

Meteosat Third Generation active fire detection multi-temporal algorithm

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Abstract

Fire detection and monitoring are essential for mitigating the environmental and societal impacts of wildfire events. Earth Observation (EO) satellites have long played a central role in this domain, with polar-orbiting sensors such as MODIS and VIIRS providing global fire detections twice daily. However, their limited revisit frequency constrains the timeliness of fire alerts. Geostationary satellites, by contrast, offer high temporal resolution through multiple scans per hour, enabling near-real-time fire detection and rapid alerting. Despite this advantage, fire detection algorithms applied to geostationary imagery have predominantly relied on single-timestamp processing, limiting their ability to exploit the full temporal frequency of these observations. In this paper, we propose a multi-temporal approach for active fire detection using data from the Meteosat Third Generation (MTG) Flexible Combined Imager (FCI). The method first applies multi-temporal cloud masking based on the 10.5 μm thermal infrared band, before implementing a multi-temporal fire detection algorithm inspired by the Robust Satellite Techniques (RST) methodology of (Filizzola et al., 2017). To improve detection reliability, a pixel is confirmed as an active fire only after repeated detection across successive timestamps. Compared to the operational single-timestamp MTG FRP-pixel product, the multi-temporal algorithm achieves higher recall with a slight reduction in precision. Additionally, the method demonstrates sensitivity to regional land-use characteristics, excluding persistent industrial heat sources and continuous gas flaring from fire detections. Finally, the algorithm retrieves Fire Radiative Power (FRP) estimates with associated uncertainty bounds, yielding an average uncertainty window of approximately 4.5 MW.

1. Introduction and background

In recent years, the increasing frequency and intensity of fire events have become a global concern. Annually, Europe faces over 60,000 forest fires, resulting in the destruction of approximately 0.5 million hectares of land (European Commission, Joint Research Centre., 2020). The situation is enhanced by the effects of climate change (Jones et al., 2022). As global temperatures rise and droughts become more frequent and severe, the ignition and rapid spread of wildfires become easier. Active fire detection is a critical asset that can prevent extensive damage.

Remote sensing is one of the tools used to monitor fire events (Yang et al., 2024). Remote sensing enables global coverage and can detect fire events in various locations, complementing ground-based detection methods like watchtowers and cameras, which are inherently local and require more maintenance (Chen et al., 2024). Currently, several satellites are used for fire detection, with the most prominent being MODIS (Moderate Resolution Imaging Spectroradiometer), VIIRS (Visible Infrared Imaging Radiometer Suite) and Sentinel-3. MODIS is an instrument onboard NASA's Terra and Aqua satellites. It observes the Earth's entire surface every 1-2 days with a spatial resolution for fire detection of 1 km at nadir (Giglio et al., 2016). VIIRS is a scanning radiometer onboard the Suomi-NPP (launched in 2011), NOAA-20 (launched in 2017), and NOAA-21 (launched in 2022). Each satellite is a sun-synchronous polar-orbiting with a global coverage every 12 hours and a spatial resolution of 375 m (LAADS-DAAC, 2025). This higher resolution allows VIIRS to detect smaller fires, providing more detailed fire

mapping compared to MODIS (Schroeder et al., 2014). Finally, Sentinel-3 is part of the Copernicus Programme and currently consists of two operational satellites, Sentinel-3A and Sentinel-3B. With near-global coverage every 1–2 days and a spatial resolution of 1 km, comparable to MODIS temporal and spatial resolution (Xu and Wooster, 2023).

These satellites are useful for fire monitoring, but their temporal resolution can be a limitation. Fires may be detected only hours after they start, leading to less useful information for firefighting efforts. Moreover, active fire products have a latency between data acquisition and availability to users. For near-real-time fire detections in Europe using VIIRS, this latency typically ranges from 1 to 3 hours, depending on satellite overpass timing, ground-station reception, and processing pipelines (Rogers et al., 2023, EFFIS, 2026). While useful for monitoring and research, this latency limits the utility of these products for operational firefighting, which requires faster information.

1.1 Single-timestamp fire detection algorithms using geostationary satellite data

Geostationary satellites offer a key solution to solve the temporal resolution problem. They orbit at approximately 35,000 km above sea level in the equatorial plane and have an orbital period equal to Earth's rotation period, meaning that they continuously scan the same area. The primary advantage of geostationary satellites is their ability to provide frequent observations of the same region with several scans per hour (Fensholt et al., 2011). The data are available with a latency of less than 1 hour for the

majority of the satellites, reaching a few tens of minutes in some cases.

In Europe and surrounding areas, the Meteosat Second Generation (MSG) series and the Meteosat Third Generation (MTG) provide data for fire detection. MSG was primarily designed for weather forecasting and climate monitoring. It is operated by EUMETSAT (European Organization for the Exploitation of Meteorological Satellites) and offers data every 15 minutes. The spatial resolution is 3 km at nadir for most channels (Eumetsat, 2023). A fire monitoring product called "Fire Radiative Power Pixel (FRP-pixel)" was implemented for MSG. This product detects fire events and estimates the radiant heat output of fires. The FRP-pixel algorithm uses spectral analysis using mainly band 3.9 μm and 10.8 μm and image processing techniques to identify fire events in images captured at one specific timestamp (Wooster et al., 2015, Roberts et al., 2015).

