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The Value of Satellite-Based Active Fire Data for Monitoring, Reporting and Verification of REDD+ in the Lao PDR

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Abstract Shifting cultivation is a dominant land-use system in Laos, and fire is the tool commonly used to clear fallow vegetation for subsequent cultivation. We assessed the feasibility of active fire data derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) for monitoring fires in Laos. Specifically, we investigated the potential of the active fire data as input into monitoring, reporting and verification (MRV) systems to assess the effectiveness of measures related to Reducing Emissions from Deforestation and Forest Degradation plus the enhancement of forest carbon stocks (REDD+). Our qualitative and quantitative accuracy assessments of the fire data yielded mixed results with varying degrees of undetected fires and false detections. Hence, at IPCC Tier 3, the uncertainties inherent in the detection accuracy become too large. Active fire data can be valuable for supporting national-level MRV at Tier 2 in combination with auxiliary data for characterizing fire-dependent local land-use systems, such as shifting cultivation.

Keywords MODIS · Fire monitoring · REDD · MRV · Slash and burn · Laos

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Introduction

Fire plays an important role in land management in continental Southeast Asia. For example, fire is used to clear forests and prepare land for agricultural purposes (Baker and Bunyavejchewin 2009). During recent decades, the higher frequency and intensity of fires in the mosaics of deciduous and evergreen forests of the region negatively affected the forest environment and human welfare (Denman *et al.* 2007; Baker and Bunyavejchewin 2009). This problem is of particular concern in the Lao People's Democratic Republic (PDR), hereafter Laos, where most forests are considered fire-dependent but where increased fire frequency and intensity threaten and may alter these forest ecosystems and their sustainability, thereby diminishing forest carbon storage capabilities and subsequent sequestration ability (Goldammer 2006; Baker and Bunyavejchewin 2009; Siegert *et al.* 2001). The global burning of biomass and soil organic matter is estimated to produce a gross carbon emission of approximately 2.0 petagrams of carbon (PgC) per year, including an estimated net emission of 0.5 PgC due to tropical deforestation and degradation (van der Werf *et al.* 2010).

In addition to their ecological, economic, health and safety impacts, fires release a variety of greenhouse gases (GHGs) and aerosols, which play a role in radiative forcing

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and thus global climate change (Page *et al.* 2002). Many of these GHGs, such as methane (CH_4) and carbon monoxide (CO), are important for atmospheric chemistry, climate and terrestrial ecology (Crutzen and Andreae 1990), and fire-related emissions of the non-CO_2 GHGs contribute a warming potential of approximately 10 % in CO_2 equivalents (van der Werf *et al.* 2009). In addition, fire results in the emission of soot particles that contain black carbon (elemental C, contained in smoke), which can dramatically impact on health and local and regional climate parameters (Ramanathan and Carmichael 2008). In general, large uncertainties remain about the extent of regional and global fire emissions because of the difficulties inherent in estimating the amount and type of biomass burned, which varies as a function of space, time and type of combustion (Andreae and Merlet 2001).

The greenhouse gas emissions associated with fire render the monitoring of vegetation fires important for activities targeted at reducing GHG emissions from land use and land-use change. Such monitoring necessitates an assessment of the land-use changes over longer time spans to capture the long-term effects of fire. For example, in many farming systems, such as shifting cultivation, the original amount of biomass may regrow if the fallow lengths are sufficiently long. Hence, the net carbon emissions will be near zero (Goldammer 2006; Crutzen and Andreae 1990). However, a reduction of fallow periods or a conversion of shifting cultivation plots to permanent annual cropping systems will most likely result in a loss of aboveground carbon and soil organic carbon. However, the amount of loss will tend to vary substantially in response to local geophysical conditions and land-management strategies (Bruun *et al.* 2009). Hence, the impacts of changes in fire activity are of increasing concern to the global community and are related to international efforts to Reduce Emissions from Deforestation and Forest Degradation plus the enhancement of forest carbon stocks, sustainable management of forests and conservation of forest carbon stocks (REDD+) under the United Nations Framework Convention on Climate Change (UNFCCC).

The most pertinent cause of vegetation fires in Laos is arguably the use of fire for the clearing of land for agricultural purposes, particularly for shifting cultivation. Shifting cultivation is still widespread in Laos and typically follows slash-and-burn practices, where the vegetation of a plot of land is cut in January or February and is left to dry for several weeks. The dried vegetation is burned toward the end of the dry season, primarily during March and April (Van Gansberghe 2005). Although no unambiguous determination of the extent of shifting cultivation is available, the number of households involved in shifting cultivation across Laos was estimated at approximately 943,000 or 17 % of the population in 2005, occupying 28 % of the country's surface (Messerli *et al.* 2009). Still, no estimates exist to specify the amount of change in shifting cultivation practices over time.

The high density of fire-dependent shifting cultivation and its importance for changes in forest carbon stocks calls for the inclusion of fire activity in REDD+-related monitoring systems in Laos. Moreover, fires serve as a proxy for land-use modifications and conversions. Changes in fire dynamics may help assess the rapid transformation of land use in upland Southeast Asia to tree plantations, mainly rubber, tea and pulp wood. Careful fire monitoring may also support the estimation of the forest degradation caused by a shortening of fallow cycles or by an increase in fire density due to other proximate causes. Finally, the regular monitoring of fire occurrences potentially allows the monitoring of the permanence (or non-permanence) of changes in fire activity under REDD+ activities.

