Validation of Active Fire Detection From Moderate-Resolution Satellite Sensors: The MODIS Example in Northern Eurasia

Ivan A. Csiszar, Jeffrey T. Morisette, and Louis Giglio

***Abstract*—This paper discusses the process of validating active fire "yes/no" binary fire detection products from moderate-resolution satellite sensors. General concepts and practical issues are illustrated by the validation of the Moderate Resolution Imaging Spectroradiometer (MODIS) active fire product in Siberia. Coincident Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) imagery is used to characterize spatial patterns of flaming at sub-MODIS pixel scale. It is shown that for proper evaluation reference fire observations are needed at the scale of the satellite pixel, as only 60% of the MODIS footprints contain single contiguous clusters of ASTER fire pixels. In Siberia the size of a single ASTER fire cluster within the MODIS footprint that has a 50% probability of being flagged as "fire" is ~ 60, compared to ~ 45 in the Brazilian Amazon, whereas previous radiative transfer simulations suggested similar detection probabilities. The lower-than-expected detection rates in Siberia are largely attributable to flaming underneath heavy smoke, which is not detected by the current MODIS algorithm. Pixel-based and cluster-based omission error rates are derived, and it is shown that the probability of flagging as "fire" a MODIS pixel which contains a given number of 30-m ASTER fire pixels is typically 3–5 times lower than detecting a contiguous cluster with the same number of ASTER fire pixels. The procedures described are recommended for a consensus active fire validation protocol, but with the inclusion of multiplatform sensor configurations to complement the near-nadir angular sampling from single-platform observations such as MODIS and ASTER on Terra.**

***Index Terms*—Fire detection, multisensor systems, remote sensing, satellites, validation.**

I. Introduction

ACTIVE fire products from moderate-resolution environmental satellites have been generated for more than two decades [1]. These products are increasingly used worldwide by a broad and diverse user community, including resource management agencies, policy decision makers, and scientific researchers [2].

There are two kinds of active fire products from satellites. The first kind is flagging pixels that contain burning as "fire." This procedure, which yields "yes/no" binary fire maps, is commonly referred to as "active fire detection." The second kind is the characterization of fires within the satellite pixel, either by partitioning the pixel into flaming, smoldering, and unburned areas and assigning temperature values to each of them [3], [4], or by calculating fire radiative power [5], [6]. In many ways, evaluation of the binary detection and continuous characterization products requires different approaches. In this paper we focus on the validation of the binary active fire detection product only.

Experience of the fire remote sensing community in producing global active fire maps and interaction with users has frequently uncovered a misunderstanding about the correct interpretation of satellite-based fire detection data [7]–[9] and to a consequent skepticism about product quality. A need therefore exists for explicit information on product accuracy, which can be achieved through validation.

Validation is defined as the process of assessing by independent means the quality of the data products derived from system outputs [10]. Independent information on fires can be obtained either by the direct observation of fires by alternative means or by observing fire effects such as atmospheric emissions or land cover change.

Validation of active fire products has been recognized to be a difficult task which lacks well-established procedures [11]. Nevertheless, pathfinding efforts have been carried out, including both direct and indirect means, ranging from visual interpretation of the fire maps to quantitative comparison with independent reference data. For example, smoke plumes were used for the accuracy assessment of fire detections from the Advanced Very High Resolution Radiometer (AVHRR) [12]. A validation study of the Moderate Resolution Imaging Spectroradiometer (MODIS) active fire detection algorithm [13] used smoke plumes detected in SPOT scenes [14]. AVHRR fire locations were compared with fire perimeters recorded by the Canadian and U.S. Forest Services [15]–[17]. Burned area survey maps were also used for algorithm intercomparison [18].

Validation has evolved into an integral part of fire product development, generation, and distribution efforts. Coordinated, global production and validation of active fire products was initiated by the International Geosphere–Biosphere Program [8]. Validation of the ATSR-based World Fire Atlas was carried out in coordination with IGBP-DIS [19], in which various direct and indirect validation methodologies were used over a number of representative target areas of the globe. The IGBP-DIS approach was also used to validate AVHRR-based global fire products [20]. Quality assessment and validation became an integral part of the MODIS Land data processing and production [21], with

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product validation status and accuracy statements distributed to the users [22].

