P1.9 CHARACTERIZING AND UNDERSTANDING THE DIFFERENCES BETWEEN GOES WF_ABBA AND MODIS FIRE PRODUCTS AND IMPLICATIONS FOR DATA ASSIMILATION

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1. INTRODUCTION

Satellite remote sensing provides automated, near real-time locations and characteristics of active fires. In addition to the challenges of detection and parameterization of fires, each satellite fire product provides different information about fire activity. Diagnostic and prognostic applications, particularly in climate and air quality modeling, benefit from the use of satellite fire products where it is important to identify emission sources to model total emissions and emission transport. Disagreement among fire products causes confusion in the user community. With a better understanding of fire product similarities and differences data fusion can provide a merged fire product that combines the strengths of each fire product to provide more information than one given fire product could provide. One of the largest problems the modeling community faces is the assimilation of active fire products. To produce an accurate multi-satellite fire product it is necessary to discriminate between fires detected by multiple satellites and fires detected by only one satellite. Some differences are expected due to orbit, instrument, and algorithm differences; however, other differences can be attributed to fire characteristics. To improve user confidence, this study employs new methods to identify collocated fire pixels and applies statistical tools to characterize and better understand the differences between the Geostationary Operational Environmental Satellite (GOES) Wildfire Automated Biomass Burning Algorithm (WF_ABBA) and MODerate resolution Imaging Spectroradiometer (MODIS) fire products for enhanced applications in model assimilation.

2. SATELLITE FIRE DETECTION

Satellite remote sensing technology provides the only automated fire detection method capable of detecting fire locations over large areas. Two popular satellite fire detection techniques are the GOES WF_ABBA and the MODIS algorithms [Prins et al., 1994; Kaufman, et al., 1998; Justice et al., 2002; Giglio et al., 2003].

2.1 Usefulness of fire detection

Geostationary and polar orbiting environmental satellites can continuously monitor biomass burning, which plays a key role in public health and environmental issues. Satellite biomass burning detection is important to air quality managers and the modeling community who are concerned with identifying pollution sources and local and long-range transport.

Incorporating both surface-based and satellite observations into models has the potential to provide more information about air pollution and chemical constituency than can be provided by surface-based observations alone. Studies have shown that it is possible to derive emission rates from satellite fire detection [Ichoku and Kaufman, 2005; Reid et al., 2004; Roberts et al., 2005; Wang et al., 2006; Wooster et al., 2005].

Fire plays an important role in terms of changing the landscape. Satellites can track the frequency of burning in a region, which can help determine the risk of fire or the need for a prescribed burn. Satellite fire detection can be used to monitor agricultural and wild fires for land use and land change applications [Prins et al., 2001].

2.2 Consistency and confidence of fire detection and characterization

Any satellite fire detection method is limited by the resolution, accuracy, and viewing geometry of the satellite instrumentation. The minimum detectable fire size depends on many factors including the fire temperature, atmospheric conditions, surface conditions, and the position of the satellite relative to the sun and to the fire.

Cloud cover is a limiting factor. IR channels used to detect fires but, clouds, water vapor, and aerosols all inhibit the ability to detect fires from space.

After identifying fire location, fire characterization can contribute to emission estimates. Determining biomass fuel availability is one of the largest uncertainties in estimating emissions. Experiments such as that done by Wooster [2002] relate the amount of available fuel to smoke emissions. Ichoku and Kaufman [2005] relate satellite detected fire characteristics to smoke emissions.

2.3 Other satellite fire detection techniques

The GOES and MODIS fire products will be discussed in detail however there are other satellite fire detection methods worth noting. The first satellite fire detection case studies used nighttime NOAA Advanced Very High Resolution Radiometer

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(AVHRR) data over industrial Detroit, Michigan and Persian Gulf gas flare fire sources [Matson and Dozier, 1981]. The Operational Linescan System (OLS) on the Defense Meteorological Satellite Program (DMSP) can detect fires at night [Cahoon et al., 1992; Elvidge et al., 1996], and BIRD (Bi-spectral InfraRed Detection), a small experimental satellite, was designed primarily for fire detection [Zhukov et al., 2006]. Another technique is fire scar detection that uses satellites typically associated with land applications to detect changes in the land surface caused by fire [Fuller, 2000; Gerard et al., 2003; Miller and Yool, 2002]. Still another method detects hot CO_2 emissions with high resolution instruments near 2400 cm^{-1} [McCourt et al., 2004].

3. SATELLITE SIMILARITIES AND DIFFERENCES

Some of the similarities and differences between the GOES and MODIS fire products are a result of satellite characteristics while others are associated with algorithmic differences.

