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Detection rates of the MODIS active fire product in the United States

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Abstract

MODIS active fire data offer new information about global fire patterns. However, uncertainties in detection rates can render satellite-derived fire statistics difficult to interpret. We evaluated the MODIS 1 km daily active fire product to quantify detection rates for both Terra and Aqua MODIS sensors, examined how cloud cover and fire size affected detection rates, and estimated how detection rates varied across the United States. MODIS active fire detections were compared to 361 reference fires (≥18 ha) that had been delineated using pre- and post-fire Landsat imagery. Reference fires were considered detected if at least one MODIS active fire pixel occurred within 1 km of the edge of the fire. When active fire data from both Aqua and Terra were combined, 82% of all reference fires were found, but detection rates were less for Aqua and Terra individually (73% and 66% respectively). Fires not detected generally had more cloudy days, but not when the Aqua data were considered exclusively. MODIS detection rates decreased with fire size, and the size at which 50% of all fires were detected was 105 ha when combining Aqua and Terra (195 ha for Aqua and 334 ha for Terra alone). Across the United States, detection rates were greatest in the West, lower in the Great Plains, and lowest in the East. The MODIS active fire product captures large fires in the U.S. well, but may under-represent fires in areas with frequent cloud cover or rapidly burning, small, and low-intensity fires. We recommend that users of the MODIS active fire data perform individual validations to ensure that all relevant fires are included.

Keywords: MODIS active fire detection; MOD14; MYD14; Clouds; United States

1. Introduction

Satellite sensors can monitor global fire patterns (Csiszar et al., 2005; Dwyer et al., 1998; Dwyer et al., 2000) and have increased our understanding of fire emissions (Kaufman et al., 1992; Seiler & Crutzen, 1980), land-use/land-cover change (Eva & Lambin, 2000), and fire risk (Chuvieco & Congalton, 1989). Satellite fire data offer clear advantages over other fire data sources. In the U.S., many public agencies keep fire occurrence records, but may not include fires occurring on private lands (Brown et al., 2002). Collecting fire data in the field is time consuming, expensive and difficult, especially in remote areas. Satellite fire observations thus offer a reliable source of fire occurrence data that may overcome some of the limitations of traditional fire monitoring (Csiszar et al., 2005; Eva & Lambin, 1998a; Flannigan & Vonder Haar, 1986; Korontzi et al., 2006). However, although satellite fire data offer valuable information, uncertainty in their detection rates can make interpretation difficult (Congalton & Green, 1999).

A variety of sensors have been used to detect and map fires. Global to continental coverage has been derived from the Advanced Very High Resolution Radiometer (Flannigan & Vonder Haar, 1986; Li et al., 1997), and Moderate Resolution Imaging Spectroradiometer (MODIS) onboard the EOS Terra and Aqua satellites (Justice et al., 2002a). Other moderate to coarse resolution sensors used for fire monitoring include Geostationary Operational Environmental Satellite (Prins & Menzel, 1992), Along Track Scanning Radiometer (Eva & Lambin, 1998a), Defense Meteorological Satellite Program-Operational Linescan System (Elvidge et al., 1996; Fuller & Fulk, 2000), Visible and Infrared Scanner (Giglio et al., 2000), and SPOT VEGETATION (Fraser et al., 2000). For regional fire mapping, finer-resolution sensors, such as Landsat (Chuvieco & Congalton, 1989; Minnich, 1983; Pereira & Setzer, 1993), Advanced Wide Field Sensor

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(Chand et al., 2006) and Advanced Spaceborne Thermal Emission and Reflection Radiometer (Csiszar et al., 2006; Morisette et al., 2005a; Morisette et al., 2005b) have been used.

Regardless of the sensor, two general approaches to fire mapping have been taken; burn scar mapping and active fire detection. Burn scar mapping involves identifying the area affected by fire after the event has occurred (Chuvieco & Congalton, 1988; Kasischke et al., 1993; Pereira & Setzer, 1993). In contrast to burn scar delineation, active fire detection maps the flaming front of fires at the time of satellite overpass (Flannigan & Vonder Haar, 1986; Flasse & Ceccato, 1996; Matson & Dozier, 1981). In this paper, we focused on MODIS active fire detections because they represent the state-of-the-art in global fire mapping and can be used as a basis for other fire products, for instance to distinguish burned areas from other disturbances (Giglio et al., 2006; Loboda et al., 2007).

Active fire detection is possible because radiant energy increases with temperature, producing a high contrast fire pixel relative to cool surrounding non-fire pixels. Small increases in an object's temperature result in large increases in radiance in the mid-IR range (3–5 μm) and slight increases in the thermal-IR range (5–12 μm) and because of this, even sub-pixel size fires can be detected (Dozier, 1981; Matson & Dozier, 1981). In practice, active fire detection algorithms either evaluate individual pixel values relative to a threshold (Flannigan & Vonder Haar, 1986; Matson & Dozier, 1981); compare a pixel's temperature contextually to its neighboring pixels (Flasse & Ceccato, 1996; Giglio et al., 2003); or track temporal changes in temperature (Cuomo et al., 2001; Lasaponara et al., 2003).

