of the lowest FRP fire pixels, many of which MODIS can detect.

Fig. 8. Relationship between total FRPs retrieved simultaneously by SEVIRI and by MODIS within spatially matched 2.5° grid cells for (a) February, (b) May, and (c) August 2004 over the African continent. The OLS linear best fit passing through the origin is shown (bold line), along with the 95% confidence intervals on the mean (dotted line) and on the prediction of $y$ from $x$ (outermost lines).

is evidenced between the results of the regression analysis for each month.

Fig. 9 shows the spatial variation in the mean ratio of SEVIRI- to MODIS-derived FRP calculated using the 2.5° grid-cell data shown in Fig. 8. The dynamic nature of fire is clearly evident from the widely varying spatial patterns illustrated here. There is no real evidence that variations in the SEVIRI view angle across the continent (i.e., away from the 0° E equatorial
reflectance-based “fire affected area” area product [56], and same region also posed a problem for the prototype MODIS consistently and more severely than in most other areas. This SEVIRI typically underestimates FRP over Mozambique more comparisons in Fig. 7.

0.5–0.7), replicating the data in Fig. 8 and producing a mean by 30%–50% (i.e., a SEVIRI-to-MODIS-derived FRP ratio of as expected, underestimates FRP when compared to MODIS fire zones,” Fig. 9(b)–(d) indicates that for most areas, SEVIRI, numbers of fires within most of these. Within these “central region is likely to result in a greater proportion of smaller active fires, having a lower per-pixel FRP, a greater proportion of which SEVIRI is unable to detect and thus which results in the reduced SEVIRI- to MODIS-derived FRP ratio.

Fig. 10 shows the SEVIRI- to MODIS-derived FRP ratio calculated for the 2.5° grid-cell data shown in Figs. 8 and 9 as a function of the total MODIS-derived grid-cell FRP. The main graph indicates that SEVIRI can both underestimate and overestimate grid-cell FRP, but the insets show that the cases of underestimation by SEVIRI (i.e., a SEVIRI-to-MODIS FRP ratio < 1.0) are far more prevalent. Generally, only in cases when the MODIS-derived grid-cell FRP is low can SEVIRI overestimate FRP significantly with respect to MODIS. Such cases occur primarily when there are relatively few SEVIRI fire pixels within the cell, meaning that even one or two fire-pixel detection anomalies (e.g., SEVIRI errors of commission or even MODIS errors of omission) can significantly affect the result. Fig. 11 shows two examples where MODIS omission errors occur. Fig. 11(a)–(b) shows a case where SEVIRI detects three fires, while for some reason, the MODIS MOD14 product only detects one fire. Fig. 11(c)–(d) highlights a further example where a MODIS pixel that clearly contains an active fire is classified as a water pixel by the landcover map used in the MODIS fire detection procedure and is therefore not passed through to the fire detection algorithm. This may possibly be a seasonal water body that in the dry season is the site of many fires.

This confirms the interpretation of the mapped data shown in Fig. 9. It is also possible that the small time difference between the SEVIRI and MODIS acquisition times also contributes to these instances of SEVIRI FRP overestimation, for example, if a few of the fires were actually burning more intensely during the SEVIRI acquisition than during the MODIS acquisition. As MODIS total grid-cell FRP increases, the SEVIRI- to MODIS-derived cumulative FRP ratio tends closer to one. Overall, the data again indicate the general trend toward SEVIRI underestimating area-based FRP at the 40%–50% level when compared to MODIS.

C. Per-Fire Comparison

To examine the level of agreement between MODIS- and SEVIRI-derived FRPs at the scale of individual fires, and the errors of omission and commission with regard to fire detection, eight MODIS images (six days and two nights) from February and August were selected as the “truth” data set, and SEVIRI data collected within 6 min of the MODIS acquisition time were used for a per-fire comparison. In total, 289 fires (each made up of a spatially contiguous set of active fire pixels) were matched. Fig. 12 shows the results, which generally show a good level of agreement between the two sensors. The observed scatter is expected to result from four primary causes: 1) uncertainty in the ambient background characterization results of each sensor [73]; 2) the small but potentially significant (≤ 6 min) time difference between corresponding MODIS and SEVIRI observations of the same fire; 3) variation in retrieved FRP