3.1 Satellite characteristics

Satellites have unique sensitivities and resolution that can either enhance or limit the ability to detect fires over various ranges of fire sizes and temperatures. With satellites that are not collocated, the satellite view angle and observation time will be different between different fire products. Fire detection is dependent on the proportion of the pixel on fire, not the absolute size of a fire, and so the minimum detectable fire size is a function of pixel size. For large satellite zenith angles, the pixel footprint is much larger and to be detected, a fire must be warmer or occupy a larger area than at smaller zenith angles.

GOES provides nearly complete coverage over most of the western hemisphere every 3 hours and coverage over most of North and South America every half hour. In contrast, MODIS provides spatial coverage over the entire world, but with coverage gaps over the course of a day. This makes it difficult to monitor diurnal fire activity and track continuously burning fires.

The spectral bands near 4 μm and 11 μm are the most critical for active fire detection. While some other bands might be more sensitive to radiation emitted by fires, these bands might be more sensitive to solar reflection or more sensitive to atmospheric conditions making it more difficult to measure the surface temperature. Though comparable, MODIS and GOES have unique spectral sensitivity and saturation thresholds in the fire channels.

3.2 Fire detection algorithm

Coupled with instrument differences, each fire algorithm is tailored to a particular satellite instrument. Fire detection algorithms are developed with subjective thresholds that define the criteria for a fire pixel. Relaxing these thresholds might yield more fire detections but it most certainly would include more false detections because noise, glint, and surface temperature anomalies would be more likely to be errantly flagged as fires. Both the GOES and MODIS active fire detection algorithms are dynamic contextual algorithms where data surrounding the pixel being evaluated are used to determine if the pixel contains a fire.

The GOES algorithm initially finds a fire pixel by identifying pixels with a relatively high 4 μm observed brightness temperature compared with the background conditions. It also considers differences in the 4 and 11 μm observed brightness temperatures compared with the background. The algorithm screens out pixels that contain opaque clouds and screens for false alarms along cloud edges using a reflectivity product. Areas with high solar zenith angles and high surface reflectivity are screened due to the potential of sun glint. The algorithm refers to a land-cover database to determine ecosystem type and estimate surface emissivity. It screens out false alarm fire detections in urban areas, over water, over bare surfaces (i.e. exposed rock and desert), and in transition zones. A correction is applied for solar reflectivity in the 4 μm band, surface emissivity in the 4 and 11 μm bands, and attenuation by total column water vapor in the 4 and 11 μm. The corrected brightness temperatures are then applied to the algorithm, improving fire detection and characterization. A temporal filter is used to screen out fire pixels that do not occur more than once over a 12 hour period. This often screens out false alarms, but it can also eliminate small short-lived agricultural fires.

The GOES WF_ABBA ASCII fire product contains information about the detected fire pixels including location, observed 3.9 and 10.7 μm brightness temperatures, estimates of instantaneous sub-pixel fire size and temperature, ecosystem type, and fire classification. The six classification categories are processed pixels (fire pixels that satisfy the criteria to have sub-pixel temperature and size calculated), saturated pixels (the observed 3.9 μm brightness temperature exceeds the maximum temperature that the GOES Imager is capable of quantifying), cloudy pixels (a fire pixel with relatively thin cloud cover), high possibility fire pixels, medium possibility fire pixels, and low possibility fire pixels. The latter category represents the largest number of false alarms as it has the least stringent requirements for fire identification.

The MODIS contextual fire detection algorithm also uses the 4 and 11 μm bands. The algorithm classifies every pixel as missing data, cloud, water, non-fire, fire, or unknown. The MODIS cloud mask is used and a water mask from a land type mask file is applied to eliminate possible false alarms. The remaining pixels are classified as either potential fire pixels or non-fire pixels based on 4 μm brightness temperatures and 4 μm minus 11 μm temperature differences. The pixels that pass as potential fire pixels must pass a sun glint test, a boundary test to help eliminate false fire detections that can occur along sharp transitions between land types (usually a transition into desert regions), and a test to help eliminate coastal false alarms that can be caused by errors in the water mask. The MODIS ASCII fire product contains information about the detected fire pixels including location, observed brightness temperature, pixel size, and fire confidence. Fire confidence is calculated by a system of equations within the algorithm and is delivered as a percentage.

Fire characterization for GOES fires includes the application of a modified Dozier technique to estimate fire size and temperature while MODIS estimates fire radiative power [Dozier, 1981; Justice et al., 2002; Prins and Menzel, 1994].

4. COMPARISON OF FIRE PRODUCT DATA

To quantify GOES and MODIS fire product similarities and differences, the products were examined using case studies from days and regions and annual statistics to determine statistically significant trends.

