

# Sub-Pixel Fractional Area of Wildfires from MODIS Observations: Retrieval, Validation, and Potential Applications

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**Abstract - Using satellite, unmanned aircraft, and meteorological data, this study develops and validates a method to retrieve sub-pixel fire area fractions from fire pixels, detected at 1 km<sup>2</sup> nominal spatial resolution, by the MODerate Resolution Imaging Spectroradiometer (MODIS). A two-component model (Dozier method) for retrieving sub-pixel fire area fraction and temperature has been available since 1981. However, in the current investigation, modifications are made to the retrieval to account for atmospheric effects by implementing output from a radiative transfer model at 3.96 and 11 μm (MODIS fire detection channels). In addition, two clustering techniques are implemented to remove potential sources of error that may exist when using individual pixels. The sub-pixel retrieval will not only provide a valuable step for improving emissions estimates and plume height forecasts, but will also allow for an investigation into the meteorological effects on fire radiative power (FRP). This may prove crucial for fire weather and air quality forecasters.**

**Keywords:** Remote Sensing, Biomass Burning, Meteorology, Wildfire, MODIS, Smoke, Airborne Sensor.

## 1. INTRODUCTION

Observed in many regions of the globe, biomass burning is a key component to the Earth-atmosphere system, climate change, and operational meteorology. Individual fires are ignited by natural causes, such as lightning strikes (Peterson et al., 2010) and from anthropogenic causes, such as agriculture and forest clearing (Koren et al., 2007). Even though a large region may be burned over the lifetime of a fire, the fire front usually comprises a very small area at any given observation time (Kaufman et al., 1998). These small hot spots are the most intense part of the fire, emit the most radiative energy, and have been correlated to the regions of greatest smoke production and total biomass consumed (e.g. Wooster et al., 2005; Val Martin, 2010). Despite much advancement, all satellite sensors, including MODIS, provide fire locations as pixels that are flagged as containing fires. Unfortunately, the pixel resolution is usually too coarse to capture the size of small hot spots, underscoring the need for obtaining accurate sub-pixel information.

In recent years, the desire for sub-pixel fire information has continued to increase, especially when attempting use satellite fire radiative power (FRP) to its full potential. FRP can be used as a quantitative indicator for fire intensity and is proportional to both the fire's fuel consumption and smoke emission rates (e.g. Wooster et al., 2005). While the use of FRP for estimating the fire emissions is well recognized, its potential use for other applications, such as estimating smoke injection heights and fire intensity, is limited by the lack of sub-pixel information for fires. This can be understood via a simple example in which the FRP value is equal for two pixels covering the same area,

but containing different burning scenarios: (i) a low fire temperature and large fire area fraction or (ii) a high fire temperature and small fire area fraction. Not surprisingly, a large difference in fire behavior and smoke injection height is expected between (i) and (ii). However, it will not be discernable in the current MODIS FRP product unless the sub-pixel information is retrieved. The implementation of a MODIS sub-pixel retrieval will allow FRP to be normalized to the fire area itself (FRP<sub>f</sub>), which will greatly improve smoke emissions and plume injection height estimates, allowing for finer-scale modeling.

Dozier (1981) made the first attempt to derive a sub-pixel fire retrieval using a bi-spectral approach. This method uses the spectral contrast between a sub-pixel hot target and the surrounding (presumably uniform) background of the pixel for the middle infrared (MIR) and thermal infrared (TIR) channels. While developed for the AVHRR, the Dozier method can be applied to any sensor having similar MIR and TIR channels. Using MODIS fire detection as an example, the calculation is performed at ~4 and 11 μm providing two equations that can be solved for the fire temperature ( $T_f$ ) and the fractional area of the pixel covered by the fire ( $P$ ), where  $0 < P < 1$ , located within a uniform background at temperature  $T_b$ . The observed radiances at 4 and 11 μm (top-of-atmosphere), denoted by  $L_4$  and  $L_{11}$ , respectively, are