SSP) have a major impact on the level of agreement with MODIS. At a few locations in Fig. 9(b)–(d), SEVIRI is seen to overestimate FRP with respect to MODIS, indicated by green, red, or white “outlier” gridcells, but the areas where this occurs are mostly located at the edge of the fire-affected zones and contain rather few fires, hence making any false fire detections a potentially significant fraction of the overall detections. These locations are also often characterized by relatively few matching samples [as shown in Fig. 9(a)] since fires were absent from many of the MODIS overpasses of these areas. For these reasons, results from the edges of the fire-affected zones can be unduly influenced by just a few anomalies (due, for example, to SEVIRI fire detection commission errors) when compared to the more central regions of the fire-affected zones where there are typically 20 or more matchups from which the mean ratio is calculated [as shown in Fig. 9(a)] and there are large numbers of fires within most of these. Within these “central fire zones,” Fig. 9(b)–(d) indicates that for most areas, SEVIRI, as expected, underestimates FRP when compared to MODIS by 30%–50% (i.e., a SEVIRI- to MODIS-derived FRP ratio of 0.5–0.7), replicating the data in Fig. 8 and producing a mean FRP ratio that is close to that found in the MODIS swath-level comparisons in Fig. 7.

An interesting feature of the August results [Fig. 8(d)] is that SEVIRI typically underestimates FRP over Mozambique more consistently and more severely than in most other areas. This same region also posed a problem for the prototype MODIS reflectance-based “fire affected area” area product [56], and

Fig. 9. Maps illustrating the ratio of FRP determined from contemporaneous SEVIRI and MODIS data within spatially and temporally matched 2.5° grid cells over fire-affected regions of Africa. (a) shows the number of matchup samples available in February 2004, whereas (b)–(d) show, respectively, the mean SEVIRI-to-MODIS FRP ratios for February, May, and August 2004 for locations where five or more matchups are available.
Fig. 10. Relationship between the ratios of total cumulative FRP, as determined by SEVIRI and MODIS over matching 2.5° grid cells, to the total MODIS FRP in each grid cell. Plots are derived from all MODIS–SEVIRI matchups found in (a) February, (b) May, and (c) August 2004. At low total MODIS cumulative FRP, the ratio between SEVIRI- and MODIS-derived grid-cell FRPs can vary widely, but tends toward one for larger grid-cell FRP values. Inner plots show the frequency of each value of this ratio, binned into increments of 0.1 and expressed as a percentage of the total number of 2.5° grid-cell samples. The vast majority of samples have a SEVIRI-to-MODIS FRP ratio that is less than one, and only for a very few samples is the ratio substantially greater than one. This indicates that, typically, SEVIRI underestimates FRP at the grid-cell scale, but that occasionally significant overestimation can occur (and the larger plots show that such instances generally happen when the total grid-cell FRP is low).

Fig. 11. Two examples where MODIS fire detection appears unusually less sensitive than that of SEVIRI. (a) and (b) show, respectively, matching SEVIRI and MODIS night-time MIR channel images where fires are visible. White circles indicate the detected fires for each data set. Of these, MODIS detects only one, but SEVIRI detects all three. (c) and (d) again show, respectively, SEVIRI and MODIS MIR channel imagery which indicate the presence of a fire, which SEVIRI successfully detects. MODIS, however, fails to detect this fire, which appears to be due to the landcover of these pixels being (incorrectly) classed as water in the landcover map used by the MODIS fire detection algorithm. Although these results indicate that some errors of omission do exist in the MOD14 fire detections with respect to SEVIRI, these are likely to be the exception rather than the norm since validation of the MOD14 product using matching ASTER data indicates strong overall performance in this environment [48].

related to the subpixel location of the fire with respect to the sensor IFOV and point spread function; and 4) the fact that “fire pixels” have to have a significantly higher minimum FRP to be detected by SEVIRI than by MODIS, and therefore, some of the individual pixels making up a fire may remain undetected by SEVIRI but will be detected by MODIS.