Internationally, validation of fire products is being promoted by the Fire Mapping and Monitoring Implementation Team of the Global Observation of Forest Cover/Global Observation of Landcover Dynamics (GOFC/GOLD) program [23], [24]. This effort is being carried out in collaboration with the Committee on Earth Observing Satellites (CEOS) Working Group on Calibration and Validation (WGCV) Land Product Validation (LPV) subgroup [25]. GOFC/GOLD-Fire and CEOS/WGCV/LPV have held a series of workshops to coordinate fire product validation activities. One of the main outcomes of these workshops is the consensus on the need of standard validation methodologies, protocols, and accuracy metrics to enable product intercomparison and the assessment of the usefulness of products for various applications [26].

The objective of this paper is to provide an overview of the issues related to active fire validation. We will use the MODIS active fire product [27] to illustrate outstanding issues and possible solutions. First we discuss what independent reference data are available for fire validation (Section II). This is followed by a description of quantitative methods to determine detection probabilities and to account for user definitions and regional fire characteristics to calculate detection rates (Section III). The last section includes some concluding remarks and an outlook to the future.

II. Reference Data for Fire Validation

A. Data Sources

For realistic accuracy assessment, comparison with independent, direct fire observations is necessary. To properly characterize detection rates, a large set of observations of fire characteristics and environmental conditions, corresponding to the whole range of satellite scanning geometry, is needed. Given the strongly dynamic nature of active fires both in time and space, collecting a large enough set of independent, coincident *in situ* observations is logistically extremely difficult. Visual "yes/no" *in situ* observations of fires are of limited usefulness in this regard; properly timed ground-based information can be collected only via prescribed burns within field campaigns. Even then, the possibility of additional burning within the satellite pixel, undetected by ground-based observations, can lead to incorrect interpretation of the data. Fire characteristics at the spatial scale of the coarse-resolution satellite sensors can be mapped by airborne observations, but to observe a sufficient number of fires from aircraft at the time of the satellite overpass is still logistically difficult.

Coincident high-resolution satellite imagery offers the only viable tool for extensive fire product validation. The Earth Observing System Terra satellite provides a unique opportunity in this regard, with the presence of the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) [28], which provides coincident, high-resolution (15 m in the visible, 30 m in the shortwave infrared, and 90 m in the thermal infrared) spectral measurements within a $\sim$60-km swath near the center of the MODIS swath. ASTER data have been used to evaluate MODIS fire detections in tropical ecosystems in Southern Africa [29] and South America [30]. Throughout this paper we present further extension of the validation process and results in a boreal ecosystem in Northern Eurasia.

For the MODIS validation in Northern Eurasia, 131 ASTER scenes were collected in Siberia and some adjacent areas (approximately between 45°N–65°N and 60°E–140°E) from 2001, 2002, and 2003, based on a coincidence search with MODIS fire locations. Following the procedures described in [30], ASTER binary fire masks were generated using a contextual detection algorithm and were visually inspected for quality control. The ASTER fire detection algorithm exploits differences between fire-sensitive and fire-insensitive shortwave and near-infrared channels that are otherwise highly correlated. As with fire detection algorithms designed for coarser resolution instruments, a contextual approach is used to compensate for variability across scenes. The resulting ASTER fire masks were then collocated with MODIS fire masks from the MOD14 Level 2 (5-min granule) thermal anomaly product [27]. Fire detection within this product is performed using a contextual algorithm that exploits the strong emission of midinfrared radiation from fires [3]. Specialized tests are used to eliminate false detections caused by sun glint, desert boundaries, and errors in the water mask. A detailed description of the detection algorithm is provided by Giglio *et al.* [13].

Fig. 1 shows an example of the MODIS 1-km grid over the ASTER image of a large fire complex in Siberia. Yellow and blue cells on the image denote MODIS fire detections with "high" and "nominal" confidence respectively, and the pixel with vertical hatching was flagged as "cloud." It can be seen that while overall the MODIS fire detection algorithm performed well over this fire complex, fires on the western (left) edge of the complex with obvious burning, but covered with smoke, remained undetected. This example shows, that in addition to quantifying the relationship between subpixel fire characteristics as mapped by ASTER and the MODIS fire mask, high-resolution imagery can also be used to identify environmental conditions that also affect fire detectability.

