Satellite-Based Active Fire Detection

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Detection of an active wildfire in a satellite image scene relies on an accurate estimation of the background temperature of the scene, which must be compared to the observed temperature, to decide on the presence of fire. The expected background temperature of a pixel is commonly derived based on spatial-contextual information. Multi-temporal information and multi-spectral information have also been exploited in estimation of the background temperature of a pixel. This review discusses different approaches of estimation of background temperature and highlights the potentiality of the estimation of the background temperature using the multi-temporal data for early fire detection and real-time fire monitoring. The perspectives of a proposed multi-temporal approach are also outlined.

remote sensing data | active fire detection | background temperature of a fire pixel | Diurnal Temperature Cycle (DTC) | data assimilation | ensemble forecasting | change detection | Geostationary Earth Orbit (GEO) satellite

1. Introduction

Data acquired from satellite sensors are widely used in the automatic detection of active wildfires. Fire detection techniques supported by such data provide the most feasible and practical means for the detection and continuous monitoring of regional and global fire activities [1]. Though data used in the design of satellite-based fire detection have been acquired from sensors onboard Low Earth Orbit (LEO) systems (mainly polar satellites) and onboard Geostationary Earth Orbit (GEO) satellites, the thermal imagery data obtained from the global system of GEO sensors are the most appropriate satellite-based data for early fire detection in the non-polar regions of the earth. In near future, data acquired from the thermal sensors on inclined highly elliptical orbits (HEOs), such as Molniya and Tundra orbits, will also provide data on temporal resolution scale same as GEO. The devastating effects of wildfires on land, atmosphere, flora, and fauna can be mitigated when wildfire outbreaks are timely detected to enable early interventions.

In thermal-based fire detection, satellites have relied on images received from the fire-sensitive Mid-Infrared (MIR) spectral window (i.e., 3–5 mm spectral range) to distinguish fire and non-fire pixels. This spectral region is highly sensitive to temperatures of subpixel vegetation fires and is less affected by solar reflections than the Shortwave Infrared (SWIR) spectral window. A pixel in a satellite image is directly or implicitly flagged as a fire pixel when the pixel’s observed temperature is significantly higher than its expected background temperature – the latter defined as the expected temperature of a pixel under non-fire condition. The first satellite-based remote sensing techniques for hotspot detection were developed using data from the LEO systems. Given the LEO system's high spatial resolution advantage, the expected background temperature was extracted from spatial-contextual information (for example, see [2][3][4][5][6][7]). A pixel's expected background temperature can also be estimated using a multi-temporal model for the evolution of a pixel's temperature. It can also be defined using multispectral information either by assuming that the temperatures derived from the fire-sensitive MIR spectral window channel and temperatures derived from the earth surface-sensitive Long-wave IR (LWIR) spectral window channel during non-fire conditions are correlated or by performing spectral unmixing [8][9]. Since GEO fire-sensitive MIR data were available, most GEO-based fire detection techniques were conceived by adapting the pre-existing LEO methods on GEO data. These techniques used the same spatial-contextual information to define the expected pixel's background temperature during fire detection [10][11][12][13][14] or fire confirmation [15][16][17]. A spatial-contextual mechanism has its drawbacks, such as Point Spread Function (PSF) effect, spatial heterogeneity, and undetected cloud-contaminated pixels that contribute to both omission and commission errors [1][18][19]. The performance of such techniques is also restricted by the low spatial resolution of GEO data. GEO sensors have a high temporal resolution, and exploiting the high temporal resolution enhances the chance of detecting a fire at ignition. Given that fires are generally small when started, the high-temporal data can then allow the detection of small and low-power fire events, typically only possible with the LEO system [20][21][22].