First, fire pixels that are collocated in time and space must be identified, but defining how close fire pixels need to be in time and space is non-trivial. As time passes between fire detections the more likely it is for fires to change radiatively. It is possible for numerous small fires to trigger fire detection, but if numerous fires are detected as one fire pixel by one satellite fire product, another product might detect these as separate fires. Fire location is recorded at the center of the pixel, so even a solitary fire will not be detected at the same location by satellites with different navigation. It is not correct to assume that a fire pixel that occurs in only one fire product is a result of a false detection. Factors discussed in section 3 (e.g. instrument and algorithmic differences) can explain how a positive detection in one fire product can go undetected in another product.

4.1 Case studies

Figure 1 shows a North America case study of GOES and MODIS fire pixels detected on 24 May 2004. Initially, this example shows numerous unmatched GOES fire pixels, however almost all disappear when GOES filtered fires are used and low confidence fire pixels are removed. It is clear that removing low confidence fire pixels and using the filtered GOES fire product eliminates a significant number of the fires that are unique to GOES. It is also apparent that GOES and MODIS are not precisely collocated so that it is necessary to allow a reasonable amount of distance to separate the fire detections while still considering them collocated fires. This can be seen more clearly in Figure 2 where in October 2005 a case study in Quebec shows that

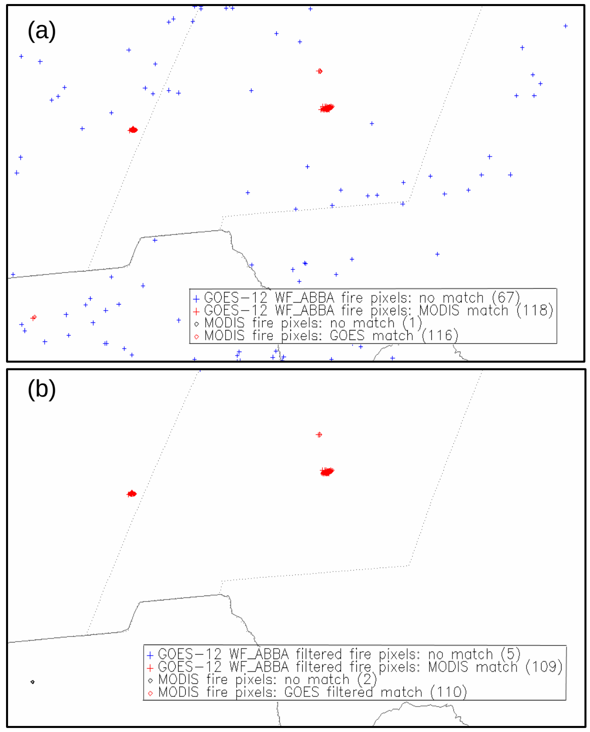

Figure 1. GOES and MODIS fire pixels with and without a match within 10 km and +/- 12 hours in the Southwestern United States on 24 May 2004. (a) All categories of GOES and MODIS fire pixels (b) GOES filtered and MODIS fire pixels with low confidence fire pixels excluded. The number in parenthesis represents the number of fire pixels in that category.

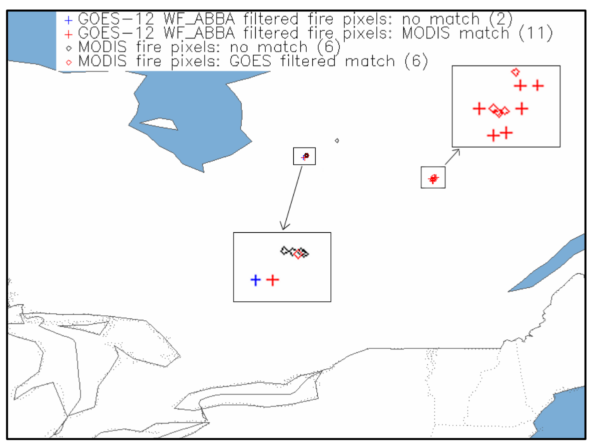

Figure 2. GOES filtered and MODIS fire pixels with low confidence fire pixels excluded on 12 October 2005 with and without a match within 10 km and +/- 12 hours in Quebec, Canada. The MODIS and GOES fire pixels in the east are within 10 km of each other and are considered matching. There are only one MODIS fire pixel and one GOES fire pixel location that are within 10 km of each other in the west while there is a nearby GOES fire pixel location and a few nearby MODIS fire pixels that are close but fail to be within 10 km, so are not considered matching fire pixels.