B. Sampling Issues

Many geophysical parameters are sampled by carefully selected validation core sites [31]. However, the spatially and temporally dynamic nature of fire occurrence allows only the selection of broader target areas. Analyses of global distribution of fire detections [32]–[34] are useful to identify representative target areas to analyze product accuracy, including the determination of commission errors. These studies have also pointed out that the spatial and temporal variability of fire activity varies over the globe. For example, in grassland and savanna areas of the subequatorial tropics, fire occurrence is quite predictable, which facilitates the selection of validation target areas. In boreal forests, however, fires are more episodic, which makes the collection of independent fire observations more problematic.

Selection of the target areas based on the presence of fire detections, however, holds the risk of omission errors to be underestimated and regions with commission errors to remain unidentified. Ideally, areas with known presence of fires of interest, but with no or few coarse-resolution fire detections should also be included in the analysis. However, with scheduling priorities of

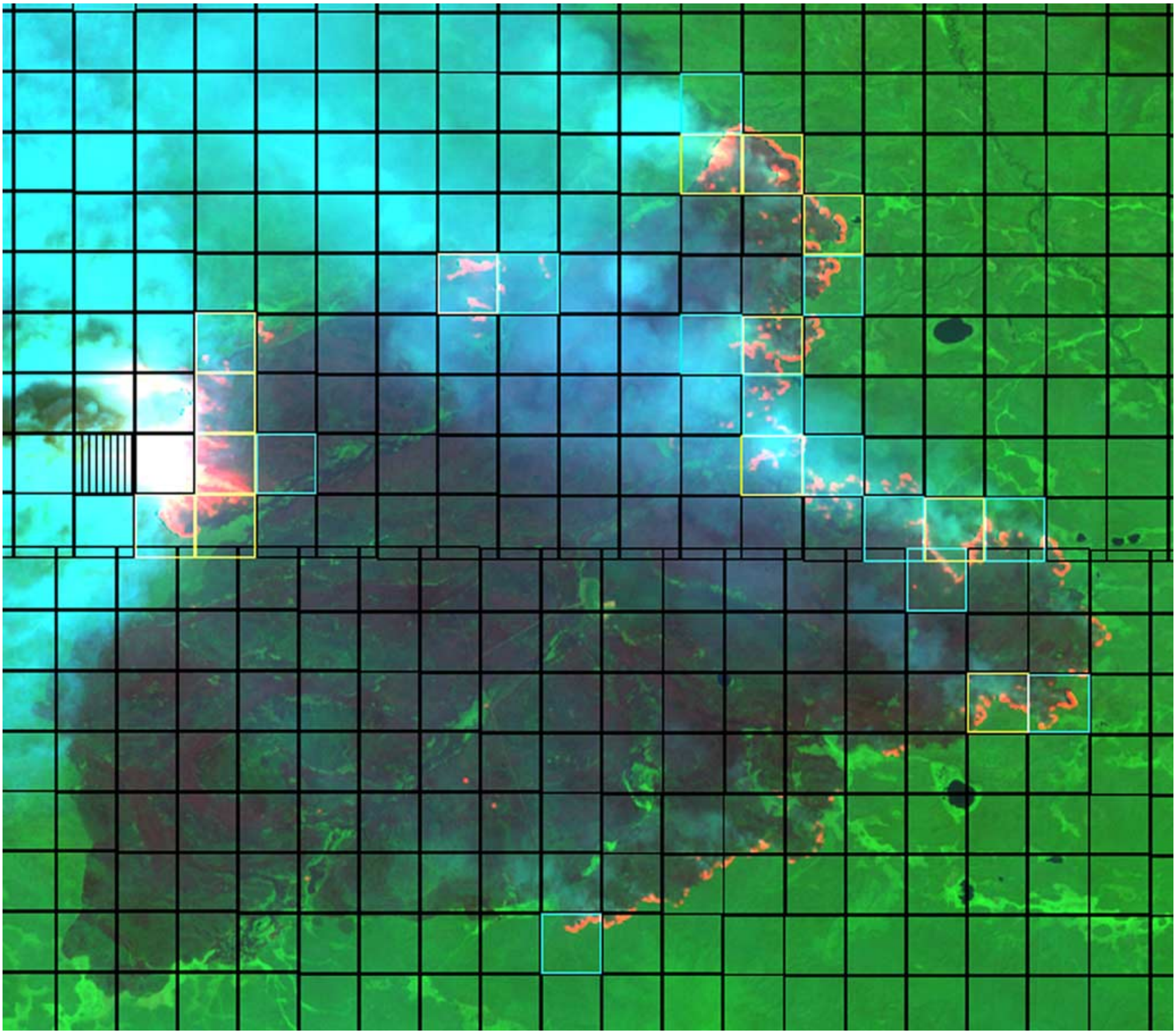

Fig. 1. MODIS 1-km grids over an ASTER 8-3-1 red-green-blue image of a large fire complex on July 23, 2002. The center of the complex is at 62.57° N 125.72° E. Yellow and blue MODIS cells correspond to "high" and "nominal" MODIS fire detection confidence, respectively. The pixel with vertical hatching was flagged as "cloud."

high-resolution data acquisition, the collection of a fully representative sample is unlikely.