Fig. 12 indicates that the level of per-fire FRP agreement is lower for fires with a MODIS-derived FRP exceeding 3000 MW, which correspond to unusually large and/or intensely burning fires that are most likely the subject of the effects of SEVIRI MIR detector saturation [54]. Fortunately, the incidence of such fires is rather low; therefore, the effect of SEVIRI pixel saturation is limited when considering the regional-scale comparisons such as those shown in Section VI-A. For example, during February 2004, SEVIRI detected 1.3 million fire pixels, of which only 0.1% were saturated in the level-1.5 data. In May and August, the numbers were 0.9 million (0.5% saturated) and 1.7 million (0.6% saturated), respectively. A further effect that mostly impacts retrievals over high FRP fires is that the SCE cloud mask sometimes flags the thick smoke from particularly large fires as cloud. In the MIR, it is possible to detect fire pixels through such smoke, but because the site of the fire pixel is flagged as cloud in the cloud mask, it will remain undetected. Visual inspection of a number of large fires indicates that such occurrences are rare, but do occur and contribute to the increased FRP underestimation over the highest FRP fires. The agreement between the MODIS- and SEVIRI-derived per-fire FRPs is also considerably worsened.
for fires detected by SEVIRI where the MODIS-derived FRP was less than 40 MW. Such fires correspond to a SEVIRI MIR brightness temperature increase of only a few kelvin above the background (\(\sim 2-3\) K, depending on the ambient temperature and the levels of incoming solar radiation), thus indicating that they are at the very limit of detectability and most subject to uncertainty in the background characterization (as illustrated by Wooster et al. [73]). For comparison, the FRP detection limit with the prior algorithm in [54] was \(\sim 80-100\) MW, which is more than twice the value of the minimum per-pixel FRP seen here. Considering all 289 matchups shown in Fig. 12, 76% of the dual-sensor FRP values agree to within 33%, a proportion that increases to 79% when considering those whose FRP, as derived from MODIS, fell within the 40 MW < FRP < 3000 MW limit. Within this limit, the data show a minimum bias with respect to MODIS (only 3.7 MW between the SEVIRI- and MODIS-derived per-pixel FRP measures). Again, this is a significantly elevated performance when compared to the results shown in [54] and gained with the prior geostationary fire detection algorithm.

D. Errors of Omission and Commission

The analysis of errors of omission indicates that, although SEVIRI successfully detects many fires each month, when MODIS and SEVIRI image the same area at the same time, SEVIRI fails to detect many fires that MODIS does detect. In February 2004, 54% of MODIS-detected fire pixels (a total of 140,000 pixels) had no corresponding SEVIRI fire pixel, although it should be remembered that when interpreting these results, a large number of these MODIS pixels would have been in clusters such that many MODIS fire pixels might correspond to only one “missing” SEVIRI pixel. For May, the equivalent results were 101,000 missed MODIS fire pixels (57%), and for August, the equivalent results were 198,000 fire pixels (57%). This is overwhelmingly due to the missing fire pixels being below the aforementioned limit of FRP detectability with SEVIRI, and this will be discussed further in Section VI-E. Corresponding rates of false alarms by SEVIRI were rather small, at 6% (February), 8% (May), and 6% (August), which is a level comparable to the \(<10\%\) rate quoted for the Tropical Rainfall Measuring Mission active-fire product [24]. The FRP of these false detections accounts for 3% (February), 6% (May), and 3% (August) of the months’ cumulative FRP total for the continent, indicating that the falsely detected fires have typically low FRP values. They also have a lower fire-pixel detection confidence when compared to the correctly identified fire pixels, as shown in Fig. 13. Here, the similar degree of commission error seen in each of the three months is reflected in the similar frequency distribution of the confidence parameter. May has a distribution peaking toward a slightly lower confidence, which reflects its slightly higher level of commission error. Also included for comparison is the confidence parameter for all fire-pixel detections (the vast majority of which are correctly identified as actively burning fires). The confidence values of these data have a peak correctly shifted toward higher confidence values when compared to that of the false detections, and thus, the confidence parameter is behaving sensibly in this regard. The majority of the false-alarm fire pixels still have a confidence value exceeding 0.5, and this is simply a result of the brightness temperature limits used to define a strong confidence and weak confidence fire pixels (10) and the fact that the detection algorithm is designed only to confirm potential fire pixels as true fire pixels when there is a reasonable level of confidence that this is correct (i.e., to minimize errors of commission as far as possible). A similar effect relating to relatively high confidence values for false-alarm fire pixels has been noted in the MODIS fire products [20]. The analysis of
the false detections made by SEVIRI indicates that the vast majority (73%) have $\text{FRP}_{\text{SEVIRI}} < 75 \text{ MW}$, which is actually already below the limit of fire-pixel detectability with SEVIRI previously specified by Roberts et al. [54]. Conversely, 22% of the false-alarm pixels have $\text{FRP}_{\text{SEVIRI}} > 100 \text{ MW}$, and these false detections typically result from isolated subpixel cloud or (warmer) clear-cut areas within a cooler forest zone or, in some cases, are actually real fires that erroneously were not detected by MODIS (such as those shown in Fig. 11).