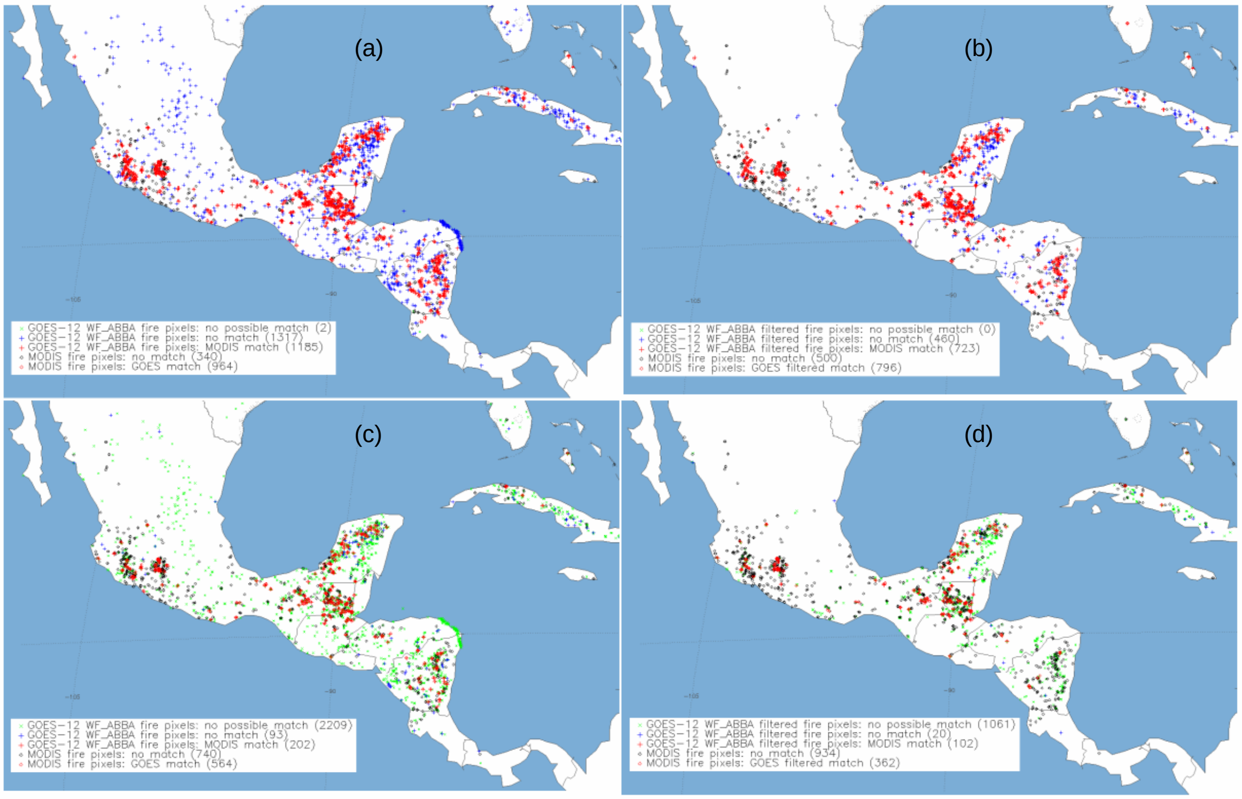

Figure 3 Fire pixels from 24 April 2004 in Central America with and without a match within 10 km. (a) GOES and MODIS fire pixels are shown with and without a match within +/- 12 hours. (b) GOES filtered and MODIS fire pixels with low confidence fire pixels excluded with and without a match within +/- 12 hours. (c) GOES and MODIS fire pixels are shown with and without a match within +/- 0.25 hours. (d) GOES filtered and MODIS fire pixels with low confidence fire pixels excluded with and without a match within +/- 0.25 hour. Notice, the no possible match category indicates GOES fire pixels with no corresponding MODIS overpass within the specified amount of time.

although GOES and MODIS fire pixels appear close, the eastern fire cluster results yields matching fire pixels but the western fire pixels are too far apart to be considered matches even though it does appear that they are representing the same fire activity.

At lower latitudes near the sub-satellite point, GOES resolution is much finer and therefore smaller or less intense fire activity within a pixel is required to trigger fire detection. MODIS orbits over Central America and equatorial South America occur closer to the mid-day diurnal peak in fire activity compared to the overpass times at higher latitudes. The climate, land type, and agricultural practices are in general more conducive to fires in South America and Central America than the higher latitudes in North America.

Figure 3 illustrates fire activity on an active spring day on 24 April 2004 in Central America. Of the GOES fire pixels, 47% have a MODIS match while 74% of the MODIS fire pixels have a match with GOES within +/- 12 hours. The filtered GOES fire product reduces the number of unmatched fire pixels as does removing low confidence fire pixels, but the number of MODIS fire pixels with a GOES match decreases. In areas covered by MODIS, within +/- 0.25 hours of a GOES fire detection, 83.6% of the GOES filtered fire pixels with low confidence fire pixels excluded, have a match with MODIS. Of the MODIS fire pixels, 43% have a matching GOES fire pixel within +/-0.25 hours of a MODIS fire detection.