Another constraint is the limited spatial and temporal coverage of current high-resolution sensors. The sampling of the entire view angle range of the swath of the coarse-resolution sensor with single-satellite, multisensor configurations, such as MODIS and ASTER on Terra, is contingent on the pointing capability of the high-resolution sensor. The maximum pointing angle of ASTER is 8.5°, which allows only a swath of 272 km to be sampled within the much wider MODIS swath (but to be observed only a 60-km strip of it at a time). Mechanical problems of the pointing systems can further reduce this range.

Multisatellite, multisensor configurations allow more flexibility in angular sampling. In the case of polar orbiting satellites, however, this is often accomplished at the expense of temporal coincidence due to constraints arising from orbital differences. Collection of coincident reference high-resolution imagery for geostationary satellites is a much easier task due to the high temporal frequency of observations. However, as the reference imagery is typically collected by sensors on sun-synchronous satellites, only fire observations corresponding to certain local times can be evaluated.

III. Quantitative Methods for Accuracy Statement

A. Detection Limits

The validation of the presence/absence active fire products involves the determination of absolute detection capabilities, i.e., the probability that a fire of a certain "size" can be detected by the given satellite sensor and algorithm. Fire detectability depends on a wide range of environmental and observing circumstances. Ideally, accuracy estimates are given in the form of positive detection rates and as a function of the fraction, temperature and reflectivity of flaming, smoldering, and unburned surfaces within the satellite pixel, viewing and illumination angles, and atmospheric conditions. False alarm rates are given as a function of the temperature and reflectivity of unburned surfaces within the satellite pixel, viewing, and illumination angles, and atmospheric conditions.

Radiative transfer calculations provide theoretical limits of performance, commonly referred to as the envelope of resolvable fires [35]. Giglio *et al.* [35] have also shown that detection envelopes can vary considerably even among different detection algorithms for the same sensor. Radiative transfer simulations have shown that, in theory, the lower detection limit of the currently operational MODIS fire algorithm ("version 4"; [13]) under ideal conditions ranges from fires as small as 10 m^2 at 1200 K to as large as over 1000 m^2 at 500 K. But such radiative transfer calculations, however sophisticated, provide only theoretical detection rates. To derive realistic detection rates coincident reference data are needed.

In our MODIS example, we generated ASTER fire masks for each MODIS pixel. In doing this, we accounted for the fact that the actual footprint of each MODIS pixel includes approximately half of the neighboring pixels due to the triangular point spread function (PSF) of the MODIS sensor in the scan direction [36]. Thus, for a subsatellite 1×1 km MODIS pixel the fire mask was generated for a 2×1 km area. One effect of this procedure was that, counterintuitively, MODIS pixels flagged as "fire" that had ASTER fires in the adjacent halves of the neighboring pixels, but not within the actual pixel boundaries, were considered valid fire detections. Likewise, MODIS pixels not flagged as "fire" that had ASTER fire pixels in the adjacent halves of the neighboring pixels, but not within the pixel boundaries, were considered missed fires. In analyzing the fire masks, we did not consider the triangular shape of the MODIS PSF by adjusting the ASTER fire counts to a hypothetical rectangular PSF (i.e., uniform contribution of radiance from any part of the MODIS footprint to the integrated radiance). This procedure would require the ability to retrieve those fire intensities for each ASTER fire pixel, which is not possible due to sensor saturation; likewise, we considered the assumption of uniform fire intensity for each ASTER fire pixel unrealistic.

The geometrical mapping of ASTER fire pixels into MODIS footprints was done by considering their relative positions. This yielded a relative georegistration accuracy to within a single ASTER pixel.