Errors of commission in active fire mapping can be caused by non-fire surfaces that are highly reflective such as urban areas, senescent vegetation, bare soil, water, or clouds (Flannigan & Vonder Haar, 1986; Giglio et al., 2003; Setzer & Verstraete, 1994). Contextual algorithms sometimes exhibit commission errors where there is sharp radiometric contrast, for example, between desert and vegetation (Giglio et al., 2003). Errors of omission may occur, if there is a difference between the time of fire occurrence and satellite overpass, and these errors are particularly common when satellite overpass does not coincide with peak daily fire activity (Cardoso et al., 2005; Giglio, 2007; Prins et al., 1998). Clouds and thick smoke can also obscure fire activity (Flannigan & Vonder Haar, 1986). Theoretically, small fires should be identifiable by even moderate resolution sensors such as AVHRR or MODIS (Dozier, 1981; Giglio et al., 1999; Matson & Dozier, 1981), but in practice, they may lack the intensity needed to trigger detection thresholds and will remain undetected especially at large scan angles where the amount of energy reaching the satellite is limited (Giglio et al., 2003; Giglio et al., 1999; Schroeder et al., 2005). Contextual algorithms are more likely to miss fires in heterogeneous land-cover, which complicates the selection of an appropriate background temperature (Lasaponara et al., 2003; Schroeder et al., 2005; Wang et al., 2007).

The MODIS active fire products are produced using a contextual algorithm for the MODIS sensors on NASA's two Earth Observing System (EOS) satellites: Terra and Aqua. Interested readers should refer to Giglio et al. (2003) for details about the algorithm. The two satellites are in sun-synchronous orbits with different local overpass times; 1:30 and 13:30 for Aqua, and 10:30 and 22:30 for Terra (Lillesand & Kiefer, 1999). Aqua generally detects more fires than Terra because its afternoon overpass time is closer to daily peak fire activity in many regions (Justice et al., 2002a).

Several approaches have been taken to quantify errors in fire data, including simulation models, comparison with independent but simultaneously collected satellite data, and comparison with field data. Simulation models predict that commission errors of MODIS and other satellites' fire detections are very low (Giglio et al., 2003; Giglio et al., 1999). However, errors of omission are likely and simulations show that MODIS has a 50% probability of detecting a 100 m^2 flaming fire (~1000 K) or a 1000–2000 m^2 smoldering fire (~600 K; Giglio et al., 2003; Kaufman et al., 1998). Detection limits are generally similar among biomes, but somewhat lower for dry tropical savannas (Giglio et al., 2003; Giglio et al., 1999). These simulation results suggest that small fires can be detected under ideal conditions, but validations with real fire data are needed to fully understand the detection capabilities of MODIS.

Quantifying fire activity on the ground at satellite overpass times is logistically difficult (Roy et al., 2005). One approach is to use data collected by the ASTER sensor, also onboard the Terra satellite with MODIS. ASTER senses energy in the 0.5 to 10 μm wavelengths, has finer spatial resolution (15–90 m) than MODIS, and its simultaneous but independent observations of fire events can validate MODIS active fire products (Csiszar et al., 2006; Justice et al., 2002b; Morisette et al., 2005a; Morisette et al., 2005b). Comparisons with ASTER suggest commission errors in the MODIS active fire data are rare (0.01% in Brazil (Morisette et al., 2005b) and 0.002% in northern Eurasia (Csiszar et al., 2006). Errors of omission are more common, especially for small fires. For instance, MODIS has a 50% detection rate when fire activity spanned clusters of 47 or more ASTER pixels (30-m resolution each) in Brazil (Morisette et al., 2005b), 25–34 ASTER pixels in southern Africa (Morisette et al., 2005a) and ~60 ASTER pixels in northern Eurasia (Csiszar et al., 2006). When aggregated to MODIS resolutions, the actual fires mapped by ASTER can be composed of many individual fire components and each fire component potentially has a different temperature. In contrast, the theoretical simulations of MODIS fire detection capabilities ignore the heterogeneity of individual fire components and are based on one temperature describing the entire active fire area. It is impossible to know what portion of each ASTER pixel was actively burning at the time of image capture, but results from ASTER validation studies suggest the actual MODIS 50% detection threshold could be considerable larger than theoretical predictions (Giglio et al., 2003).

The true fire size detection threshold of MODIS may be even lower because the ASTER imagery is restricted to a portion of the MODIS viewing area. The MODIS sensors collect data over a 2330 km wide swath. In comparison, ASTER collects SWIR and TIR data in 60 × 60 km segments within ± 116 km of the center of MODIS Terra's path (Yamaguchi et al., 1998). Results from validation studies based on ASTER data are limited to that range and may overestimate MODIS detection rates because detection capabilities are reduced at the periphery of MODIS' swath (Schroeder et al., 2005). Furthermore, ASTER provides no information about fire activity occurring at times different from MODIS Terra overpass (10:30/22:30; Csiszar et al., 2006; Morisette et al., 2005a; Morisette et al., 2005b).