4.2 Annual comparisons

Case studies provide in-depth examples of fire activity and detection in a given region, but it is also important to consider fire activity over a long period of time to establish trends.

4.2.1 Characteristics

Fire pixels with a GOES/MODIS match have different bulk characteristics than fire pixels without a match. GOES fire pixels with a MODIS match, on average, have a higher 4 μm observed brightness temperature, occur with higher confidence fire categories, and are found in regions with higher 4 and 11 μm emissivities than GOES fire pixels without a MODIS match. Fires with a match tend to occur later in the year, corresponding to the Southern Hemisphere springtime fire season, and tend to be found further south than unmatched fire pixels. Fire pixels with a match tend to have smaller satellite zenith angles than fire pixels without a match. In general, the standard deviation for all of the fire characteristics is larger for unmatched fire pixels than for matched fire pixels.

4.2.2 Statistics

Expanding the temporal window for comparison increases the number of GOES fire pixels with a matching MODIS fire pixel. For example, 62.8% of the GOES filtered fire pixels (when low confidence fire pixels are excluded) have a MODIS match within +/- 1 hour in 2004, this is more than any other temporal window. Expanding the time window increases the number of GOES matches with MODIS, but the percentage of GOES fires with a match decreases with increasing time. Considering the GOES filtered product, and removing low confidence fires, decreases the number of matches with MODIS fire pixels, but the proportion of GOES fire pixels with a match increases. Nearly all MODIS fire pixels are in areas covered by GOES within +/- 0.25 hours, but relatively few GOES fires are in areas covered by MODIS within +/- 0.25 hours. The GOES WF_ABBA fire product is produced every half hour, with many fire pixels detected in only one or two time periods, while the MODIS fire product is available every 12 hours for each satellite. Expanding the time window does not increase the number of MODIS fire pixels to consider as it does when expanding the time window for GOES fire pixels. The most MODIS fire pixels with a GOES match occurs at +/- 12 hours (even more matches would be found if the time window continued to expand). Of the MODIS fire pixels (excluding low confidence fire pixels), 65.6% have a GOES fire pixel match.

The majority of fire pixels are found in South America, and fire pixels in South America are detected by multiple satellites more often than in other regions. In 2004, 63.7% of GOES fire pixels have a MODIS match within 10 km in South America, and MODIS fire pixels had a GOES match 68.3% of the time. In Central America (defined as land south of 25°N and north of the South American continent) 50.0% of GOES fire pixels have a MODIS match in 2004, and 55.5% of the MODIS fires have a GOES match. In North America (north of 25°N), 61.5% of the GOES fire pixels had a MODIS match, while 48.5% of MODIS fire pixels had a GOES match.

Characteristics of collocated GOES/MODIS fire pixels are different from fire pixels that are not collocated. Figures 4 and Figure 5 show fire pixel characteristics for GOES fire pixels with and without a MODIS match within +/- 1 hour (when the ratio of collocated fire pixels is highest). Similarly, Figures 6 and 7 show MODIS fire pixels with and without a GOES match within +/- 12 hours (when the ratio of collocated fire pixels is highest).

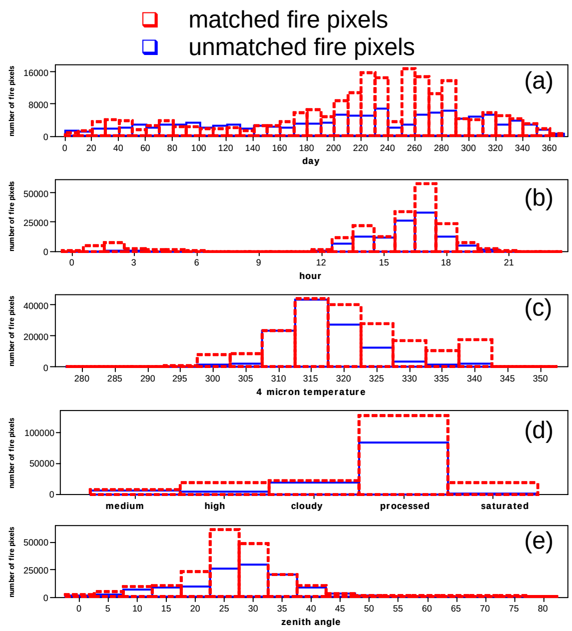

Figure 4. Histograms show the differences between GOES filtered fire pixels (excluding low confidence fire pixels) with and without a MODIS fire pixel match within +/- 1 hour and within 10 km for 2004. (a) day of the year (b) hour of day (UTC), (c) 4 μm observed brightness temperature (K), (d) confidence category, and (e) satellite zenith angle on the bottom.