EUMETSAT launched Meteosat-12, the first satellite of MTG series, in December 2022. After a commissioning phase involving calibration, testing, and orbit adjustment, the satellite was declared operational in December 2024. With a spatial resolution of 1 km at nadir and a temporal resolution of 10 minutes, MTG provides a spatial resolution comparable to polar-orbiting satellites like MODIS, but with much higher frequency. MTG is a geostationary satellite system located at 0° longitude and 0° latitude scanning Africa, Europe, part of west Asia and east South America. The MTG instrument Flexible Combined Imager (FCI) has spectral bands similar to those of MSG, enabling their use for fire detection. In particular, the 3.8 μm band is sensitive to active fire emissions, while the 10.5 μm band primarily characterizes the thermal background, as illustrated in Figure 1. An operational method referred to as Active Fire Monitoring (FIR) has been implemented to provide a fire probability at individual time steps. The resulting products have been distributed since July 2025, with the processing of historical data extending back to January 2025 (EUMETSAT, 2025). The MTG FRP-pixel, an algorithm analogue to the MSG FRP-pixel also started to be distributed in a demonstration version on LSA SAF.

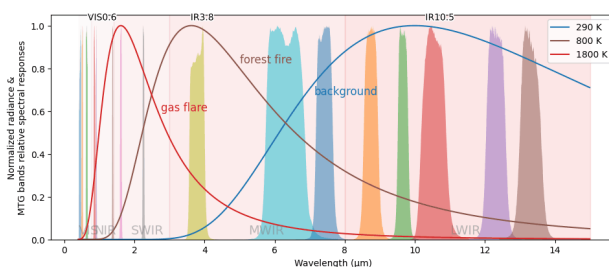


Figure 1. Spectral response of MTG FCI instrument: Comparison with Planck functions of gas flares, forest fires, and background radiation.

The Geostationary Operational Environmental Satellites (GOES) are geostationary satellites operated by NASA and NOAA. GOES-East and GOES-West are positioned over America at approximately -75.2° and -137.2° longitude, respectively, along the equator (0° latitude). Active fire detection from GOES is computed using the Fire Detection and Characterization Algorithm (FDCA). This algorithm uses the contrast between thermal infrared bands centered near 4 μm and 11 μm , where brightness temperature differences are indicative of active fires (Schmidt, 2020).

The Himawari satellite also provides fire detections as it is for GOES, MSG and MTG. Himawari is a Japanese geostationary meteorological satellite operated by the Japan Meteorological Agency (JMA) and is positioned at 140.7° longitude. The fire detection algorithm is primarily based on thresholding techniques, with some improvements incorporating random forest method to remove false alarms (Jang et al., 2019).

1.2 Multi-temporal fire detection algorithms using geostationary satellite data

All the algorithms presented earlier rely mainly on spectral analysis and image-processing techniques and do not exploit the high temporal frequency of geostationary satellite observations for fire detection. Moreover, these algorithms do not explicitly account for regional characteristics, such as complex topography or mountainous terrain. To address these limitations, several methods have been developed that take advantage of the high temporal frequency of geostationary satellites to identify fire events.

For instance, Filizzola et al (Filizzola et al., 2017) developed a multi-temporal, regionally adaptive fire detection algorithm for MSG data based on the Robust Satellite Technique for fire detection (RST-FIRES). This approach identifies fire-affected pixels as temporal anomalies with respect to their typical behavior, estimated using a multi-year temporal average of brightness temperatures. Cloudy pixels are identified during the pre-processing stage using the MSG Cloud Mask product and a temporal cloud mask derived from deviations relative to the multi-year brightness temperature reference values (Cuomo et al., 2004).

Koltunov et al. (Koltunov et al., 2016) developed the GOES Early Fire Detection (GOES-EFD) algorithm, which uses the high temporal resolution of GOES geostationary satellites. The algorithm first constructs a multi-temporal database of representative historical images for the region of interest and uses these to define the expected behavior of each pixel. For each new observation, the current image is compared against a reference image derived from this database, and pixel-level residuals are computed, particularly in the mid-infrared 3.9 μm band sensitive to fire emissions. Large residuals indicate abnormal thermal changes that may correspond to fire and are further evaluated using contextual tests, including spatial comparison with neighboring pixels and temporal filtering, to reduce false positives. Cloudy pixels are similarly identified using the Operational Cloud Masking based on residual anomaly detection.

1.3 Paper objective and outline

All the multi-temporal methods described in this section rely on multi-year analyses of GOES and MSG data. For the MTG dataset, which only extends back to January 2025, no multi-temporal fire detection or cloud masking methods have yet been developed. To address this, a the multi-temporal RST-FIRES technique based on a single year analysis is presented in this paper. This method relies only on the MTG data and is adapted to each geographical region. First, a pre-processing stage is described, with particular focus on a multi-temporal cloud masking. Next, the multi-temporal algorithm is presented, followed by a comparison with the MTG FRP-pixel fire products to evaluate the algorithm's performance. Finally, Fire Radiative Power (FRP) values are derived to quantify fire intensity.