E. Frequency-Magnitude Relations

Fig. 14 shows the results of the frequency-magnitude analysis of per-pixel FRP. The FRP frequency-magnitude relationships for SEVIRI and MODIS show extremely strong agreement, departing from the power-law relationship only at the highest FRP values (where there are very few detections and where SEVIRI MIR channel saturation has an influence) and at the lowest FRP values where fire-pixel detection becomes problematic due to the low signals. The increased sensitivity of the current version of the geostationary fire detection algorithm is evidenced by the fact that the departure from power-law behavior occurs at $\sim 30–40 \text{ MW}$, which is equivalent to a fire-pixel brightness temperature raised only a few kelvin above the background level and thus at the very edge of detectability, whereas for the algorithm in [54], it occurred at $\sim 80 \text{ MW}$. MODIS shows no such departure at this FRP level and is, in fact, capable of detecting fire pixels with an FRP below 10 MW due to its higher spatial resolution.

F. Comparison Summary

Given the fact that the pixel area of SEVIRI at the SSP is around an order of magnitude greater than that of MODIS, the intercomparisons presented here indicate the strong performance of the geostationary (SEVIRI) fire detection algorithm developed herein. By all assessment measures considered, the algorithm performance is clearly improved when compared to that of the prior prototype algorithm reported in [54]. On average, SEVIRI detects $\sim 60\%$ of the regional-scale FRP detected by MODIS, with the vast majority of the difference caused by the inability of SEVIRI to detect the large number of fire pixels whose FRP is below the detection threshold but which MODIS can detect. Comparisons to MODIS indicate that the reliable SEVIRI FRP detection threshold with the new algorithm is $\sim 50 \text{ MW}$, as compared to $\sim 100 \text{ MW}$ with the prior algorithm. Although some FRP values less than this are detected, they are substantially underrepresented by SEVIRI. A component of the regional-scale FRP difference seen between MODIS and SEVIRI could be explained by atmospheric effects, which potentially affect the signals observed by MODIS and SEVIRI slightly differently due to their differing bandpasses [54]. However, since the per-fire FRP comparison (Fig. 12) shows a minimum bias between the two data sets, this is not considered to be a major contributor to the regional-scale FRP differences, and the radiative transfer modeling conducted by Roberts et al. [54] confirms this.