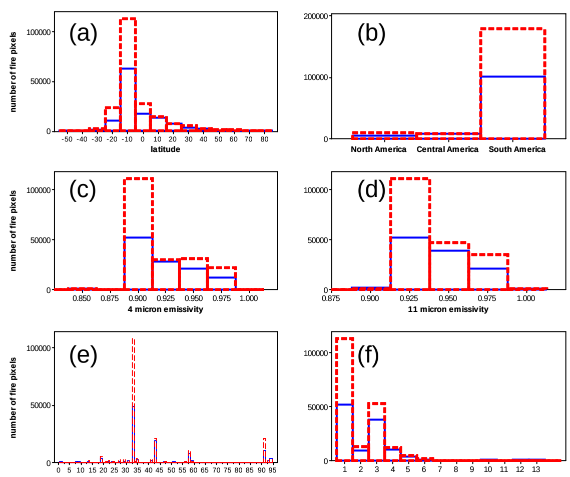

Figure 5. Histograms show the differences between GOES filtered fire pixels (excluding low confidence fire pixels) with and without a MODIS fire pixels within +/- 1 hour and within 10 km for 2004. (a) latitude, (b) geographical region, (c) 4 μm emissivity, (d) 11 μm emissivity, (e) ecosystem of the fire pixel and (f) simplified ecosystem classification.

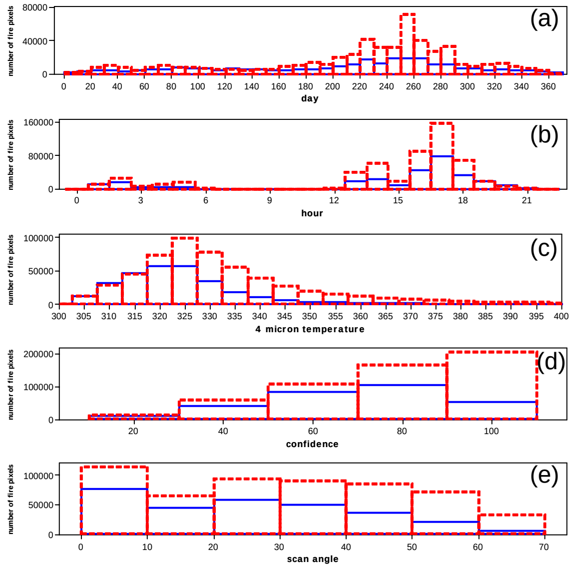

Figure 6. Histograms showing the difference between fire pixel characteristics of MODIS fire pixels with and without a GOES match within +/- 12 hours and 10 km for 2004. (a) day of the year, (b) hour of day (UTC), (c) 4 μm observed brightness temperature (K), (d) confidence category, and (e) satellite zenith angle.

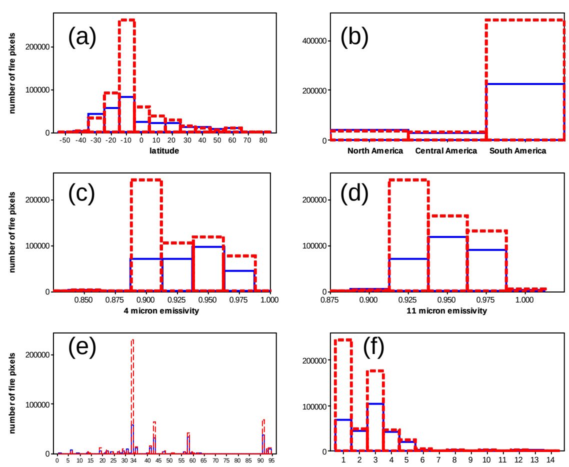

Figure 7. Histograms showing the difference between fire pixel characteristics of MODIS fire pixels with and without a GOES match within +/- 12 hours and 10 km from 2004. (a) latitude (b) geographical region, (c) 4 μm emissivity (d) 11 μm emissivity (e) ecosystem of the fire pixel (f) simplified ecosystem classification.

Fire detection shows a diurnal signature. Fire activity peaks at around 17 UTC and there is a trend for more fire pixels to have a match at this time of day than not to have a match.

Fire pixels with warmer 4 μm observed brightness temperatures are more likely to have a collocated MODIS fire pixel than not. A similar trend is seen where cooler fire pixels are more likely to be unmatched, however cooler fire pixels are more likely to be low confidence fire pixels and are not plotted.

Similar to brightness temperature, fire confidence provides clues about the likelihood of matched or unmatched fire pixels. Higher confidence categories more often have fire pixels with a match than lower confidence categories. The lowest confidence fires are not plotted, but they would show a trend where unmatched fire pixels would be more common than matched fire pixels at the lowest confidence level.