2. Methods

2.1 Data pre-processing

Fire events appear as local bright region with a high brightness temperature in band 3.8 μm . Moreover, the contrast in brightness temperature between band 3.8 μm and band 10.5 μm is an indicator of active fire. However, other natural phenomena can also lead to a similar spectral signature and thus can lead to false positives. The data pre-processing aims to mask clouds, water bodies and areas affected by sunlight reflection.

2.1.1 Multi-temporal cloud masking The multi-temporal cloud mask detector is based on the 10.5 μm infrared band of MTG where clouds appear as cold bodies. It is performed by extracting 30 consecutive images at the same timestamp, for example, between 03:00 and 03:10 on 30 consecutive days to maintain relatively consistent solar properties throughout the selected period (Filizzola et al., 2017). The algorithm steps are described in Figure 3 and are further detailed in the following paragraphs.

By focusing on two images—an image of interest at day 1 and a comparison image at day 2, as shown in the first two panels of Figure 2, we observe that the black regions, which represent cold bodies (and thus clouds), are not located in the same positions, indicating cloud movement. When computing the difference between them (image of interest - comparison image), areas with clouds in the image of interest result in negative values (black color), while areas with clouds in the comparison image have positive values (white color) as shown in the last panel. Retaining all negative values would lead to an overestimation of the cloud-covered area, because the MTG instrument has an intrinsic variability that affects the measured brightness temperature, and temperature vary from one day to another thus a cloud free pixel would not have the exact same brightness temperature in band 10.5 μm for two different days.

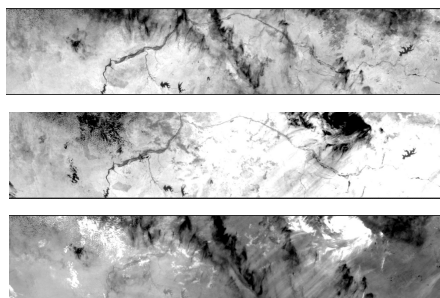


Figure 2. Brightness Temperature 10.5 μm : **Upper:** image of interest (Day 1). **Middle:** Comparison image (Day 2). **Lower:** Difference (Image of interest - comparison image). Dark colors refer to cold areas while white colors refer to warmer areas.

To estimate the band 10.5 μm brightness temperature variability, the MTG level 2 cloud mask product is employed. Only cloud-free pixels in the level 2 product that are common to both timestamps are retained. This ensures that the computed brightness temperature differences are not influenced by cloud contamination. Calculating the temporal difference over one month of 10.5 μm data makes it possible to compute the mean and standard deviation of the brightness temperature variability: the mean represents the average and day to day variability of the signal, while the standard deviation reflects its dispersion. Using this method, a mean close to zero and a standard deviation of 1°K are obtained.

Therefore, for each pair of consecutive timestamps, only temperature differences below -1°K are considered and the median of the values is then computed. Pixels with temperature below this median are classified as cloudy. Using the median as a threshold helps suppress the influence of extreme outliers and small fluctuations that may arise from thin clouds.

By applying this process across all 30 images in the dataset, a cloud probability scale ranging from 0 to 29 is created. On this scale, higher values indicate a greater likelihood of cloud presence, as they represent pixels that are consistently classified as cloudy. Specifically, a value of 29 indicates that the pixel was classified as cloudy in all 29 comparisons. A value of 0 suggests that the pixel was classified as cloudy in no image. Intermediate values reflect the frequency of cloud classification across the time series as shown in Figure 3.

To generate the final cloud mask, only pixels with relatively high cloud probability are retained, specifically, those identified as cloudy in more than one fifth of the total comparisons.

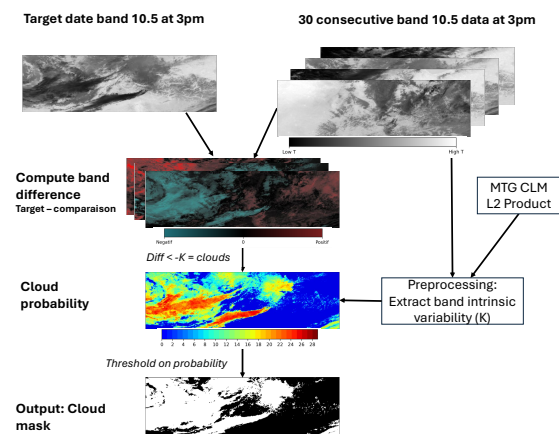


Figure 3. Schematic representation of the multi-temporal cloud masking algorithm applied to MTG data

2.1.2 Water mask To compute a water mask in the MTG grid, the Normalized Difference Water Index (NDWI) was employed. It is calculated based on two MTG spectral bands in the visible spectrum: $VIS0.8$ at 0.865 μm and $VIS0.5$ at 0.510 μm .

$$NDWI = \frac{VIS0.5 - VIS0.8}{VIS0.5 + VIS0.8} \quad (1)$$

NDWI values above 0.5 indicate the presence of a water body (McFEETERS, 1996). By computing this index over multiple days or time periods, we can extract all water pixels in an area. This multi-temporal approach allows us to classify all pixels more accurately, addressing the issue of cloud cover over water bodies. Clouds can lead to misclassification of water bodies in a single image, but as they move, water pixels hidden in one image may become visible in another.