$$L_4 = PB(\lambda_4, T_f) + (1 - P)B(\lambda_4, T_b) \quad (1)$$

$$L_{11} = PB(\lambda_{11}, T_f) + (1 - P)B(\lambda_{11}, T_b) \quad (2)$$

where  $B(\lambda, T)$  is the Planck function and  $T_b$  is estimated from other datasets. The target (fire) and background are assumed to be blackbodies and their emissivities are assumed to be identical in both channels (Giglio and Kendall, 2001). With these assumptions, the surface kinetic temperatures,  $T_f$  and  $T_b$ , can be considered as brightness temperatures and can be used for both channels; otherwise equations (1) and (2) are not valid. In addition, all atmospheric effects are neglected, allowing the computation of  $B(\lambda, T)$  to be considered a top-of-atmosphere value. Unfortunately, these assumptions are unrealistic (Giglio and Kendall, 2001) and the resulting fire fractions are hard to validate.

The goal of this study is to experimentally implement a modified sub-pixel retrieval algorithm for the MODIS fire product, and validate its performance with high-resolution, field campaign data. Many early studies could not validate the results of sub-pixel retrievals due to the dearth of suitable data sources. However, multispectral, high-resolution data, obtained from the airborne Autonomous Modular Sensor (AMS) are now available for numerous fire events in the western United States. Using AMS, this study conducts a quantitative validation of MODIS sub-pixel fire information for several fire events and investigates several potential applications. This is accomplished by (1) developing an algorithm to retrieve sub-

pixel fire information for MODIS, (2) developing a fire (hot spot) detection algorithm for the AMS sensor and using the results to validate the MODIS retrieval, (3) quantifying the potential sources of error and limits of the MODIS retrieval, and (4) applying the results from (1-3) to investigate the meteorological effects on fire intensity, fire size, and smoke emissions.

## 2. DATA AND STUDY REGION

Using the Aqua and Terra MODIS sensors, three data products, provided at 1 km<sup>2</sup> spatial resolution, are required to obtain sub-pixel information: (1) level 1B radiance data, (2) geolocation data, and (3) level 2, collection 5 fire product data. Data sources (1) and (2) provide the radiance of the entire pixel and all relevant geometry information, such as solar zenith, relative azimuth and viewing zenith angles, while the fire product (3) provides information on fire locations, background temperature, and FRP.

An AMS sensor, flown aboard a NASA Unmanned Airborne Vehicle (UAV), provides the high-resolution data for this study. The AMS spatial resolution is controlled by the UAV's altitude and commonly falls in a range from 5 to 50 meters, (Ambrosia and Wegener, 2009). The AMS sensor is a multispectral instrument with 12 spectral channels in the visible through thermal-infrared. Fire hot spots are detected using channel 11 (3.75  $\mu\text{m}$ ) and channel 12 (10.76  $\mu\text{m}$ ) (Ambrosia and Wegener, 2009). In contrast to MODIS, a fire detection algorithm does not exist for the AMS sensor, which requires an algorithm development step (Section 4). The major concern with AMS data is saturation in the 4  $\mu\text{m}$  channel, which occurs between 510 and 530 K. However, with saturation occurring at such a high temperature, the separation of fire hot spots from background pixels is not compromised.

Several AMS flight scans, from August - October 2007, are available to this study, which include multiple fires across the western United States. With a wide range in topography and biomass type, the western United States is known to experience a wide variety of burning conditions. These variables affect the fire rate of spread, which can reach 34 meters per minute (~0.5 km per 15 minutes) in the chaparral of Northern California (Stephens et al., 2008) suggesting that some fires may change drastically in a short time period. Therefore, the temporal difference between AMS and MODIS is limited to a maximum of 15 minutes. With this temporal limitation, a total of six contiguous burning areas imaged by both sensors are available, which include day, night, nadir, and off-nadir MODIS observations (54 MODIS pixels total). Four of the collocations are from a single Santa Ana burning event in Southern California (24-28 October 2007) and two additional cases are from a fire event in Northern California on 9 September 2007.