We also grouped the ASTER fire pixels into contiguous fire clusters to study spatial patterns at a sub-MODIS pixel scale. For each MODIS pixel we then calculated two summary statistics: the total number of the ASTER fire pixels, and the mean fire cluster size. To characterize omission errors, MODIS fire detection probabilities were calculated as a function of these ASTER summary statistics based on logistic regression models as described in [29] and [30]. From the analysis we excluded MODIS pixels that were flagged as "cloud" or "water" by the MODIS fire detection algorithm. Fig. 2 shows the detection probabilities. The slope of straight lines formed by the dots and circles is determined by the number of fire clusters within the MODIS footprint, with 1 : 1 line along the diagonal corresponding to single clusters. Fig. 2 shows also that fewer ASTER pixels, clumped together in larger clusters, yield the same detection probability as more ASTER pixels spread over multiple clusters.

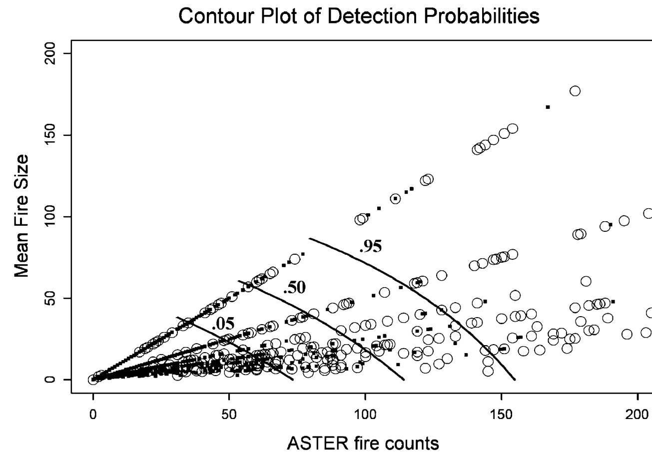

Fig. 2. Detection probabilities as a function of the total number of ASTER fire counts and the mean cluster size expressed as the number of ASTER fire pixels. The open circles and dots denote MODIS pixels with and without fire detection, respectively.

A comparison of the results of the logistic regression analysis for Siberia and the Amazon showed that in Siberia detection probabilities are considerably lower for the same values of the summary statistics than in the Amazon [30]. For example, in Siberia the size of a single ASTER fire cluster within the MODIS footprint that has a 50% probability of being flagged as "fire" is $\sim$60, compared to $\sim$45 in the Brazilian Amazon. This is inconsistent with the simulation results reported by Giglio *et al.* [13], who found comparable theoretical detection rates for tropical rainforest and extratropical deciduous forests, and lower detection rates for dry tropical savanna. A scrutiny of the results revealed that the lower detection rates in Siberia were caused by the MODIS pixels that indeed included ASTER fire detections, but also included large amounts of smoke from nearby fires. This can be seen in the western (left) size of the fire complex in Fig. 1, where only one pixel in the area of heavy smoke was flagged as "cloud." Fires within many of the pixels with smoke remained undetected and the pixels were flagged as "clear land" instead. This example shows that extreme atmospheric conditions can significantly alter the detection probabilities derived from idealized radiative transfer simulations (yet the algorithm does not flag these atmospheric conditions as "clouds").

Frequency distributions of ASTER fire counts within MODIS footprints are shown in Fig. 3(a). More than 50% of the MODIS footprints contain less than ten ASTER fire pixels, which are unlikely to be detected based on our logistic regression analysis (Fig. 2).

B. Error Rates

The statistics derived in the previous section provide a tool to assess the detection capabilities of a given sensor and algorithm for a given set of conditions. They are the primary metrics of product accuracy and are indispensable for accuracy assessment, algorithm development, and specification of desired characteristics of future sensors. However, these accuracy measures are not necessarily useful for the user community. To derive practically meaningful accuracy metrics, first there needs to be an understanding of the definition of “fire” by the producer and user communities.

For data producers fire detection is flagging the smallest mapping unit of the sensor (i.e., a pixel), when the observed total radiative energy for that pixel represents a thermal anomaly. However, user communities seldom are concerned with sensor characteristics or observed energy per se. For the user community “fire” generally means a significant amount of vegetation combustion. For instance, for the fire management community, it is a fire that is larger than the smallest “actionable” fire (but including the early detection of such fires). For the global change research community, a fire of interest is larger than the smallest nonnegligible fire event either individually, or aggregated in space and/or time. Consequently, desired detection error rates will vary according to user specifications of “fire” and regional fire characteristics.