2.1.3 Sun glint It is an optical phenomenon that occurs when sunlight reflects off the surface at the same angle that a satellite is viewing it. This can cause a bright glare in satellite imagery, particularly over bodies of water. Sun glint angle is defined as :

$$\theta_g = \cos^{-1}(\cos(\theta_v) \sin(\theta_s) - \sin(\theta_v) \sin(\theta_s) \cos(\phi_r)) \quad (2)$$

With θ_v being the satellite viewing zenith angle, θ_s being the sun zenith angle, and ϕ_r the relative azimuth angle defined as

the difference between the viewing azimuth angle and the sun azimuth angle. We use the criteria proposed by (Wooster et al., 2015) to detect sunglint-affected pixels. A pixel is affected by sunglint if it verifies one of the following conditions:

$$\theta_g \in [0^\circ, 5^\circ] \text{ and } \frac{L_{3.8 \mu m}}{L_{0.6 \mu m}} \leq 1.$$

The second condition is used to determine whether a pixel's elevated infrared radiance is attributable to solar reflected radiation, which would also influence the 0.6 μm channel.

2.2 Multi-temporal fire detection algorithm

The Robust Satellite Techniques for fires detection (RST-FIRES) is a multi-temporal method that aims to use the diversity and high frequency of data acquisition in a geostationary satellite for fire detection. It detects changes in the signal of a pixel compared to its value in normal conditions using the Absolute Local Index of Change of Environment (ALICE) (Filizzola et al., 2017).

$$\lambda(x, y, t) = \frac{|b(x, y, t) - \mu_b(x, y, t)|}{\sigma_b(x, y, t)} \quad (3)$$

Where (x,y) represents the location of a pixel, t is the data acquisition time, b(x,y,t) is the variable value at the specific location and time. μ_b and σ_b represent the value of a signal in normal conditions. It is computed by calculating the mean and standard deviation of the pixel values over one month at the same timestamp. The choice of using a specific timestamp for a month-long period maintains approximately the same solar characteristics, ensuring consistency in illumination conditions. To obtain a reliable reference value, cloudy pixels are excluded from the mean and standard deviation computation. Additionally, values above twice the standard deviation threshold are clipped to suppress extreme events, such as fire occurrences.

The ALICE index quantifies the deviation of the current pixel value from its expected reference, normalized by the standard deviation. As the reference is computed for each pixel, it automatically adapts to different world regions and their specific characteristics without requiring manual calibration, or a day/night calibration. This makes the method widely applicable across diverse geographic areas covered by the MTG satellites. The multi-temporal fire detection algorithm steps are described in Figure 4 and are detailed in the following paragraphs.

For MTG fire detection, the ALICE index on the brightness temperature of band 3.8 μm is computed and it will be referred to as $\lambda_{3.8}$.

$$\lambda_{3.8}(x, y, t) = \frac{B_{3.8}(x, y, t) - \mu_{3.8}(x, y, t)}{\sigma_{3.8}(x, y, t)} \quad (4)$$

where $B_{3.8}(x, y, t)$ is the brightness temperature of the 3.8 μm band, $\mu_{3.8}$ is the mean brightness temperature, and $\sigma_{3.8}$ is its standard deviation. Fire events are characterized by elevated brightness temperatures; therefore, the index $\lambda_{3.8}$ is expected to be high for a fire pixel.

To this first index, another ALICE index based on the brightness temperature difference between band 3.8 μm and band 10.5 μm ($BTD = B_{3.8} - B_{10.5}$) is added. The BTD represents the temperature excess between the band 3.8 μm and the band 10.5 μm . Fire events are expected to have a high BTD. It will be referred to as λ_{BTD} .

$$\lambda_{BTD}(x, y, t) = \frac{BTD(x, y, t) - \mu_{BTD}(x, y, t)}{\sigma_{BTD}(x, y, t)} \quad (5)$$

Finally, a spatial ALICE index that compares the central pixel brightness temperature to its surroundings is used. The index is based on a spatial difference: $B_{3.8\Delta_s} = B_{3.8\text{central}} - \langle B_{3.8\text{neighborhood}} \rangle$ Where $\langle B_{3.8\text{neighborhood}} \rangle$ is the average brightness temperature in a 19×19 window around the central pixel, excluding the central pixel, its 15 direct neighborhood and cloud pixels. Since fire events correspond to local maxima in brightness temperature, they are distinguishable from the surrounding background, and are expected to have a high spatial difference value. The spatial ALICE index will be referred to as $\lambda_{B_{3.8\Delta_s}}$.

$$\lambda_{B_{3.8\Delta_s}}(x, y, t) = \frac{B_{3.8\Delta_s}(x, y, t) - \mu_{B_{3.8\Delta_s}}(x, y, t)}{\sigma_{B_{3.8\Delta_s}}(x, y, t)} \quad (6)$$