## 3. SUB-PIXEL RETRIEVAL FOR MODIS

Since MODIS data became available in January of 2000, few attempts have been made to implement a MODIS sub-pixel retrieval, which is likely a result of the potential for error, especially from atmospheric effects (Giglio and Kendall, 2001). In this study, output from the Santa Barbara DISORT Atmospheric Radiative Transfer (SBDART) model is used to provide a representation of atmospheric effects prior to the calculation step, which avoids creating additional terms for atmospheric transmittance. Specifically, SBDART considers many processes known to affect the ultraviolet through the infrared wavelengths allowing for detailed computations of

plane-parallel radiative transfer within the Earth's atmosphere and at the surface (Ricchiuzzi et al., 1998). The inclusion of SBDART output into the sub pixel retrieval process allows the effects of various atmospheric profiles on the resulting fire area fraction and temperature to be investigated. In addition, SBDART makes it possible to remove the solar impact for daytime retrievals (primarily at 4  $\mu\text{m}$ ).

As a preliminary step, a lookup table is created for the for the 3.96 and 11.0  $\mu\text{m}$  (MODIS fire detection) channels. Specifically, SBDART is modified to include the MODIS spectral response functions for each channel and then run repeatedly for the possible range of geometry values, background temperatures, and fire (hot spot) temperatures. The input temperature values are the kinetic temperatures (not brightness temperatures) at the bottom of the atmosphere and the atmospheric profile is assumed to be a representative mid-latitude summer profile due to the location and time of the events. Input temperatures range from the lower limits for a background temperature (277 K) to the upper limit for a fire hot spot (1500 K). While the process is computationally intensive, SBDART provides a top-of-atmosphere radiance, based on the input surface temperature, solar zenith, viewing zenith, and relative azimuth angles.

The actual retrieval implements the lookup tables to aid in solving the 4 and 11  $\mu\text{m}$  equations (similar to equations 1 and 2) for each MODIS fire pixel contained within the spatial boundaries of the collocated cases. However, the non-linear equations require the use of a multistep, iterative process to obtain fire area fraction and temperature. To begin, the observed MODIS geometries and the respective hot spot temperature are matched to the lookup table to obtain the top-of-atmosphere radiance of the fire hot spot. The algorithm then cycles through all possible fire temperatures and calculates the fire fraction using a variation of the method developed by Shephard and Kennelly (2003), which assumes that the fire fraction ( $P$  in equations 1 and 2) is the same, regardless of channel.

A residual calculation is used to keep track of the fire temperature and area fraction corresponding to the best fit in the observed radiances for the 4 and 11  $\mu\text{m}$  channels and the final fire temperature and area fraction are selected based on the lowest residual. Coregistration error and other random errors are addressed via two clustering methods. The first is a general summation method, where each individual retrieved fire fraction is summed to obtain the area of the entire fire. The second is a single retrieval method, which performs a single retrieval for all MODIS fire pixels corresponding to the same fire event.

The accuracy of the MODIS background temperature at both channels must be considered because it is an essential component of the sub-pixel calculation. When compared to 4  $\mu\text{m}$ , the accuracy of the 11  $\mu\text{m}$  background temperature may be less certain because the MODIS fire detection process focuses heavily on the 4  $\mu\text{m}$  channel and only uses 11  $\mu\text{m}$  for enhancement (Giglio et al., 2003). As an example, 5 out of the 54 MODIS fire pixels used in this study have a pixel brightness temperature that is less than the background temperature at 11  $\mu\text{m}$  (an unphysical scenario), while the 4  $\mu\text{m}$  temperature displays no such mischaracterization. This unusual observation may be a result of a small actively burning area surrounded by pixels dominated by large burn scars or a relatively warm, heterogeneous background. Regardless of the reason, sub-pixel information cannot be retrieved for these pixels.