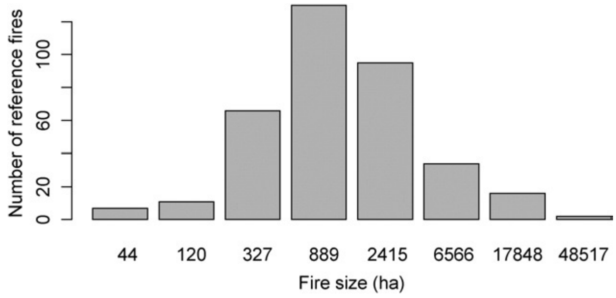

Fig. 1. Histogram of the fire size distribution of the reference fires used for comparison with the MODIS active fire products. *X*-axis increments follow a log scale.

Validation efforts based on independently collected fire data are thus important. Ground-based validations can include small fires and fires that are not actively burning during satellite overpass. Unfortunately, only few ground-based studies have validated the MODIS active fire product. In one study examining MODIS fire detection rates in Brazil (Cardoso et al., 2005), errors of commission were high with only 33% of MODIS active fires confirmed on the ground. Errors of omission were even greater; only 0.7% of all the fires observed on the ground were identified by MODIS. The Cardoso et al. (2005) covered only a small study area, and was limited to one biome, but it raises the question what proportion of fires is captured by the MODIS active fire product. Simulation studies and ASTER validations alone can not answer this question, and additional ground-based accuracy assessments are needed to interpret the MODIS fire data.

Our objective was to determine how well the MODIS active fire products capture broad-scale patterns of fire activity. We took an approach different from prior MODIS active fire validation efforts and used a set of fire perimeters spanning a wide range of environmental conditions across the United States as reference data. The specific questions we sought to answer were:

1. What proportion of fires is detected by the MODIS active fire product?
2. Do detection rates change if lower confidence MODIS active fires are excluded?
3. Are there differences in cloud cover between detected and undetected fires?
4. Are there differences in size between detected and undetected fires?
5. Are there regional differences in fire detection rates?

Our goal was to provide information that will enhance the interpretation of MODIS fire data in national-level assessments of fire activity, fire risk modeling, disturbance ecology, and biogeochemical cycling.

2. Methods

2.1. Reference fires

We selected reference fire polygons from the U.S. Geological Survey (USGS)/U.S. National Park Service (NPS) Burn Severity Mapping program and the USGS/U.S. Forest Service (USFS) Monitoring Trends in Burn Severity program. These polygons represent fire perimeters of burn scars, manually interpreted from pre- and post-fire Landsat images close to the peak of the growing season. The fires mapped by these projects were selected from existing fire databases, such as the federal incident reports. Small fire perimeters exist in the data but mapping priority was given to fires large enough to leave visible scars in Landsat imagery ($\geq$202 ha in the East and $\geq$404 ha in the West). We selected these fire polygons as reference data because there was little spatial uncertainty in the location of fires, unlike other fire data sources such as the Federal Fire Occurrence Database (Brown et al., 2002).

We only used reference fire perimeters after 2003, the date at which both MODIS Terra and Aqua were operational. Reference data included perimeters of 38 fires from 2003, 31 from 2004, and 16 from 2005 from the NPS/USGS National Burn Severity Mapping project (http://burnseverity.cr.usgs.gov/) and 276 fires from 2004 from the USGS/USFS Monitoring Trends in Burn Severity project (http://svinetfc4.fs.fed.us/mtbs/index.html). These were all the fires available through the two burn severity mapping projects at the time this study was performed. The size of reference fires ranged from 18 ha to 48,360 ha (Fig. 1).

We converted the reference fire polygons to raster images with the same spatial resolution as the MODIS active fire data (1 km). Although MODIS georeferencing errors are reported as being low (approximately 0.1 pixels; Wolfe et al., 2002), we expanded the reference fire perimeters by a 1-km buffer to account for potential georeferencing errors and pixel overlap (Fig. 2).

2.2. MODIS active fire data

We compared the reference fire data to MODIS Terra and Aqua daily active fire data (MOD14a1 and MYD14a1, Collection 04). MODIS data were acquired from the Land Processes Distributed Active Archive Center (LPDAAC, http://edcdaac.usgs.gov/modis/dataproducts.asp). For each day, the MOD14a1 or MYD14a1 files were mosaicked and reprojected to Albers Equal Area with the 1983 North American Datum using the MODIS Land Data Operational Product Evaluation tools (LDOPE; http://edcdaac.usgs.gov/landdaac/tools/ldope/).