Satellite zenith angle indicates how far from nadir a fire pixel occurs. For GOES, relatively few fire pixels are found at small zenith angles because there is relatively little land surface at the lowest zenith angles. For MODIS, there is no relationship between regions and zenith angles. For GOES fire pixels, those with zenith angles between 20° and 30° are much more likely to have a MODIS match than any other zenith angle. For MODIS, as the scan angle increases the number of fire detections generally decrease. While scan angles above 50 are relatively rare, these pixels approach the same size as a GOES pixel at nadir, and proportionally more MODIS pixels have a GOES match when MODIS has a large zenith angle than the proportion of fire pixels with a match at low MODIS zenith angles.

Fire pixels are most frequently found around 10°S latitude, a similar maximum might be expected around 10°N latitude, however there is comparatively less land there (and it is primarily mountainous not tropical rainforest). In general, fire pixels in the southern hemisphere are more likely to have a collocated GOES/MODIS fire pixel. The only exception would be that south of around 30°S MODIS fire pixels become less likely to have a corresponding GOES fire pixel because GOES coverage in southern South America is less frequent.

The most common ecosystem types tend to have a high proportion of matched fire pixels compared to unmatched fire pixels. Emissivity at 4 and 11 μm shows that different land surfaces (with different emissivities) provide clues towards the likelihood of collocated GOES/MODIS fire pixels.

In addition to allowing a range of time between collocated fire detections, it is equally valid to consider a range of spatial criteria. With more rigid criteria fewer matches occur; only 51.4% of GOES fire pixels (filtered fire pixels with low confidence fires removed) had a MODIS match within 5 km in 2004 (compared to 62.8% within 10 km). Similarly only 50.5% of MODIS fire pixels had a GOES match within 5 km in 2004 (compared to 65.6% within 10 km). Stringent match criteria improves the likelihood that matched fires represent the same fire and share similar radiative properties, but it is unrealistic to expect fires to be this close due to navigational differences, instrument resolution, and other sources of error. Expanding the spatial window, allowing fires within 25 km to be considered matching fires is especially valid at high latitudes where GOES resolution is coarse - even a spatial resolution of 25 km can be too small to capture a single GOES pixel. With less stringent criteria, up to 76.7% of GOES fires (filtered with low confidence fires removed from consideration) have a MODIS match within 25 km in 2004. MODIS fire pixels also have more matches with GOES fire pixels at 25 km compared to 10 km; 79.8% of MODIS fires (with low confidence fires removed) had a match within 25 km in 2004.

4.2.3 Analysis

The characteristics of GOES/MODIS fire pixels that are collocated and fire pixels that are not collocated are different. It is possible to use statistical tools that apply fire pixel characteristics to predict if a particular fire pixel will have a matching fire pixel from another satellite product based only on the characteristics of the fire pixel without referring to the other satellite fire product. To do this, the statistical method, discriminant analysis, is applied and uses characteristics such as 4 μm observed brightness temperature, latitude, and fire confidence to forecast if a fire pixel will have a collocated fire pixel from another fire product without referring to data from the second fire product. The results show that fire pixel characteristics provide clues about the likelihood for a fire pixel to be detected by a second satellite fire product.

Results can be presented in a contingency table format where there are four possible outcomes: a collocated fire pixel with a correct discriminant analysis forecast, a collocated fire pixel with an incorrect discriminant analysis forecast, a fire pixel with no match from the other fire product with an incorrect discriminant analysis forecast, and a fire pixel with no match from the other fire product with a correct discriminant analysis forecast. Statistics that are important for fire pixel analysis include accuracy or proportion correctly forecast (PC), the Heidke Skill Score (HSS), and Peirce Skill Score (PSS) [Wilks, 2005]. PC is a measure of accuracy and indicates the proportion of fire pixels correctly forecast by discriminant analysis. The Heidke Skill Score accounts for the fire pixels correctly identified by discriminant analysis compared to the amount that would be correctly identified by a random forecast. Lastly, the Peirce Skill Score accounts for the fire pixels that discriminant analysis correctly forecasts minus the fire pixels discriminant analysis misclassified.

A sample of results is shown in Table 1. Discriminant analysis is most successful where the PC score is highest. Data sets for various products and temporal windows are shown. The PC score and ratio of fire pixels with a match do not necessarily occur concurrently. The Hiedke and Peirce skill scores further indicate that the discriminant analysis technique, based on fire pixel characteristics, has skill that is not dependent on the ratio of collocated fire pixels.

Discriminant analysis can identify fire pixels from one fire product that have a matching fire pixel from another product (as well as fire pixels that do not have a matching fire pixel) with more success than a random forecast (based on the proportion of fire pixels with a match).