2. Multi-temporal Fire Detection Algorithms

Multi-temporal fire detection algorithms define the expected pixel's background brightness temperature in MIR in different ways. The detection statistic termed intensity index [23][24] defines the pixel's expected background temperature as the mean of observed temperatures at the same time of the day and month of the year. Likewise, the temporal test for fire confirmation proposed by [17] defines the pixel's expected background temperature as the mean at same time of the day in a series of thirty days, and the temporal test in the fire detection method proposed by [25][26] that exploits the polar-orbiting NOAA-AVHRR MIR spectral channel, is determined as the mean of the brightness temperatures over a number of days prior to the inspected day. The change detection algorithm proposed by [27][28] defines the expected difference between a pixel's background temperature and an auxiliary temperature at the current time as the difference of observed brightness temperature and auxiliary temperature at an anterior non-fire time. The time to an anterior time can be fixed to the minimum time between successive images up to and not exceeding twenty-four hours, and the auxiliary temperatures are modeled as temperatures that represent the natural evolution of temperatures and can be among others, non-fire atmospherically corrected temperatures of the current day or previously observed DTC with no cloud or fire-contaminated samples. In computation of a detection statistic named 'time differential index', a fire detection method proposed by [24] predicts the expected difference between a pixel location's background temperature at the current time to its background temperature at a previous time – the previous time and the current time are at the same time of the day and month of the year. Instances of cloud cover or missing samples in the available data up to the inspection time hinder the derivation of the expected background temperature in these multi-temporal fire detection methods. The problem can be solved by interpolating the invalid values due to cloud cover or fire events. The interpolation is achievable by fitting available valid brightness temperatures to a physics-based or data-driven DTC model to produce the expected DTC of the current day of a pixel location that can be used to define the expected background temperature at an inspection time. Given the presence in observed temperatures at Top of the Atmosphere (TOA) of outliers, mainly cloud or fire-contaminated samples, the fitting can be undertaken by first detecting and removing outliers. However, instances of missed detection of clouds or fire events negatively affect the results of the estimation of the expected background temperatures. Another option is to use methods from robust statistics to avoid the need for screening outliers from the data. A robust fit of a DTC model on past observed DTCs has been used to represent a pixel's background temperature [29][30][31]. Some fire detection techniques apply, in one of their multiple tests, a dynamic threshold on observed MIR brightness temperature, and the threshold varies with the solar zenith angle [15][28][32]. This dynamic threshold that is also used by the current version (i.e., the third version) of the EUMETSAT FIR product [13][33], implicitly represents the pixel's background temperature dynamics. Similar to the robust fit on previous DTCs, the dynamic threshold avoids the influence of both cloud and missed fire events on the result of the fire detection, but does not consider the particularity of a day: the dynamic threshold does not change with the day, and the robust fit on previous DTCs assumes that the previous days define the whole of the current day. To include all past temporal information on a pixel when deriving its expected brightness temperature, methods based on recursive Bayesian estimation adjust the expected brightness temperature of a pixel each time new information becomes available. The background temperature is derived by a Kalman filter-based prediction using one of the physics-based or data-driven DTC models as the forecast model that determines the time evolution of the background temperature [29][34][35][36]. The new valid observed brightness temperature, when available, is assimilated into the background temperature model.