2.3. Data analysis

To compare fire detection rates between the two sensors, we determined the proportion of reference fires detected for three different combinations of the MODIS Aqua and Terra active fire products: (1) Aqua only, (2) Terra only, and (3) Aqua and Terra combined. In the combined MODIS data, pixels were flagged as having an active fire if either Aqua or Terra detected a fire. A reference fire was considered detected if it was within 1 km of at least one MODIS active fire pixel from either satellite during the year the reference fire was reported (Fig. 2). For this analysis, we included all MODIS active fires of low confidence or greater.

We also assessed how many reference fires were detected by the MODIS active fire product when lower confidence MODIS fires were excluded. We used the same three data combinations as in the detection rates between MODIS sensors (Aqua only,

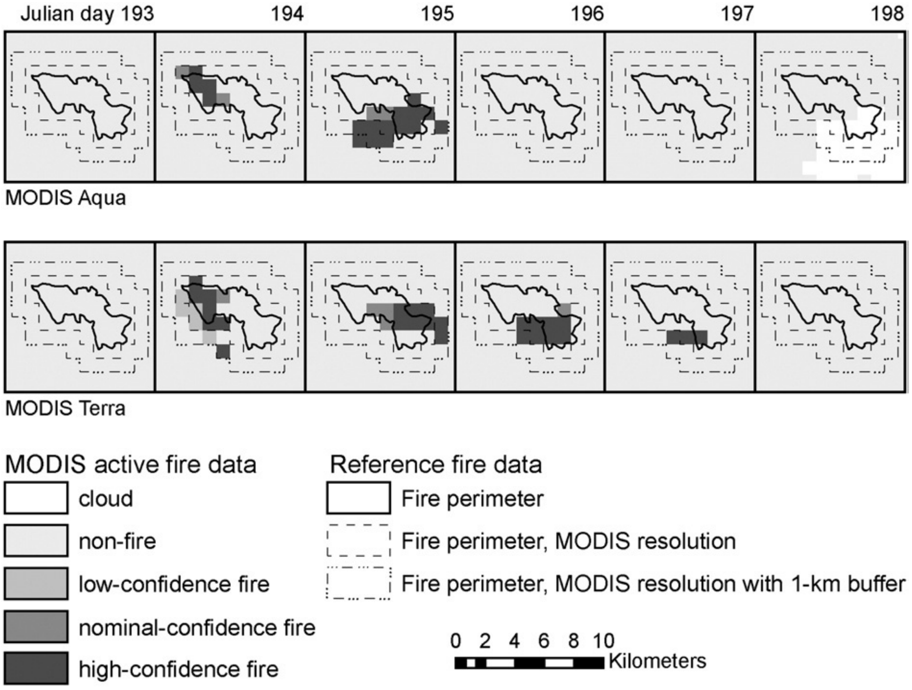

Fig. 2. Example of fire data used to determine MODIS active fire detection rates. Data are shown for the Balcony House Fire in Wyoming, 2003. Reported start date was Julian date 196 (July 15). Reported stop date was Julian date 221 (August 9); however, no MODIS fire pixels occurred within the perimeter after Julian day 197 (July 16).

Terra only, and Aqua or Terra). When the Aqua and Terra data were combined, we retained the highest confidence level for detected fires.

To examine the effects of cloud cover on MODIS active fire detection rates, we compared the number of cloudy days between detected and undetected reference fires. The MODIS active fire product implements a simple mask to exclude areas covered by optically thick clouds from processing (Giglio et al., 2003). Optically thin clouds might also be present but are generally considered to have negligible effects on fire detection and are not identified by the masking algorithm. We assumed that the presence of any cloud pixels within the reference fire perimeters was indicative of cloud or smoke cover that might have obscured fire activity.

For each reference fire, we calculated the number of days with cloud cover between the fire's start date and 14 days after the start date. End dates were not reported for many fires. However, visual examination of the MODIS data showed that most fire activity occurred within two weeks of the reported start date, so we constrained our cloud cover analysis to that time span. We used two-sided t-tests assuming unequal variance to determine whether there was a statistically significant difference in the number of days with cloud cover between detected and undetected fires.

In order to assess the effects of fire size on detection rates, we related reference fire size (x) to the proportion of reference fires not detected by MODIS (P) using a logistic regression with the logit-link function (Agresti, 1996).

$P = \frac{e^{\pi}}{1+e^{\pi}}$, where $\pi = \beta_0 + \beta_1 x + \varepsilon$ (Eq. (1); β_0 = intercept; β_1 = slope).

We calculated the size at which 50% of the reference fires were not detected as $x_{50\%} = \beta_0 / \beta_1$ (Eq. (2); Agresti, 1996).

To make regional comparisons of MODIS active fire detection rates, we subdivided the United States into three areas by grouping Omernik Level 1 ecoregions (Omernik, 1987). The West included

Table 1
Mean number of cloudy days for reference fires that were detected and undetected by the MODIS active fire products

		Entire US	East	Great Plains	West
	Degrees of freedom	359	109	63	183
Combined	Detected	0.45	0.75	0.81	0.21
	Undetected	1.20	1.42	1.15	0.75
	p-value	<0.0001	0.0032	0.2996	0.0006
Aqua	Detected	3.14	3.68	4.62	2.49
	Undetected	4.08	4.65	4.65	2.87
	p-value	0.0036	0.0645	0.9666	0.4430
Terra	Detected	2.88	3.36	4.59	2.31
	Undetected	4.00	4.21	4.69	2.97
	p-value	0.0001	0.0883	0.8754	0.1749

p-values indicate significance for two-sided t-test of difference in mean number of cloudy days assuming equal variance.