VII. BIOMASS BURNING IN THE SOUTHERN AFRICA DRY SEASON

As an example of the results available from the longer term use of the algorithm with the high temporal resolution SEVIRI data, an analysis of four months of data covering southern Africa is shown in Figs. 15 and 16, derived from in excess of 11 000 images. Fig. 15 indicates that the number of fires peaks in early July, with a gradual decrease through August and a sharper decrease from mid-September onward. The time of peak burning occurs between midday and 14:00 GMT, and the strong diurnal variability illustrates one of the benefits provided...
by geostationary sensors and cautions against inapposite use of night-time-only fire products in such environments (e.g., the World Fire Atlas [7]). Fig. 16 shows the temporal evolution of the observed FRP and daily FRE over the same period, indicating that during the July peak, a minimum of 140 t of fuel biomass were being consumed per second over the southern Africa (based on the conversion coefficients in [73] tested in this environment). It is also evident that the presence of clouds becomes more widespread toward the end of the dry season (October) when the observed and cloud-weighted FREs diverge to a greater extent. Over the four-month period analyzed here, the observed FRE is 345 × 10^9 J, whereas the cloud-weighted FRE equates to 379 × 10^9 J when calculated on a 1° × 1° basis, or 451 × 10^9 J when calculated on a 5° × 5° basis. Adjusting for the SEVIRI MIR channel atmospheric transmission of 0.89, which is calculated for southern Africa by Roberts et al. [54], and for the observed ratio of 0.55 between the SEVIRI and MODIS regional-scale FRP observations over southern Africa found herein, we obtain a fuel consumption estimate of 259–339 Tg. Although this value does not take into account the fact that there is a class of very low FRP fires that MODIS also fails to detect (and, therefore, will not be included in our SEVIRI-to-MODIS FRP adjustment), this cannot explain the large difference between these estimates and that of 860 Tg provided by the Global Fire Emissions Database (GFED v2 [67]) for the same area and time. Analysis of the GFED data indicates that the mean fuel load for this area and period is set at 2.7 kg · m⁻² and that the mean combustion factor is 0.71. These values appear far greater than the measures of these same parameters presented in [62], which are derived from a fieldwork in South Africa and Zambia, albeit conducted in 1992. In that study, the measured fuel loads ranged from 0.37 to 0.48 kg · m⁻² (in South Africa) and 0.32 to 0.74 kg · m⁻² (Zambia). Matching combustion factors were found to lie between 0.03 and 0.73 for woody debris, whereas grass consumption exceeded 0.95 at all burn sites measured. The fuel loads presented by Shea et al. [62] do not include standing tree stems or biomass higher than 2.5 m, which are accounted for in the GFED scheme and which may help explain some of the differences. However, apparently, only by including substantial burning of such fuels could the data in [62] and GFED v2 be reconciled. Our FRE-derived biomass combustion estimates are more similar in magnitude to some of the estimates derived by other studies, for example, the 174 Tg calculated by Korontzi [40] for the year 2000 and the similar figure calculated by Scholes et al. [59] for the year 1989. Barbosa et al. [8] also had the same study for the year 1989, calculating a higher combustion total of 459 Tg. The fact that such studies demonstrate large (hundreds of Tg) ranges, sometimes for the same year, reflects the varying fuel loads and combustion completeness factors assumed and, to some extent, the variability in burned area measures [41]. Further insight into which estimates are more indicative of the true situation will likely come through detailed comparisons between such “bottom-up” approaches and the results of top-down atmospheric inversion scheme. Currently, the geostationary FRP-derived estimates are the only “bottom-up” emission estimates calculated without the requirement to assume fuel load and combustion completeness parameters, although other assumptions such as the level of obscuration by cloud and overlying vegetation canopies are made in the conversion between FRE and fuel consumption [54], [73].

The corresponding active-fire detection map of southern Africa is shown in Fig. 17, which indicates the significant spatial extent of biomass burning and the spatio-temporal shifts that occur over the dry season. Both MODIS and SEVIRI record broadly the same pattern, with fires in the southern part of Democratic Republic of Congo (DRC), eastern Tanzania, and northern Angola tending to start in early July and activity then generally shifting from the west to the east over time. The majority of late dry season fires occur in Mozambique, northeast Zambia, and eastern Tanzania. These trends largely mirror precipitation patterns in the region and have been noted many times previously (see, e.g., [67]). Some discrepancy between the MODIS- and SEVIRI-based records occurs over central DRC, where the spatial pattern of the MODIS fire detections is more clustered than that from SEVIRI. The level of false alarms in the SEVIRI fire product was found to be higher than the average over this region, suggesting that some of this difference may be due to false fire detections by SEVIRI. Another area of difference is in Botswana and Namibia, where SEVIRI identifies a greater fire-affected area than does MODIS. In this case, inspection of a number of raw SEVIRI images confirms that these are true active fires rather than false alarms. Either the fires were relatively brief and occurred between MODIS overpasses, or some other aspect of the MODIS fire detection procedure used to create the MOD14 product prevented their identification.