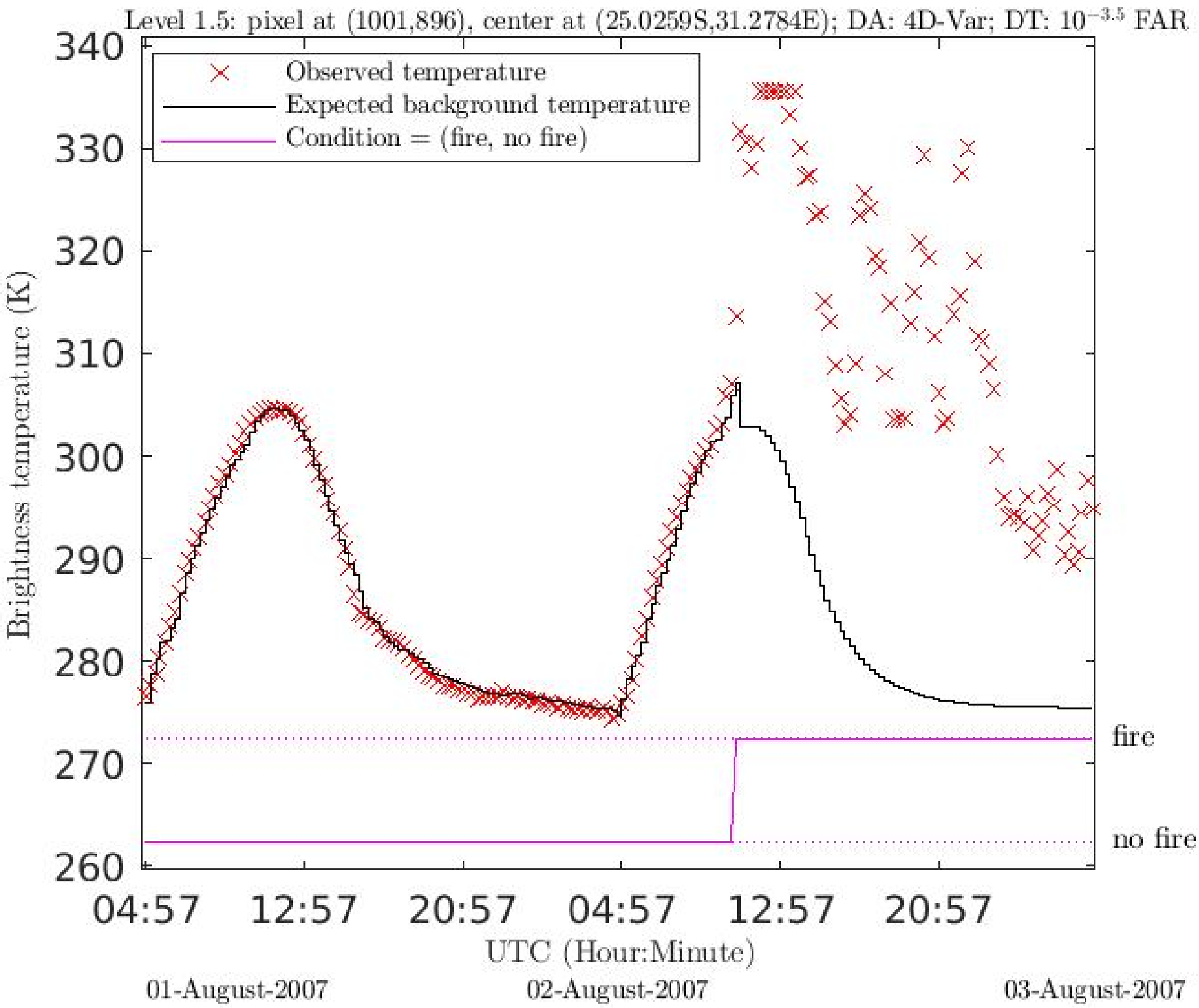
The expected background temperature can also incorporate both multi-temporal and spatial information. For example, the spatial differential index proposed by [24], regressing the inspected image in the current scene on a number of past images of the scene [37][38], expected background temperature of a pixel as a convex combination of a spatial-contextual estimate and a temporal estimate [39], and a fire detection method proposed by [40] determines the expected rise of a pixel's background radiance with respect to its neighborhood's background temperature from a recent image, acquired at the same time of the day, of a non-fire condition on the pixel location and its neighbors. The background temperature can also be derived from information extracted from both multi-temporal and multi-spectral information. For example, the method proposed by [41] predicts MIR background temperature from the earth sensitive LWIR temperature using a linear relation derived from the principal components of a temporal sequence of non-fire MIR and LWIR brightness temperatures.

The current multi-temporal fire detection methods based on recursive Bayesian estimation, first derive the expected DTC of a day (i.e., the model of a day) online before the start of the day and data are assimilated at observation time into the expected DTC. The derivation of the expected DTC of a day allows only for the inclusion of recent observed DTCs with a short period of invalid data (cloud or fire-contaminated data or missing data) into the training set but observed DTCs with a long period of invalid data are not included. The model of a day is also expected to change with land cover (or land use) change, season, and even weather. Given that the model of a day is derived from previously observed DTCs, the required number of recent valid DTCs to include in the training set might not be available for a given period of no change in a pixel location. This approach, therefore, does not adapt rapidly to non-fire change on land or in the atmosphere, for example, in the aftermath of a fire on a pixel location. With the aim of rapid adaptation to normal change, a proposed method derives the background temperature by assimilating data into the model of DTC's parameters of a pixel location each time valid observations are available to estimate the vector of the best DTC model parameters, which is the initial value of the forecast. The ensemble forecasting approach is applied from the data assimilation time for a skillful forecast that is used to determine the expected background temperatures of a pixel location onward. Two types of data are assimilated into the model of the DTC parameters at each data assimilation cycle, namely, the observed TOA brightness temperatures derived from the MIR window data and the observed offsets of the thermal sunrise (i.e., the start time of a DTC) of a day to the sunrise of the same day. The latter is assimilated to transition from one DTC to the subsequent DTC.

A proposed fire detection method achieves an early active fire detection by subtracting the observed temperature from the expected background temperature to obtain the prediction residual at an inspection time in a given pixel location. The residual value is compared to an adaptive threshold computed using a Constant False Alarm Rate (CFAR) framework to decide whether the pixel location is burning. To produce a smooth continuous data assimilation result in the temporal dimension, three data assimilation methods – each offering different assimilation advantages – were separately used. A variational data assimilation method, which emulates the weak-constraint Four-Dimensional Variational Assimilation (4D-Var) and is implemented only in the time dimension (one-dimensional analysis), performs a point estimation of the posterior. Two sequential data assimilation methods, namely the classical Ensemble Kalman Filter (EnKF) and Sampling Importance Resampling (SIR) particle filter, estimate the posterior probability density function. The three methods are compared in terms of detection performance that depends on their ability to estimate the dynamics of the background brightness temperatures. The expected background brightness temperature is the observational forecast determined through model integration from the initial state and defined at a given False Alarm Rate (FAR). Observational forecasts are assumed to be uncorrelated across spatial and temporal dimensions, and the same for real observations. The observational forecasts and real observations are also assumed uncorrelated, and as result, each pixel is assessed independently from its neighbors and only the temporal dimension used to compute the expected background temperature.