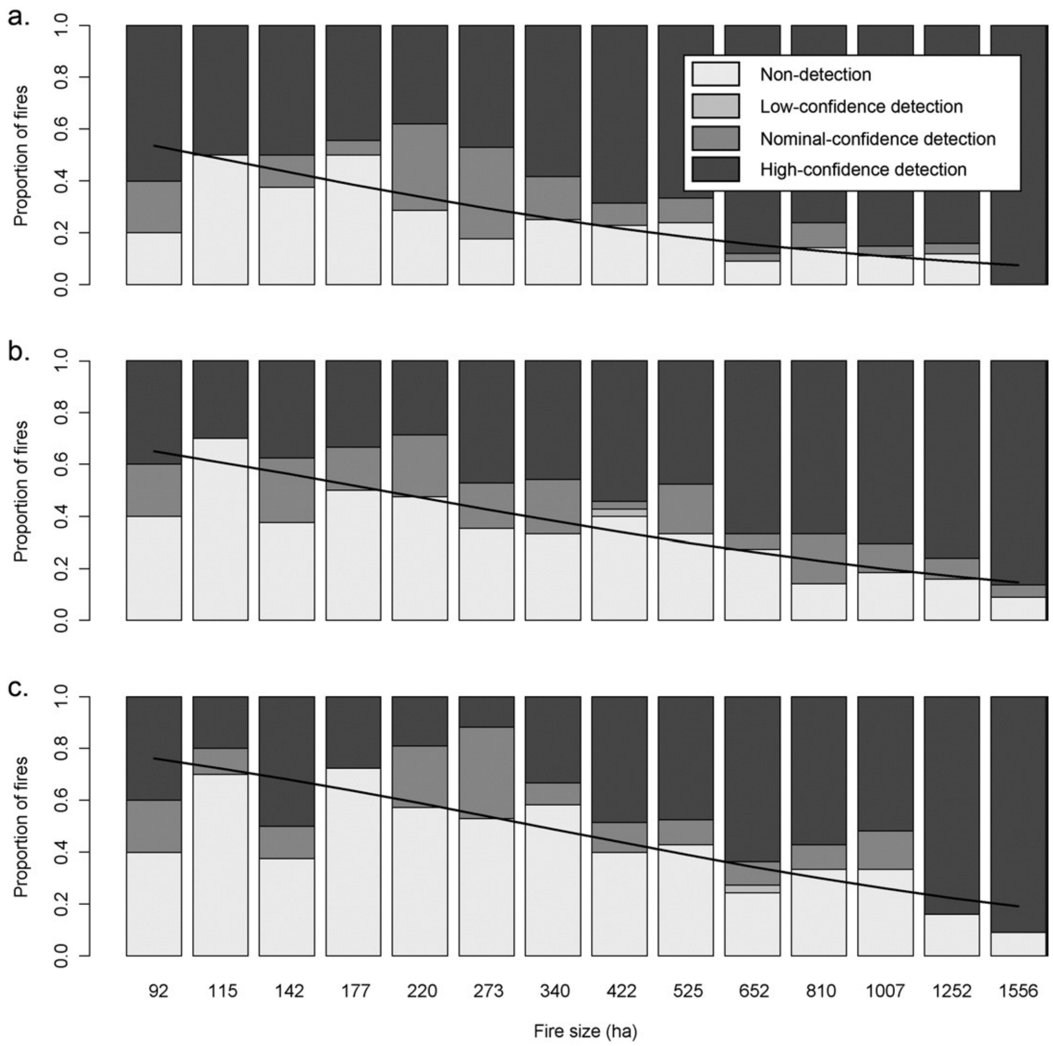

Fig. 3. MODIS active fire product detection rate in relation to reference fire size for (a) Aqua or Terra combined, (b) Aqua only, and (c) Terra only. *X*-axis increments follow a log scale. Black lines show the fitted logistic regression curve for the proportion of fires not being detected by MODIS against log(fire size).

Omernik's Northwestern Forested Mountains, Marine West Coast Forest, North American Deserts, Mediterranean California, Southern Semi-arid Highlands, and Temperate Sierras. The East included Omernick's Northern Forests, Eastern Temperate Forests, and Tropical Wet Forests. The Great Plains was composed solely of Omernik's Great Plains ecoregion. Within each region, we calculated the proportion of reference fires detected by each sensor individually and combined.