A pixel is classified as a fire event if it meets several criteria simultaneously. Specifically, the values of $\lambda_{3.8}$, λ_{BTD} , and $\lambda_{B_{3.8\Delta_s}}$ must exceed their respective thresholds. Additionally, the pixel must be land based, cloud free and not affected by sunglint. The thresholds applied to λ_{BTD} , $\lambda_{B_{3.8\Delta_s}}$, and $\lambda_{B_{3.8\Delta_s}}$ are 0.5, 1.5, and 2.5, respectively. These values were calibrated through image analysis and validated using VIIRS observations. In addition to this primary temporal aspect, a second orthogonal temporal component is added: a pixel is classified as a fire event not only if it passes the previously described tests, but also if a fire event occurs in its temporal neighborhood. Specifically, a pixel is considered a fire if a detection occurs within a 20 minute window before it, in any of the surrounding 3×3 spatial neighborhood pixels. Fires are expected to last longer than 10 minutes and should therefore be detected more than once as shown in Figure 4. The purpose of this final temporal filter is to reduce false detections in the algorithm.

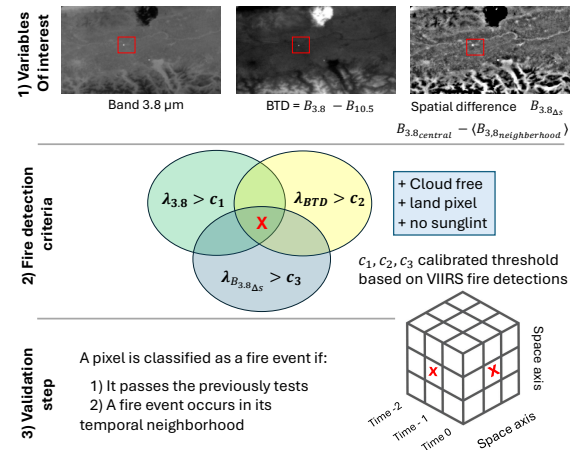


Figure 4. Schematic representation of the multi-temporal active fire detection algorithm applied to MTG data

2.3 FRP computation

Fire Radiative Power (FRP) is the rate at which radiative energy is emitted by a fire, serving as an indicator of fire intensity. It is typically expressed in megawatts (MW). Satellites estimate FRP at the moment of observation by detecting the infrared radiation emitted by active fires. The FRP is computed using the following formula as used in (Wooster et al., 2015):

$$FRP = \alpha \frac{\sigma A_p}{\cos(\theta_v)} (L_{3.8} - \overline{L_{3.8}^b}) \quad (7)$$

where α is a calibration coefficient, (Wooster et al., 2003), σ denote the Stefan–Boltzmann constant, A_p the area of the pixel in km^2 , $L_{3.8}$ the radiance of the fire pixel in the $3.8\mu\text{m}$ band, $\overline{L_{3.8}^b}$ the average background radiance in the same band, and θ_v is the viewing angle.

The background value is computed based on the mean radiance over 30 days as it was performed from the ALICE index. Moreover, in addition to the mean radiance, the variability around the mean is also provided, allowing us to obtain not just one FRP value but an uncertainty range of the FRP computed with the standard deviation of the background.

2.4 Evaluation method

To validate the fire detections from the MTG algorithm, VIIRS active fire data from the Fire Information for Resource Management System (FIRMS) were used. By reprojecting VIIRS fires onto MTG grid, a fire identified by the MTG algorithm is classified as a true positive if there is a corresponding VIIRS fire detection within a 3×3 pixel neighborhood occurring within a 10-minute window of the MTG detection. In contrast, false negatives are defined as VIIRS fire pixels that lack a corresponding MTG fire detection within the 3×3 pixel window during the 10-minute timeframe. The performances of the algorithm will be evaluated using two metrics: the precision and the recall.

$$\text{Precision} = \frac{TP}{TP + FP} \quad (8)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (9)$$

where TP = True Positive
 FP = False positive
 FN = False negative

The algorithm will be applied to two regions: one in Africa and the other in Europe, each representing a chunk of the MTG dataset. Chunk are small part of the full disk that can be easily transmitted and allowing a fast access for users. Every chunk is associated with a specific world region divided on a horizontal basis as shown in Figure 5. The center Africa region correspond to chunk 24, while the European region correspond to chunk 36. To assess performance, both our algorithm and the MTG FRP-pixel algorithm (provided by LSA SAF, a single-time-step approach) will be evaluated against VIIRS fire detections over the same periods. Precision and recall will be computed for each algorithm, enabling a comparison of their respective performances.

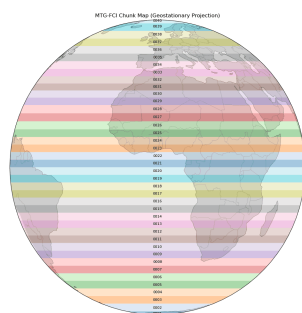


Figure 5. MTG FCI chunk map in geostationary projection CRS, providing a satellite view of chunk segmentation