The proposed method has less computational complexity in terms of time than methods that rely on fitting past observations to a DTC model to determine the expected background temperature [29][31][34][35][36]. The computation time is reduced because the model fits are only required when the proposed detection system is launched to determine the initial values at launch. The proposed method is expected to achieve higher accuracy than that of other temporal fire detection methods because the estimation of background temperature is based even on the most recent non-fire observation without relying on the expected DTC of a day, and the detection uses a CFAR threshold to adapt to any non-fire condition in a single pixel location and to adapt to any region. Since the MIR spectral window is affected by solar reflections, cloud cover increases both omission and commission errors. Cloud detection and the masking of cloud-contaminated samples are usually undertaken as a pre-processing step, and fire detection results depend then on the accuracy and detection threshold of the cloud detection mechanism of choice. No step is taken to clear cloud samples from data in this proposed algorithm. The potential improvement to the proposed method includes the assimilation of data in more dimensions than just the temporal dimension and the assimilation of more types of data to better characterize the background temperature dynamics under cloud cover. The identification of a water body is implemented as a post-processing step. This is done to set water body pixels, which might have been falsely classified as fire or undecided, to a non-fire status.

GEO satellite temporal MIR data are assimilated into the model of DTC parameters of a pixel to describe non-fire background temperature dynamics to aid the early detection of wildfires. Temporal information incorporates land surface characteristics, but to also consider the weather and atmosphere, a combination of temporal, spatial, and spectral information must be assimilated into the background temperature model of a pixel. The figure below shows an example of the fire detection at $10^{-3.5}$ FAR that uses the 4D-Var with an assimilation window length equal to 6 samples to assimilate brightness temperatures acquired from the GEO sensor the Meteosat Second Generation (MSG)-SEVIRI into a DTC model[42]. Data correspond to an MSG pixel location whose center is at (25.0259^0 S, 31.2784^0 E). The sensor MODIS observes the pixel location four times a day. The MODIS MOD14/MYD14 fire product reports fire in the two DTCs of the examined MSG pixel location shown in the figure below on 2 August 2007 at 11:45 (six MODIS fire pixels whose centers fall in the MSG pixel, all with high detection confidence); and in the outer window of a 3 x 3 pixel array around the examined MSG pixel, on 2 August 2007, at 11:45 and during times of all MODIS night overpasses, and on 3 April 2007 during times of morning overpasses of both Terra and Aqua. A fire product that reports MSG fire pixels, namely EUMETSAT FIR, reports the fire in the pixel on 2 August 2007, first at 10:30 (reports the fire before Aqua overpass, i.e., before MODIS MOD14/MYD14 report) as a low-confidence fire event (i.e., possible fire), thereafter it reports probable (high confidence) fire events at 10:45, 13:45, 15:30, 16:30, 16:45, and 19:45 during the duration of the fire activity in the time frame shown in the figure below. In a 5 x 5 MSG pixel array around the examined pixel location, no MODIS MOD14/MYD14 fire reports before 11:45 and no EUMETSAT FIR fire reports before 09:45 on 2 August 2007. By assuming a single ignition time for the fire events of 2 August 2007 in the examined pixel, the fire detection at $10^{-3.5}$ FAR that uses the 4D-Var with an assimilation length equal to 6 for the analysis (results shown below) detected the fire ignition at the same time reported by EUMETSAT FIR fire product at 10:30. An example where the proposed algorithm detects the fire ignition at the same time as the EUMETSAT FIR report and at the time before MODIS MOD14/MYD14 report. The proposed method continues in this case to report fire uninterrupted while EUMETSAT FIR fire product misses some fire events. Noting that, on 1 August 2007 in a 5 x 5 array around the examined pixel, no fire was reported either by by EUMETSAT FIR report or MODIS MOD14/MYD14 report.



This figure serves as the graphical abstract of the manuscript accepted for publication in MDPI Remote Sensing journal. The texts in this review are mainly from the Introduction section of the same manuscript with few additions. All MSG Data © 2007 and 2020 EUMETSAT.

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