3. Results

When active fire data from both MODIS satellites were combined, 82% of the reference fires were detected. The combined detection rate was greater than when either of the MODIS sensors were considered individually (73% for Aqua and 66% for Terra). Excluding low-confidence MODIS active fire detections had little effect on detection rates, decreasing the total number of fires detected by 1 for Aqua and 2 for Terra. However, excluding nominal-confidence MODIS active fire detections had a greater effect, decreasing the number of fires detected by 12% and 14% for Aqua and Terra respectively.

The number of cloudy days during the first two weeks of fire activity was generally low, but reference fires not detected by MODIS had more cloudy days (Table 1). The difference was statistically significant (p-values <0.05) for the combined MODIS Aqua and Terra data when all fires across the U.S. were considered, as well as in the East and in the West. When Aqua and Terra were treated individually, the pattern of more cloudy days for

Table 2
Logistic regression parameters, standard errors and z and p-values for proportion of references fires that were not detected by the MODIS active fire products from 2003 to 2005

	Coefficient	Estimate	Standard Error	z-value	p-value
Aqua or Terra combined	β_0	13.0267	3.1901	4.083	<0.0001
	β_1	−0.9379	0.2094	−4.478	<0.0001
Aqua	β_0	12.2055	2.7944	4.368	<0.0001
	β_1	−0.8433	0.1819	−4.637	<0.0001
Terra	β_0	13.8224	2.7396	5.045	<0.0001
	β_1	−0.922	0.1775	−5.196	<0.0001

β_0 = Intercept, β_1 = Slope, sample size = 361 fires.

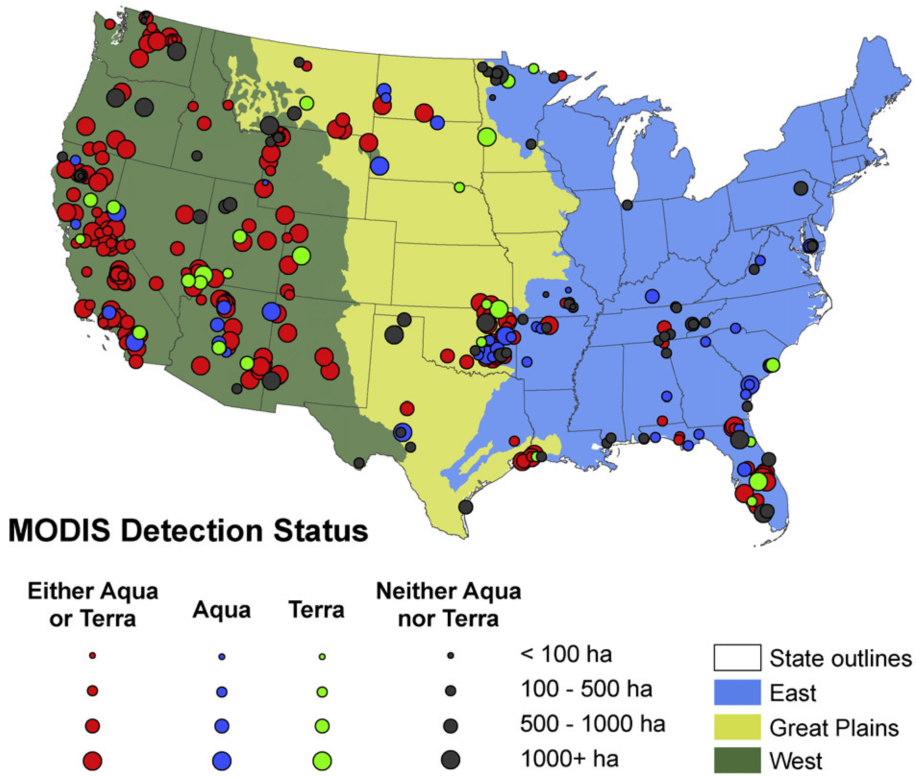

Fig. 4. Geographic distribution of reference fires detected and not detected by the MODIS active fire product between 2003 and 2005. Total number of reference fires was 361.

undetected fires persisted, but was only significant when all fires across the U.S. were considered. At regional levels (East, Great Plains, and West), cloud cover effects on Aqua or Terra fire detections were most pronounced in the East.

There were significant differences in the size of fires detected and undetected by MODIS for Terra and Aqua. The smallest reference fire detected by Aqua was 17.6 ha versus 27.8 ha for Terra. Mean fire sizes of detections were 915 and 1044 ha for Aqua and Terra respectively, while mean fire sizes of non-detections were 364 and 346 ha for Aqua and Terra. The largest fire not detected by Aqua was 2638 ha and 2484 for Terra.

The proportion of reference fires detected increased with reference fire size (Fig. 3, Table 2). The models including both Aqua and Terra sensors and the model based on Aqua alone generally exhibited greater detection rates relative to fire size than the model based on Terra alone. This is demonstrated by the threshold at which >50% of fires were detected: 105 ha (combined Aqua and Terra), 195 ha (Aqua only), and 334 ha (Terra only).