#### 4. AMS HOT SPOT DETECTION

The AMS data are used to validate the retrieved MODIS fire fractions (described in Section 3). Similar to MODIS, AMS fire detection requires the use of thresholds, which can be somewhat subjective (Kaufman et al., 1998; Giglio et al., 2003). Due to the shift in the Planck Function toward shorter wavelengths at high temperatures, fire detection thresholds are typically based on the 4  $\mu\text{m}$  channel. However, several sensors, such as MODIS and GOES, consider the 11  $\mu\text{m}$  channel to varying degrees (Giglio et al., 2003; Prins and Menzel, 1994). For example, MODIS incorporates the 4 and 11  $\mu\text{m}$  temperature difference and the early GOES algorithm set a specific fire detection threshold for the 11  $\mu\text{m}$  channel. In the case of AMS, an 11  $\mu\text{m}$  fire threshold is used as a secondary check when saturation is reached at 4  $\mu\text{m}$ . Through an automated process, the AMS fire detection thresholds are allowed to vary for each MODIS pixel and adapt to the unique characteristics of the AMS instrument. The AMS algorithm described here is not meant for operational purposes and is specifically targeted at any AMS data points contained within a single MODIS pixel.

Within any MODIS pixel in our sample, there are between 4000 and 9000 AMS data points depending on the location relative to nadir (AMS or MODIS) and the AMS flight altitude (Figure 1). These data points allow for a detailed investigation of the ‘mixed’ MODIS fire pixels, which commonly contain a background, smoldering, and actively burning region (e.g. Kaufman et al., 1998). AMS fire detection is currently aimed at obtaining the mean state of temperature and fire size of two groups: (1) the data points of actively burning fires, and (2) the data points of the remaining region (including areas of smoldering fire, areas previously burned, and unburned areas).

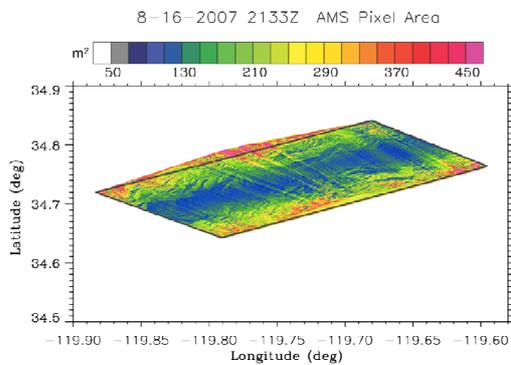


Figure 1. Map showing the variation in AMS pixel size based on location within a single AMS flight scan. Cool colors indicate regions of higher resolution and warm colors indicate the coarsest resolution.

The AMS fire detection process is based on the histogram at 4 and 11  $\mu\text{m}$  and begins with background temperature selection (Figure 2). Secondly, any AMS data points that are obviously not fire hot spots are removed and only the remaining AMS data points move on to be considered as fire hot spots. The actual AMS fire detection thresholds (day and night) are calculated for both the 4 and 11  $\mu\text{m}$  channels (orange lines in Figure 2) using the temperature histograms of each channel. Specifically, each histogram is searched for a region of separation between the actively burning regions and the cooler, smoldering regions. Any AMS data points with a temperature greater than the 4 and 11  $\mu\text{m}$  fire thresholds are subsequently

flagged as fire hot spots (red shading Figure 2). The area of these pixels is then summed to calculate the fire hot spot area within the MODIS pixel under consideration (validation data). If necessary, the smoldering component can also be considered by using additional thresholds.

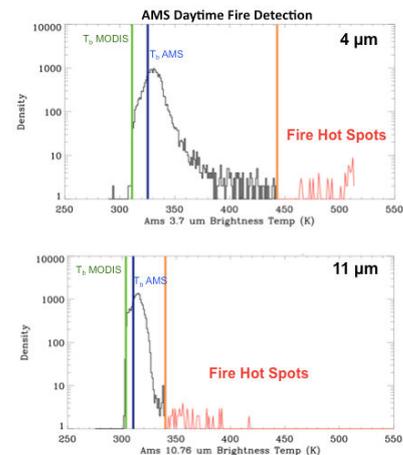


Figure 2. Histograms at 4  $\mu\text{m}$  (top) and 11  $\mu\text{m}$  (bottom) for an AMS fire detection within a single MODIS pixel. Fire detection thresholds are displayed as orange lines and the MODIS and AMS background temperatures are displayed as green and blue lines, respectively. Red shading indicates the final AMS fire detection.