3. Results

3.1 Multi-temporal cloud masking

First lets focus on the output of the multi-temporal cloud mask and compare it to the output of the cloud mask provided in the MTG level 2 products. Figure 6 shows the different steps of the temporal cloud mask applied to a region in central Africa for the 17th of march 2025. A cloud probability map is derived from the $10.5\mu\text{m}$ band as shown in the second panel. Pixels in the neighborhood of cloud structures have lower probability values and may therefore be excluded from the final cloud mask. The multi-temporal cloud mask enables cloud detection by emphasizing cold bodies in the $10.5\mu\text{m}$ band. A comparison between the temporal cloud mask and the MTG Level-2 Cloud Mask (MTG CLM L2) shows that the MTG CLM L2 identifies a larger number of cloudy pixels. The last panel of Figure 6 shows the output of the MTG CLM L2, cloud-filled pixels are shown in white, cloud-contaminated pixels in light grey, and cloud-free pixels in dark grey. A larger number of pixels are classified as either cloud-filled or cloud-contaminated compared to those identified by our cloud mask. The use of the MTG CLM L2 product would therefore result in an overestimation of cloud coverage, masking regions affected by partial or semi-transparent clouds where fire signatures may still be detectable.

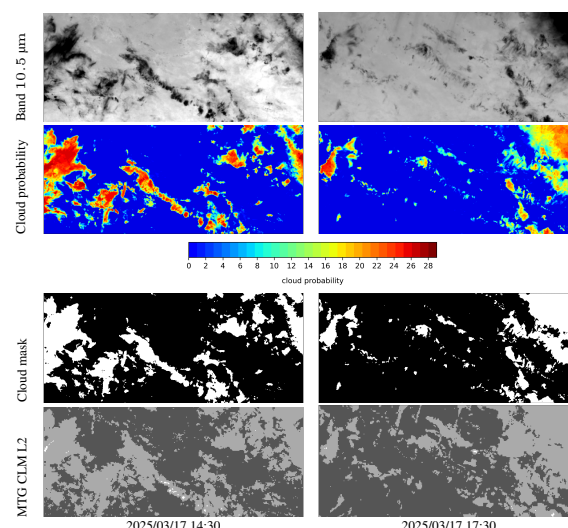


Figure 6. Temporal cloud mask process on 2025/03/17 over an African region at two times: 14:30 (left) and 17:30 (right). The first panels show band $10.5\mu\text{m}$ brightness temperature, the second panels show cloud probability, the third panels show the derived cloud mask, and the last panels show the MTG CLM L2 product (cloud-filled pixels are shown in white, cloud-contaminated in light grey, and cloud-free in dark grey).

Figure 7 shows several fire events identified by bright pixels in band $3.8\mu\text{m}$. Fire pixels are highlighted using red boxes. For each fire event, the corresponding $10.5\mu\text{m}$ band image, the MTG CLM L2 product, and the derived cloud probability are also shown. Some fire events are flagged as cloudy in the MTG CLM L2 product, while the cloud probability indicates no cloud presence. This difference is primarily due to the presence of thin clouds, as shown in the $10.5\mu\text{m}$ band. The fire pixels might be detected in this case when using the multi-temporal cloud mask but not using the MTG CLM L2. With the MTG CLM L2 they would be flagged as cloudy and will be suppressed from the fire detection algorithm workflow. By focusing on another region

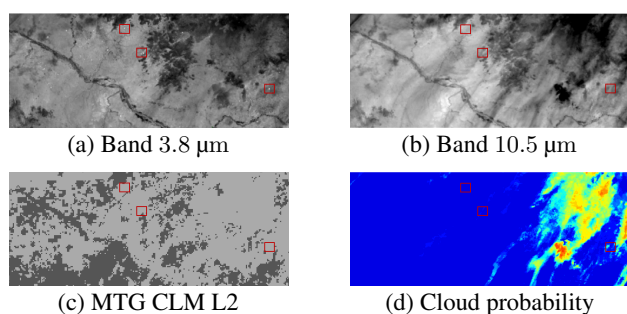


Figure 7. Highlighted fire events (red box) in Central Africa on 2025/03/01 at 10:10, with their brightness temperature in the $3.8 \mu\text{m}$ band (panel a), brightness temperature in the $10.5 \mu\text{m}$ band (panel b), the MTG cloud mask product (panel c), and the derived cloud probability (panel d).

in Europe, as shown in Figure 8, a similar trend is observed: the MTG CLM L2 product shows more cloudy pixels. In Europe, the MTG CLM L2 has also more cloud-filled pixels as shown in the last panel in white. In what follows, all results are based on the multi-temporal cloud mask.

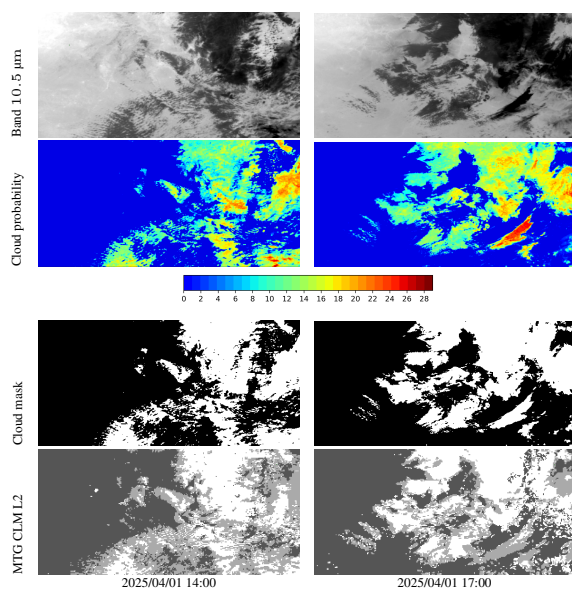


Figure 8. Temporal cloud mask process on 2025/04/01 over a European region at two times: 14:00 (left) and 17:00 (right). The first panels show band $10.5 \mu\text{m}$ brightness temperature, the second panels show cloud probability, the third panels show the derived cloud mask, and the last panels show the MTG CLM L2 product (cloud-filled pixels are shown in white, cloud-contaminated in light grey, and cloud-free in dark grey).