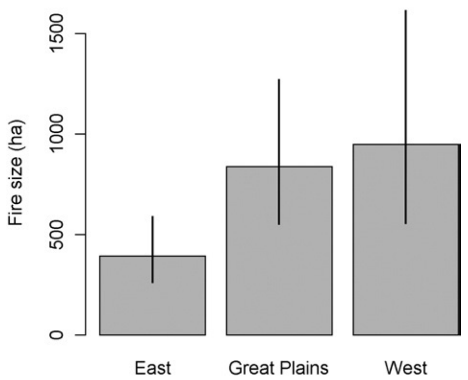

Fig. 5. Mean size of reference fires among regions of the U.S. Error bars show ±95% confidence levels. Fires were significantly smaller in the East compared to the U.S. (ANOVA difference of means p-value <0.0001).

MODIS fire detection rates also varied regionally across the United States (Fig. 4). When the Aqua and Terra sensors were combined, overall detection rates were greatest in the West (89%), slightly lower in the Great Plains (80%), and lowest in the East (60%). When the sensors were considered individually, Aqua and Terra performed equally well in the West, where both sensors detected 81% of the reference fires. However, we found different detection rates between sensors in the Great Plains, where detection rates were 69% for Aqua and 60% for Terra, and in the East where detection rates were 58% for Aqua and 39% for Terra (Fig. 5).

4. Discussion

Overall, we found that the MODIS active fire products detected the majority of our reference fires. Detection rates were greatest when the active fire product data from both MODIS Aqua and Terra were used together, and individually Aqua outperformed Terra. The difference in the detection rates between the two MODIS sensors is most likely related to their overpass timing. Fire activity follows a diurnal cycle, often peaking in the afternoon, when weather conditions are most favorable for burning (Giglio, 2007; Prins et al., 1998). Aqua's early afternoon (13:30) overpass is closest to this peak and is the most likely reason for Aqua's higher detection rates. The daily data for Terra did detect a small number of fires not found by Aqua, about 9% of 361 total fires. These additional fires represent early morning or late evening fires that were not active at Aqua's overpass times (1:30 and 13:30). Unless there is specific interest in diurnal variability in fire activity, we recommend combining the Aqua and Terra active fire observations to obtain the greatest detection rates.

Almost no additional reference fires were detected when low-confidence MODIS active fire pixels were included in the analysis. Low-confidence fire pixels tended to occur at the periphery of clusters of high and nominal-confidence active fire pixels, and these reference fires would have been detected by the nominal and high confidence active fire pixels alone. Including low-confidence fire pixels might be desirable for other applications such as mapping clusters of fire activity (Loboda & Csiszar, 2007) or approximating burned area (Giglio et al., 2006); however, low-confidence fire pixels did not improve detection rates for our analysis of large fires.

Clouds are a confounding factor affecting estimates of fire activity by reducing satellite fire detection rates (Flannigan & Vonder Haar, 1986). We observed a significantly greater number of days with cloud cover for undetected reference fires. This pattern was strongest in the Eastern U.S., where the spring and fall fire seasons may coincide with higher cloud cover. However, in most cases the difference in the number of cloudy days was small. We had little information on when and where fires were active within our reference fire perimeters. Because of this, we assumed the presence of at least one MODIS cloud pixel within the reference fire perimeter represented clouds or smoke that could obscure fire activity. This assumption might have overestimated the influence of clouds on MODIS detection rates. However, cloud cover is clearly an important factor affecting MODIS detection rates and satellite fire detections will underestimate true fire activity in regions with persistent cloud cover.

MODIS active fire detection rates decreased as the size of reference fires decreased. There are several reasons why this might have occurred. First, the duration a fire burns might decline with total fire size. Shorter duration fires have fewer chances of being detected at MODIS overpass. It was not possible to test this because of the limited temporal information associated with our reference fires; however our reference fires were typically large fires that likely burned for multiple days. Another possible explanation for the decline in detection rate with fire size is that small reference fires lacked the energy output needed to trigger the thresholds of the MODIS active fire product algorithms (Giglio et al., 2003). For instance, a small surface fire burning leaf litter under a deciduous forest canopy might not have generated temperatures high enough for MODIS detection.

Even though detection rates increased with fire size, the MODIS active fire products failed to detect two large fires (>2000 ha, Fig. 4). One of these was a shrub fire in west-central Washington and the other was a grassland fire in southern Florida. The number of days with cloud cover for both fires was between 3 and 4, but there were no days where the view of both satellites was entirely obscured by clouds. Fires in flashy fuels such as shrubs and grasses can burn rapidly and often lack large fuels that would continue to burn after the fire front has passed. It is possible that these two large fires, and other reference fires, were not detected by the MODIS active fire products because they had rapidly moving flaming fronts that were extinguished before, and left little residual heat at MODIS overpass time. This is a plausible explanation, but to fully address this question, detailed information about the location of the fire front at the time of MODIS overpass would be needed. Unfortunately, this information was not available and we were not able to perform such an analysis.