#### 5. RESULTS AND DISCUSSION

At the pixel level, AMS and MODIS comparisons (Figure 3) show the retrieval has some skill for a fire area greater than  $\sim 0.001 \text{ km}^2$  (1000  $\text{m}^2$ ), which corresponds to a fire area fraction of 0.001 in a 1  $\text{km}^2$  MODIS pixel. While the results show a very low bias, there is a large pixel-by-pixel variation producing a relatively low correlation ( $R = 0.49$ ). However, this variation decreases with larger fires (e.g.  $> 0.015 \text{ km}^2$ ) and increases below  $0.01 \text{ km}^2$ . Several MODIS pixel fire fractions are within 25% of the AMS fire fraction while others deviate by more than 75%. These results are expected based on potential coregistration issues and other random processes (e.g. Giglio and Justice, 2003). The potential impacts from variations in AMS pixel geometry are also considered (color scheme Figure 3), but this does not seem to have a major impact on validation results.

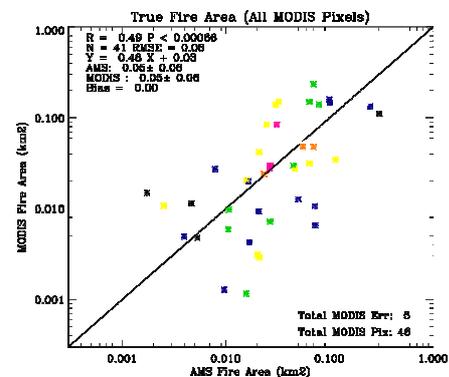


Figure 3. Comparison between retrieved MODIS fire area (per pixel) and AMS fire area from six collocated cases. The color scheme indicates the variation in AMS pixel size (based on Figure 1). Black indicates AMS mean pixel dimensions less than 10x10 meters and pink indicates AMS pixel dimensions greater than 15x15 meters within any 1  $\text{km}^2$  MODIS pixel.

In contrast to pixel-level retrievals, results from the clustering approach (Figure 4) show stronger agreement. The clustering sum method produces the highest correlation ( $R = 0.97$ ) suggesting that the random variation can be reduced by averaging, when looking at a fire event as a whole. The single retrieval method also produces a high correlation ( $R = 0.96$ ), but may be limited by the larger area used in the retrieval.

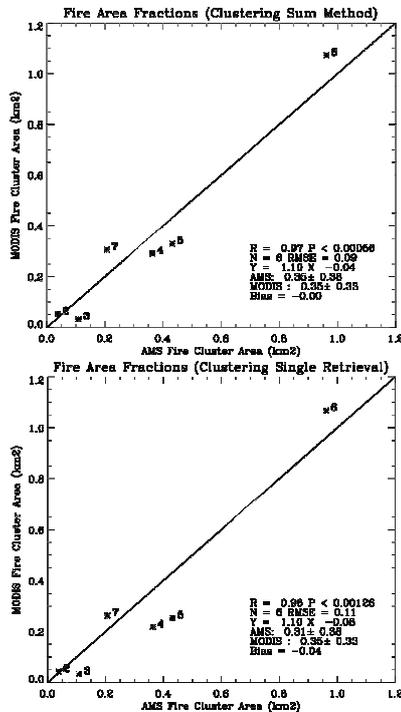


Figure 4. Comparison between retrieved MODIS fire fractions and AMS observations using the sum clustering technique (top) and the single retrieval method (bottom) for all six collocated cases.

## 6. CONCLUSIONS AND FUTURE WORK

This study has developed a sub-pixel retrieval algorithm that can be used with any MODIS granule and a validation algorithm via the AMS sensor. Preliminary comparisons are encouraging, especially at the cluster level. With time, a method will need to be developed to define what constitutes a cluster for various fire events. As of now, only six collocations are available, but the search for additional cases is still ongoing using Aqua data. Future work will sort the cases into nadir, off-nadir, daytime, and nighttime categories to examine how each situation affects the retrieval. In addition, the potential for error from the MODIS retrieval and AMS data will be quantified. When the final product is available,  $FRP_f$  will be used, in combination with a wide variety of metrological variables, to investigate the meteorological effects on fire intensity, smoke production, and/or plume height.

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