Fig. 18 highlights an interesting region of the active-fire maps: two rivers (one in South Africa and one in the DRC) along which fires have been detected. Initially, these were thought likely to be sunglint-contaminated pixels, but the inspection of the raw MODIS and SEVIRI imagery indicates them to be true fires burning along the river courses.
FIG. 17. Fire-pixel detections over southern Africa, color coded by day of year (DOY) between July and October 2004. (a) SEVIRI and (b) MODIS.

FIG. 18. Examples of fire detections made along rivers. (a) and (b) show a 300 × 300 km region extracted from the SEVIRI and MODIS fire maps shown in Fig. 17(a) and (b), respectively. The border between DRC and the Republic of Congo is shown as the vector. (c) and (d) show a 150 × 50 km region along the Orange River in southern Africa. In both cases, linear clusters of active-fire detections are seen to run along the rivers.

FIG. 19. Mean FRP per-fire pixel derived from SEVIRI data collected at 15-min intervals between July and October 2004 and classed into four land-cover classes using the GLC2000 database. The spike in early October is caused by the partially missing SEVIRI data on October 4–7.

Fig. 19 shows the time series of mean FRP per-fire pixel within each of four landcover classes defined according to the GLC2000 database. This mean per-pixel FRP variable displays a progressive increase in grasslands and shrublands and, to a lesser extent, in croplands and woodlands, throughout the dry season, until mid-October which sees a marked decrease. Studies by Korontzi [40] and Hoffa et al. [28] indicate that combustion completeness increases through the dry season as vegetation moisture content decreases, and the results from SEVIRI are fully consistent with this. As shown in Fig. 19, the mean per-pixel FRP (and, therefore, the mean rate of biomass combustion) changes by a factor of two in the case of grassland over this period, and such a variation has important implications for studies relying only on active-fire-pixel detections to quantify pyrogenic emission sources.

VIII. CONCLUSION

This paper has presented a new algorithm for the detection and characterization of actively burning fires using the SEVIRI imaging radiometer onboard the geostationary Meteosat-8 satellite. The algorithm has been applied to many months of SEVIRI data at the full temporal resolution of 15 min and is shown to be a significant improvement over the prototype presented previously in [54]. This is particularly so in terms of the algorithm’s ability to detect lower FRP fire pixels and to adapt smoothly to changing Earth surface conditions. Detailed comparisons to MODIS active-fire detections made over three full months indicate that the geostationary fire detection algorithm performs well given the constraints imposed by the lower spatial resolution of the sensor when compared to that from most polar orbiters. The geostationary algorithm demonstrates a 6%–8% error of commission with respect to the MODIS (MOD14) active-fire detections, which is comparable to that of other satellite-derived active-fire products where this statistic has been evaluated. Since the false detections are generally weakly radiating fires, they are responsible for less than 4%
of the total cumulative FRP observed. On a per-fire (fire-pixel cluster) basis, SEVIRI shows a strong level of agreement with MODIS, with a small (3.7 MW) bias and with 76% of the FRP values agreeing to within 33% of those from MODIS despite an up to 6-min time difference between the two image acquisitions.

At the regional scale, the total FRP measures derived from MODIS and SEVIRI show the latter to underestimate FRP significantly due to the nondetection of the lowest FRP fire pixels, which, although weakly emitting, can be numerous. Adjustments for this can be made using frequency analysis statistics, and after this adjustment, biomass combustion estimates for southern Africa between July and October 2004 are 259–339 Tg, which are similar to many earlier estimates but substantially lower than that reported in the GFEDv2 database. Comparisons to top-down inversion-derived emission estimates maybe required if we are to improve our understanding of the variability between the estimates provided by the various bottom-up approaches used.

The fire detection algorithm discussed herein is being considered for possible operational application to SEVIRI data and also for application to data from other geostationary satellites covering different areas. Work by Cooke et al. [11] and van der Werf et al. [67] and many others illustrates the large interannual variability of biomass burning, including in Africa, thus strengthening the argument for longer term monitoring using the kinds of satellite-based techniques described herein. Our comparisons between SEVIRI and MODIS suggest that additional information and precision could be obtained by combining polar orbiting and geostationary satellite observations in order to make optimum use of the temporal and spatial characteristics of each sensor.

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