Across the United States, MODIS active fire detection rates were lowest in the East and greatest in the West. Fire sizes tended to be smaller in the East than in the Great Plains and West (Fig. 5). However, we believe the different detection rates were primarily caused by differences in forest types, landscape pattern, fuel loadings, and fire behavior. The majority of fires in the Great Plains and eastern U.S. occurred in grasslands and deciduous forests that typically experience surface fires. Fuels in these ecosystems experience limited post-frontal combustion and if fires are not active during MODIS overpass there will be little chance of detection. In contrast, many forests in the Western U.S. are coniferous and experience a variety of fire behavior including intense crown fires (Agee, 1993). Heavy fuels in western fires may continue to combust after the fire front has passed. The increased energy output of active western fires and their remaining residual heat makes them more likely to be detected by the MODIS active fire products.

Most of our reference fires occurred on state and federal lands. As a consequence, our results may not be valid for substantially different vegetation types and fuel loadings. For instance, agricultural lands in the United States experience frequent fire activity that is clearly visible in the MODIS imagery (Korontzi et al., 2006; McCarty et al., 2007). Fuel loadings in forests and grasslands are quite different than those found in agricultural fields where fires tend to be small and short in duration (McCarty et al., 2007). Hence, we would expect detection rates for agricultural fires to be slightly less than those we observed for wildland fires.

If all fire activity is considered, there are many small fires (<1 ha; Brown et al., 2002). However, our reference fires were burn scars mapped from Landsat imagery. Using these data limited our analysis to fires that were large enough to make a visible burn scar in 30 m Landsat imagery; the smallest reference fire we included was 18 ha. Data for small fires, 1 ha or less, with the necessary spatial accuracy were not available for analysis. For that reason, our results tell us little about MODIS active fire detection rates for such small fires. However, given that the size threshold at which 50% of the reference fires were detected was 105 ha, we believe it is safe to assume that most small fires remain undetected by the MODIS active fire products.

How can we improve efforts to monitor global fire activity in the future? Our results highlighted that the size detection threshold above which fires on the ground are likely detected by the MODIS active fire product is fairly large (105 ha). However, these results are specific to the United States and differed depending on ecoregion. More studies in other biomes are needed to understand the spatial variability of the detection threshold and field-based studies on errors of commission are needed to interpret the MODIS active fire data fully. The primary limitation of the fire detection capabilities of the MODIS sensors appears to be the temporal gaps between satellite overpasses. During these gaps, it is not possible to monitor small fires or rapidly burning fires that extinguish before the next overpass. More frequent observations offered by geostationary systems, i.e., GOES (Prins et al., 1998; Prins & Menzel, 1992) and multi-sensor approaches (Eva & Lambin, 1998b; Giglio, 2007) offer promise to fill the gaps between MODIS overpasses and provide a more comprehensive record of fire occurrence.

Small and low-intensity fires are less likely to be detected by the MODIS active fire products. Increased sensor resolution might help to detect small, low temperature fires, but simulations and ASTER validation studies suggest that these fires are quite visible if active during MODIS overpass (Csiszar et al., 2006; Giglio et al., 2003; Giglio et al., 1999; Morisette et al., 2005a; Morisette et al., 2005b). Detection is heavily dependent on fire intensity, which varies with fuel loads, moisture levels, and weather; regional fire detection algorithms, tuned to local variability in fuels and fire behavior might offer greater fire detection than global algorithms (Loboda et al., 2007; Wang et al., 2007).

Our results have consequences for the use of the MODIS active fire product in fire management. Fire fighting is most effective when fires are detected before they become large, but the MODIS active fire products may be of limited value as an early-warning system because small fires are often undetected. The use of MODIS active fire data to differentiate burn scars from other disturbances may be questionable, because small fires are less likely to have an active fire detect, and burned area estimates would be downwardly biased. The accuracy of the MODIS active fire product also has consequences for estimating the effects of fires. For instance, wildfire aerosol and trace gas emission estimates relying on the MODIS active fire data (Kaufman et al., 2003) may be low because not all fires are included. However, since the undetected fires are likely to be small, they should have a relatively small effect on total emissions. The active fire data are quite useful for tracking large fires and since large fires account for the majority of area burned, the MODIS active fire products should be useful to quantify relative differences in fire activity among regions with similar biophysical characteristics. In summary, the MODIS active fire product provides important data for fire management, but the interpretation of the data needs to take the detection size threshold into account to avoid false conclusions.

5. Conclusions

MODIS active fire products provide a valuable source of data about fire activity that capture spatial and temporal patterns not represented in other fire data. Based on our analysis, overall detection rates of fires by the MODIS active fire products were high (82%) when data from both the Aqua and Terra sensors were combined. However, small fires were less likely to be detected than large fires. MODIS fire detection rates varied across the country, being greatest in the West and lowest in the East. We suggest that the MODIS active fire data are appropriate for applications where relatively large and intense fires are of primary interest. We recommend that users of the MODIS active fire data perform an individual quality assessment to ensure that fires relevant to their application are represented.

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