		PC	HSS	PSS	match ratio
GOES	+/- 0.25 hour	0.672	0.730	0.357	0.399
	+/- 1 hour	0.679	0.744	0.374	0.401
	+/- 3 hour	0.674	0.766	0.376	0.390
	+/- 6 hour	0.659	0.799	0.365	0.361
	+/- 12 hour	0.652	0.827	0.356	0.334
GOES filtered	+/- 0.25 hour	0.677	0.622	0.355	0.483
	+/- 1 hour	0.691	0.610	0.381	0.508
	+/- 3 hour	0.671	0.570	0.339	0.511
	+/- 6 hour	0.645	0.569	0.297	0.482
	+/- 12 hour	0.628	0.590	0.286	0.452
MODIS	+/- 0.25 hour	0.718	0.536	0.226	0.289
	+/- 1 hour	0.675	0.625	0.350	0.476
	+/- 3 hour	0.693	0.512	0.370	0.576
	+/- 6 hour	0.698	0.466	0.372	0.613
	+/- 12 hour	0.699	0.424	0.355	0.633
MODIS filtered	+/- 0.25 hour	0.751	0.452	0.176	0.222
	+/- 1 hour	0.693	0.536	0.245	0.353
	+/- 3 hour	0.674	0.671	0.356	0.444
	+/- 6 hour	0.684	0.621	0.369	0.492
	+/- 12 hour	0.684	0.596	0.366	0.510

Table 1 Discriminant analysis for fire pixels in the Western Hemisphere for 2004. PC indicates the proportion correctly forecast by discriminant analysis, HSS is the Hiedke Skill Score, and PSS is the Peirce Skill Score. Match ratio is the number of fire pixels with a match compared to the total number of fire pixels.

5. CONCLUSIONS

Each satellite fire product has unique strengths and limitations. Examining fire pixels that are collocated between two satellite derived fire products is a first step in understanding the characteristics of fires that can be detected in both fire products and the characteristics of fires that can only be detected in one satellite fire product. It is not correct to assume that unmatched fire pixels are false detections just as it is not correct to assume that collocated fire pixels are positive fire detections without performing a more rigorous validation study.

In general, the highest proportion of GOES fire pixels with a match is found when the temporal criteria is +/- 1 hour. On the other hand, MODIS coverage is nearly complete over a period of +/- 12 hours and this is the amount of time that yields the highest ratio of MODIS fire pixels with a GOES fire pixel match. Similarly it is necessary to allow a certain amount of space between the center of fire pixels. The results are better for fire pixels that are required to be within 10 km to be considered collocated than 5 km. At 25 km (or more) there would be a higher percentage of fire pixels with a match, but this reaches the point where it is unlikely that matching fire pixels are representing the same fires; the exception would be at higher latitudes where the GOES resolution is coarse.

The frequency that a fire product detects a collocated fire pixel (compared to how often it detects a unique fire pixel) needs to be understood. Unfiltered GOES fire pixels contain the most matches, but filtered GOES fire pixels, with low confidence fire pixels excluded provide the fewest unmatched fire pixels. Similarly, MODIS fire pixels have the most matches when considering unfiltered GOES fire pixels of any confidence while MODIS fire pixels with low confidence fire pixels excluded yields the fewest unmatched fire pixels. As high as 62.8% of GOES (filtered fire pixels with low confidence fire pixels removed) fire pixels had a match (within 10 km), but including unfiltered fire pixel with a match and only excluding the unmatched low confidence fire pixels yields 72.4% of the pixels with a match. For MODIS, 69.1% of fire pixels had a match (within 10 km with low confidence fire pixels excluded), but including low confidence fire pixels with a match and only excluding low confidence fire pixels without a match increases the match ratio to 73.3%.

Examining collocated GOES and MODIS fire pixels shows some important trends. The fire pixels that are collocated tend to have warmer 4 μm observed brightness temperatures, have a higher confidence value, and tend to occur at lower satellite zenith angles than fire pixels that are not collocated. Ecosystem and emissivity contain categories where collocated pixels are more common than the overall sample. Statistical methods, such as discriminant analysis can identify differences in fire pixel characteristics between fire pixels that are unmatched compared to fire pixels that do have a match. Identifying the characteristics of matched and unmatched fire pixels is a step towards forecasting if a fire pixel will be collocated with a fire pixel from another satellite without actually referring to data from the other satellite.

This study can help users understand fire product differences that can be explained by differences in satellites, fire algorithms, and fire pixel characteristics. It is not correct to assume that all fire product differences are caused by false detections. Data assimilation can benefit from a technique that gives priority to fire pixels that have characteristics that are more prevalent in fire pixels that appear in multiple products. In the end, a merged data product can benefit from high temporal resolution GOES data and high spatial resolution MODIS fire product to provide more information than either product could provide alone.

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