3.2 Multi-temporal fire detection algorithm

In this u the multi-temporal fire detection algorithm described in Section 2.2 is applied first to detect fire events in chunk 24 in Africa (Figure 5) then in chunk 36 in Europe.

Performance in chunk 24 - Africa

For the months of February and March 2025, a total of 249 timestamps were analyzed. In February, 124 timestamps were examined, containing 69,433 fire pixels detected by VIIRS, while in March, 125 timestamps were analyzed, containing a total of

53,535 fire pixels detected by VIIRS. Table 1 reports the 25th percentile, median (50th percentile), and 75th percentile of the precision and recall of our multi-temporal fire detections compared against VIIRS. In addition, the performance of both the multi-temporal algorithm and the MTG FRP-pixel algorithm are evaluated to enable a direct comparison between the two approaches.

The multi-temporal algorithm slightly reduces precision, with the median value decreasing from 0.951 (resp. 0.949) for the MTG FRP-pixel algorithm to 0.913 (resp. 0.932) for the multi-temporal algorithm in February (resp. March). Thus, among all fires detected by the multi-temporal algorithm, 91.3% correspond to true fire events identified by VIIRS in February, while 8.7% are false detections. In contrast, an increase in recall is observed, with the median value rising from 0.174 (resp. 0.180) for the FRP-pixel algorithm to 0.382 (resp. 0.252) for the multi-temporal algorithm in February (resp. March). This demonstrates that the multi-temporal algorithm detects a larger fraction of fire events than the FRP-pixel algorithm. The difference in recall improvement between February and March may be attributed to a reduction in fire activity over the region. In Central Africa, peak fire activity is primarily associated with agricultural burning during the dry season, which mainly occurs in January and February and extends into early March in the region corresponding to chunk 24.

Moreover, since VIIRS has a spatial resolution of 375 m, it can detect smaller fires than MTG, which has a resolution of 1 km at nadir. This difference in spatial resolution explains the low recall values observed for both the FRP-pixel and the multi-temporal algorithms. However, the use of the high temporal frequency in the fire detection algorithm process enables additional fire detections, partially compensating for the coarser spatial resolution of MTG.

MTG FRP-pixel				
Month	Metric	Q25	Q50	Q75
February	Precision	0.856	0.951	1.000
	Recall	0.065	0.174	0.271
March	Precision	0.881	0.949	1.000
	Recall	0.085	0.180	0.282
Multi-temporal algorithm				
Month	Metric	Q25	Q50	Q75
February	Precision	0.812	0.913	0.966
	Recall	0.252	0.381	0.507
March	Precision	0.835	0.932	0.990
	Recall	0.136	0.252	0.406

Table 1. Performance of the MTG FRP-pixel product and the multi-temporal algorithm over 10 detection days in February and March in chunk 24, evaluated against VIIRS detections. Q25, Q50, Q75 denote the 25th, 50th, and 75th percentiles.

Performance in chunk 36 - Europe

The same comparison is performed over Europe for chunk 36. In contrast to the Central African region, Europe shows fewer fire events during the March analysis period. Additionally, among the detected pixels, VIIRS classifies certain industrial facilities as fire events due to elevated surrounding temperatures, which increases the total number of fire pixels while it does not represent

real wildfires. On the other hand, one of the characteristics of the multi-temporal approach is its ability to capture region-specific behavior. For instance, a persistently bright pixel can be a stable high temperature source, such as an industrial facility (e.g. steel plants). Using the multi-temporal method, pixels that remain continuously bright over time are not classified as fire events. Because their brightness temperature remains consistently high, the temporal averaging increases the expected pixel temperature, leading to their exclusion from fire detections. To ensure consistency in performance analysis, fire pixels associated with industrial sites are excluded from both MTG and VIIRS. In what follows, we present some of the extracted industries. These industries were extracted in the chunk 36 representing part of Europe. Steel plants are extracted in Italy, Austria, Ukraine, and other cities. Figure 9 shows a persistent bright pixel in Italy corresponding to a steelworks facility.

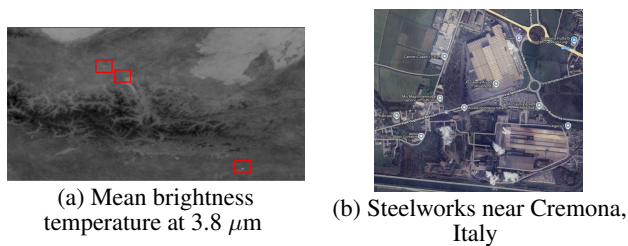


Figure 9. Industrial facility detection: temporal mean brightness temperatures for a steelworks facility.