Once specifications for “fire of interest” are established, omission and commission error rates can be determined through an error matrix using independent fire observations as reference data and the coarse-resolution fire product as classified data. Morisette *et al.* [30] determined omission and commission rates as a function of the minimum number of ASTER fire pixels within the MODIS pixel to be flagged as “fire.” In a statistical sense, the establishment of such a classification threshold is required to generate a 1-km ASTER fire map that is directly compatible with the MODIS 1-km fire product. In fact, however, it can also be considered as the definition of “fire” for various applications; and a conversion of the probability statistics, defined as a function of fire characteristics, to error rates, based on the percentage of “fires of interest” detected or omitted in the region.

The pixel-based error rates are useful for sensor-specific algorithm evaluation, but they hold the implicit assumption that each coarse-resolution fire pixel represents a single fire event. This, however, is not necessarily the case, and coarse-resolution pixels may contain multiple active fire events (e.g., [37]), as it was also shown in Fig. 1. We found that of all the MODIS fire pixels analyzed only 60% of the footprints contained single fire clusters.

Individual fire events can also be large enough to fall within multiple coarse-resolution satellite pixels. This can also be seen in Fig. 1, where the fire complex has multiple clusters of active burning, with many fire fronts stretching over more than one MODIS pixel.

The populations of fire clusters are shown in Fig. 3(b). Comparing this with Fig. 3(a) one can see a significant difference in that the percentage of larger fire clusters is lower than the percentage of the same total number of ASTER counts. This reaffirms the fact that large total fire counts within MODIS footprints are often a result of summarizing multiple smaller clusters. An important consequence of this is that one indeed needs to map the entire footprint to properly evaluate detection capabilities, as multiple, small fires may “help” each other to produce a large enough signal for the pixel to be flagged as “fire.” However, visual ground-based observations would often record only one small fire coincident with the fire pixel, resulting in misinterpretation of the detection capabilities.

An alternative to the pixel-based analysis is to analyze detection of individual clusters. For large clusters one measure is

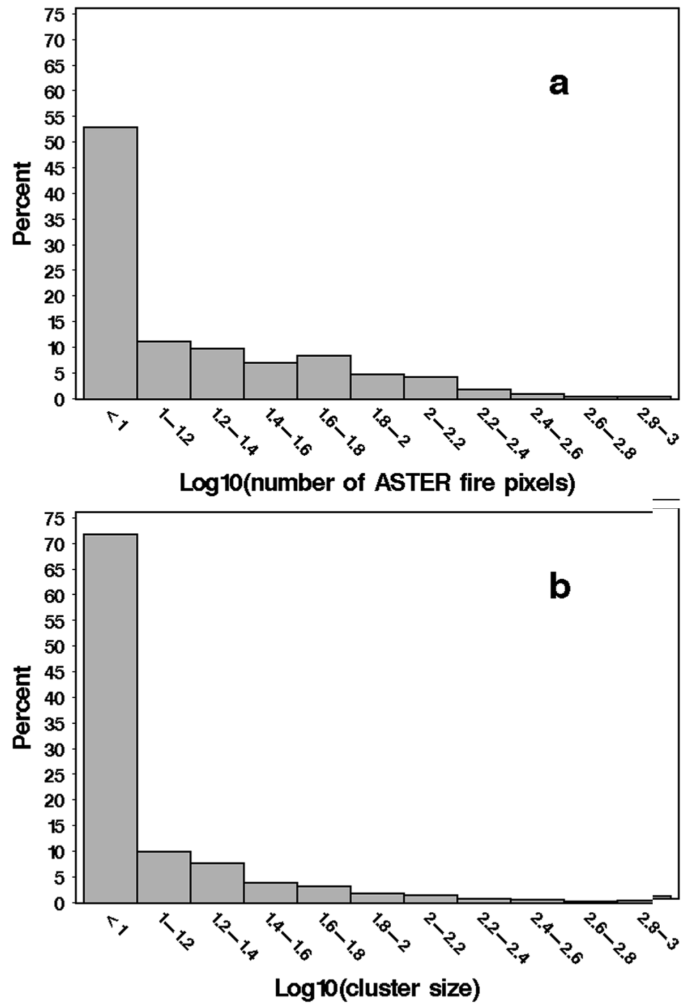

Fig. 3. (a). Frequency distribution of the number of ASTER fire pixels within 2×1 km MODIS footprints. (b). Frequency distribution of fire cluster sizes expressed by the number of ASTER fire pixels.

whether the entire spatial extent of the fire was properly mapped. One can also determine cluster-based detection rates by defining detection if any part of a contiguous cluster was detected.