Table 2 presents the performance of both the multi-temporal algorithm and the FRP-pixel algorithm against VIIRS for 2008 fire pixels extracted during the month of March over the European region. The same pattern observed in the African region is also seen here, with higher recall obtained using the multi-temporal algorithm, accompanied by a slight decrease in precision. The lower recall values in the European region compared with Africa, for both algorithms, can be attributed to the coarser spatial resolution of MTG at larger viewing angles away from nadir. At nadir, the spatial resolution of the 3.8 μm band is about 1 km, whereas over Europe it is typically closer to 2–3 km, which limits the detection capability for small fires.

MTG FRP-pixel				
Month	Metric	Q25	Q50	Q75
March	Precision	0.901	1.000	1.000
	Recall	0.040	0.047	0.141
Multi-temporal algorithm				
Month	Metric	Q25	Q50	Q75
March	Precision	0.786	1.000	1.000
	Recall	0.081	0.116	0.242

Table 2. Performance of the MTG FRP-pixel product and the multi-temporal algorithm over 10 detection days in March in chunk 36, evaluated against VIIRS detections. Q25, Q50, Q75 denote the 25th, 50th, and 75th percentiles.

3.3 FRP computation

For each detected fire, the FRP and its associated uncertainty range were determined, as described in Section 2.3. Fire pixels with high FRP values are considerably fewer than those with low FRP values, reflecting the greater frequency of small fire

events compared to large-scale wildfires as shown in Figure 10. Moreover, the FRP values and their associated uncertainty for 1,100 fire pixels in Africa. The figure presents the relative variability as a function of the mean FRP. The relative variability is calculated as the ratio of the FRP standard deviation to the mean FRP, expressed as a percentage. The average FRP variability is approximately 4.5 MW. Moreover, Figure 10 shows that higher FRP values, corresponding to more intense fires, have lower relative variability, whereas smaller FRP values are characterized by higher uncertainties due to the lower contrast of the pixel signal relative to the background.

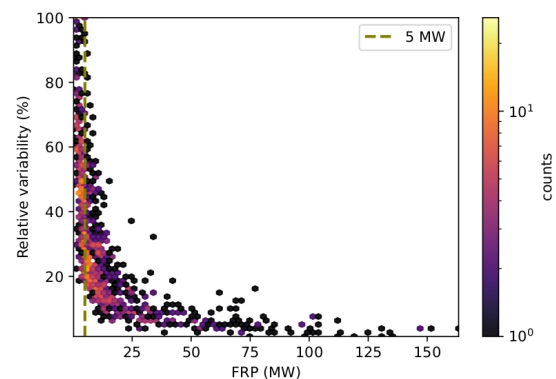


Figure 10. Distribution of the relative uncertainty as a function of the mean FRP

4. Conclusion

The MTG represents a new source of Earth Observation data for fire detection and monitoring, providing high-frequency observations at 10-minute intervals that open new possibilities for near-real-time fire surveillance. In this study, a multi-temporal cloud masking approach was developed using the 10.5 μm thermal infrared band combined with image differencing. By retaining negative difference values and constructing a cloud probability map, the method enables the extraction of cloud objects, improving the reliability of subsequent fire detection. Then a multi-temporal active fire detection algorithm was developed within the Robust Satellite Techniques (RST-FIRES) framework. Compared against the operational MTG FRP-pixel product, the proposed algorithm achieves comparable precision, maintaining a low false positive rate while delivering improved recall, resulting in a greater number of detected fire events at the cost of only a small increase in false detections. The multi-temporal design further enhances performance by improving cloud identification and masking, and by automatically excluding persistent industrial heat sources from fire detections, thereby increasing the specificity of wildfire alerts. Beyond binary fire detection, the algorithm also retrieves Fire Radiative Power (FRP) as a quantitative indicator of fire intensity, accompanied by an estimated uncertainty range for each measurement, providing operationally information for fire severity assessment. Taken together, these results demonstrate that multi-temporal processing of geostationary satellite data constitutes a powerful and promising approach for active fire detection. By fully exploiting the high temporal resolution inherent to geostationary orbits, such methods have the potential to improve fire monitoring capabilities beyond those achievable with conventional single-timestamp techniques.

4.1 Limitations

Similar multi-temporal approaches have been applied to MSG data (Filizzola et al., 2017). A key distinction in the present work is that MTG has only been operational for approximately one year at the time of writing, whereas MSG benefits from a multi-year archive. Consequently, the estimation of the background mean and standard deviation relies on a limited number of data points, which may reduce their statistical stability. As additional years of MTG data become available, the robustness of these estimates is expected to improve progressively.

Furthermore, the analysis presented here is limited to specific geographic regions and time periods. Scaling the approach to a full-disk analysis would introduce substantial computational and storage requirements, as it would involve processing several months of continuous full-disk imagery. As an indication of the data volume involved, storing one year of full-disk data for both the 3.8 μm and 10.5 μm bands would require approximately 8.6 TB of storage space, creating an additional challenge for operational deployment.

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