Commission or false alarm rates are independent of ASTER summary statistics and ASTER is used solely to confirm the absence of fires within the MODIS footprint. It should also be noted that commission errors are meaningful only in a pixel-based analysis. Commission rates can be determined as the proportion of the total number of fire-free land pixels or map cells that are incorrectly flagged as “fire.” Usually the commission error rates defined this way are numerically low numbers. For the area and time period covered by the Siberian ASTER database collected for this study, this value is 2.1×10^{-5}. However, this metric is strongly dependent on the reference area. Another way of expressing commission error is the percentage of false alarms of all fire pixels. For the Siberian dataset this was found to be 3%. Note that commission errors (as well as omission errors) based on treating ASTER fire detections as reference data implicitly include any commission and omission errors of the ASTER fire detection.

As it was shown for Brazil [30], the omission and commission error rates varied according to the minimum classification

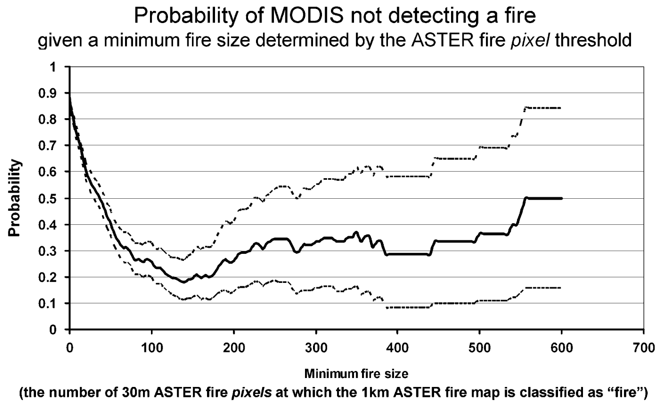

Fig. 4. Pixel-based accuracy assessment curve for Siberia with the 95% exact confidence intervals The probability of omission error as a function of minimum fire size expressed as the number of ASTER fire pixels within the MODIS footprint.

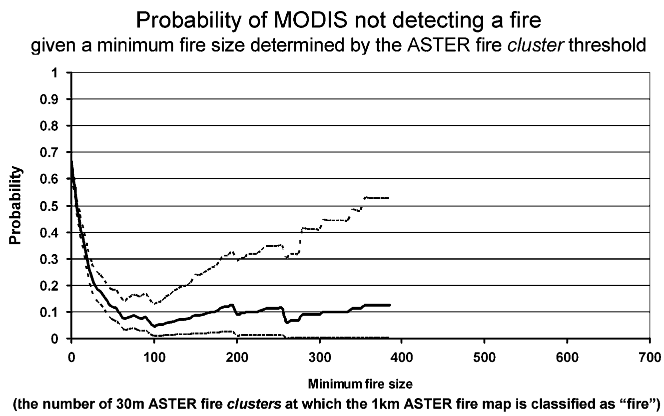

Fig. 5. Cluster-based accuracy assessment curve for Siberia with the 95% exact confidence intervals. The probability of omission error as a function of minimum size of contiguous clusters of ASTER fire pixels.

threshold for fire, yielding accuracy assessment curves [38]. Fig. 4 shows an accuracy assessment curve for Siberia with the 95% exact confidence intervals [39]. As expected, for small fires omission error rates decrease with increasing classification threshold. However, one can also observe the "instability" and slight increase of the omission error rate beyond the classification threshold of ~150 ASTER fire pixels and the increase of the confidence interval with increasing classification thresholds. Both are due to the decrease of the sample size with ASTER classification threshold (i.e., there are fewer MODIS pixels with at least that many ASTER fire pixels) and the consequent decrease of the statistical significance. At very high ASTER classification thresholds essentially a handful of MODIS pixels are considered; if only a few of those are misclassified by MODIS (most often because of thick smoke), it will increase the omission error.

To determine cluster-based omission error rates we defined detection if any part of a contiguous fire cluster fell within the MODIS pixel flagged as "fire." The corresponding accuracy assessment curve is shown in Fig. 5. Compared to the pixel based error rates shown in Fig. 4, one can see the faster decrease of cluster-based omission errors. This is a manifestation of the fact that multiple small clusters are present in many pixels. Omission errors also remain lower for larger clusters (>100 ASTER pixels) because of the more relaxed detection criterion.

IV. Summary and Conclusion

There are a number of issues associated with the accuracy assessment of satellite-based active fire detection products. Because of the binary "yes/no" nature of the product, accuracy measures can only be given as detection probabilities and commission/omission error rates. Ground truth data need to be observed at the scale of the footprint of the satellite sensor and coincidently with the satellite overpass. These requirements point toward using high-resolution satellite imagery, which can provide a large enough sample of reference data for statistically meaningful analysis.

One of the main caveats of using coincident high-resolution imagery is that the resulting reference fire map is also a product of a remote sensing algorithm and often is based on the same or similar radiometric signal. Therefore, validation of the reference high-resolution active fire product is essential. *In situ* observations from the ground and from aircraft play an important role in this effort. In most cases *in situ* data are available only from local and regional fire management agencies, which are often also users of the satellite-based fire products. For a successful validation activity, it is essential to recognize the interdependence between the developers and users of products and to ensure the engagement of the user community in the process. The interaction with the user community is also important to understand requirements and to provide useful accuracy measures. Addressing these issues is among the main objectives of the GOFC/GOLD-Fire program [40].

In addition to evaluating the accuracy of the binary fire mask, the assessment of the spatial accuracy of the product is also critical. This is important both for management and research applications. Deployment of fire crews to the correct location is important for fire management. On the other hand, correct assignment of fires to fuel is important for emission estimates. However, this issue is directly linked to sensor pixel geolocation accuracy, which should be evaluated at the appropriate processing level of sensor data. Additional evaluation is necessary only if further geolocation adjustments are made during the fire product generation process, which is often the case for AVHRR [41].

Errors corresponding to pixel-level detection capabilities are strongly affected by sensor scanning characteristics. For example, MODIS omission and commission errors are impacted by adjacency effect. Detection rates derived for individual fire events rather than pixel-based summary statistics can provide useful information for many applications.

The validation of the MODIS active fire product follows the framework developed for all MODIS land products [10]. Stage 1 validation has been achieved through analysis of a small number of ASTER data over selected regions and time periods, combined with simulation results [13], [27], [29], [30]. The validation study presented in this paper is part of the Stage 2 validation effort to analyze a widely distributed set of locations and time periods. However, it remains to be seen whether independent observations can indeed be collected for the full range of fire characteristics and environmental conditions. A further methodological challenge is to develop an approach for the most efficient combination of empirical–statistical evaluation and radiative transfer simulations. An intercalibration of the empirical and theoretical results is needed to decide whether simulations can be extrapolated to conditions not represented by independent observations.

This study in Siberia has followed many aspects of the previous MODIS/ASTER validation efforts, but also includes suggestions for further development. We determined that the probability that a MODIS pixel is flagged as "fire" is 50% when the true 2×1 km footprint includes a single cluster of $\sim$60 ASTER fire pixels. By relating such detection probabilities to actual regional fine-scale fire characteristics we also demonstrated that MODIS can detect only a fraction of the existing fires that are easily detectable by ASTER. To translate this result to detection rates that are useful for the user community, lower thresholds of "fire of interest" need to be determined and the relationship between ASTER-based metrics and actual fire characteristics need to be established. We also found that in Siberia the current fire detection algorithm does not fully account for the presence of heavy smoke, which can lead to the omission of pixels containing large fires. The suggested cluster-based analysis can mitigate this problem, however, it is recommended that the algorithm either be refined for such conditions or at least such pixels be flagged accordingly. The cluster-based analysis has also revealed that small fire clusters can often be located within MODIS footprints that include additional fires, increasing thus their overall probability of detection.

The MODIS validation procedure is unique in that it takes advantage of the availability of the ASTER sensor on Terra. Further work needs to be done to develop more generic multiplatform, multisensor schemes. A common validation baseline will also facilitate the use of fire products from various coarse-resolution sensors in an integrated observing system.

The importance of validation has gained broad acceptance in the terrestrial remote sensing community. Validation plans for future systems exist. For example, the validation of the fire product from the the Visible Infrared Imager/Radiometer Suite [42] will build on the MODIS experience. This transition of technology and know-how from the experimental domain to operational systems is an important step toward ensuring continuous, high-quality fire observations from satellites.

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Louis Giglio, photograph and biography not available at the time of publication.