Satellite data can facilitate the detection of vegetation fires (GOFC-GOLD 2009; Justice *et al.* 2006; Kaufman *et al.* 1998). Satellites can capture the time and location of actively burning fires at the time of the satellite overpass and can therefore provide an indication of the density of fire activity (Csiszar *et al.* 2006). Increasing fire return intervals can indicate, for example, shorter fallow periods in shifting cultivation systems. Decreasing fire activities in one location but increasing fire activity in neighboring locations may imply a local shift in fire use. More fires over time per unit area may inhibit tree growth and the regeneration of successional vegetation into young closed forests, with potentially detrimental effects on soil fertility and above- and belowground carbon sequestration. Therefore, an assessment of both the spatial distribution and the temporal dynamics of vegetation fires is important (GOFC-GOLD 2009) and may offer a useful component of monitoring activities for REDD+.

This work originated from a REDD+ project of the Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ), which is currently being implemented in Laos. The project strives to monitor, report and verify emission reductions from REDD+ payments over time and space. Because fire is a major land management tool in Laos, fire monitoring with remotely sensed data may be both an effective and an efficient component of a related national monitoring, reporting and verification (MRV) system. We investigated the utility of the active fire products derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor. We focus on two different levels of analytical complexity that were categorized by the Intergovernmental Panel on Climate Change (IPCC) and that are relevant for countries that practice the emission reduction goals of REDD+: Tier 2 (country level) and Tier 3 (sub-country level). At higher Tiers, the accuracy increases, but the analytical complexity and data requirements increase as well (Maniatis and Mollicone 2010; Penman *et al.* 2003). Our overall objective is to assess the feasibility of the active fire data derived from MODIS to monitor vegetation fires in Laos at Tier 2 and Tier 3. We investigated the value of these data as an input into national MRV systems by assessing the suitability of the information on active fires for sub-national and national-level monitoring.

Data

Fire Monitoring and Mapping with MODIS

A large number of studies have demonstrated the value of optical and thermal remote sensing for quantifying fire occurrences and the areas affected by fire (Giglio *et al.* 2006a; Eva and Lambin 2000; Roy *et al.* 2002). The MODIS sensor from NASA is the first sensor to include fire-monitoring capabilities in its design. To date, MODIS is one of the most important data sources for the global mapping of both fire locations and burned areas. MODIS sensors are mounted aboard the Terra and Aqua satellites, which cross the equator daily at approximately 10:30 am and 10:30 pm and 1:30 am and 1:30 pm, respectively. Shortly thereafter (for the *post meridiem* [pm] overpasses) and shortly before (for the *ante meridiem* [am] overpasses), the satellites record data for Laos. The Sun-synchronous orbit allows both satellites to pass over the same area at the same time in every 24-hour period.

Both satellites make up to two land observations each per day, which are used to generate a range of products that capture the location of a fire event, the energy emitted and the flaming and smoldering ratio, and they allow the area burned to be estimated (Justice *et al.* 2006; Davies *et al.* 2009). Because of the long data record with daily observations from two satellites since 2002, MODIS-derived fire products may also permit assessment of the seasonality, timing and interannual variation of fires (Giglio *et al.* 2006a) and may thus allow the effectiveness and efficiency of REDD-related management interventions to be characterized (GOFC-GOLD 2009).

MODIS Active Fire Data

The fire detection algorithm from MODIS identifies and characterizes actively burning fires (e.g., wildfires and agricultural fires) and other thermal anomalies (e.g., volcanoes) with thermal information. The fire detection algorithm is fully automated and identifies pixels with one or more actively burning fires for the entire globe. These pixels are commonly known as "fire pixels". Each fire pixel may contain one or more fires burning within the pixel area. The actual ground area observed by each pixel varies with the viewing angle of the satellite, that is, the pixel size increases further away from the nadir (Giglio 2010).

The size of a fire can be much smaller than the 1 km^2 pixel size (Fig. 1) because the actively burning area is frequently below 1 km^2 even in large fires. This generalization applies particularly to Laos, where small fires predominate because most are related to agricultural activities. The size of detectable fires depends primarily on the fire temperature, fire area, vegetation cover and sensor viewing angle. The MODIS sensor can detect flaming fires (~1,000 Kelvin, K) as small as 100 m^2 under ideal conditions with a 50 % detection probability, and it can detect a 1,000-2,000 m^2 smoldering fire (~600 K) (Hawbaker *et al.* 2008; Giglio *et al.* 2003; Kaufman *et al.* 1998). The detection rates will be higher if the daily peak fire activity coincides with the time of satellite overpass (Schroeder *et al.* 2005).

Detection confidence is estimated in the detection procedure and ranges from 0 to 100 % (Giglio *et al.* 2003). The confidence level is used to classify all fire pixels as low confidence [<30 %], nominal confidence [30-80 %] or high confidence [>80 %]. Higher confidence levels can be applied to reduce the number of false alarms (errors of commission) at the expense of a lower detection rate (Giglio 2010).

Davies *et al.* (2009) gave an overview of the MODIS active fire data products and described their delivery via the Fire Information for Resource Management System (FIRMS). The data are also accessible through the Global Fire Information Management System (GFIMS) of the FAO or the MODIS Fire Information System (FIS) at the Asian Institute of Technology (AIT). We proceed by concentrating on the information delivered by FIRMS (http://earthdata.nasa.gov/data/nrt-data/firms). Fire pixels are represented in the FIRMS system as points located at the center of the fire pixel, which may not correspond to the actual location of the fire. We used data from the MODIS Data Processing System (MODAPS), which generates preprocessed, quality-checked active fires and is recommended by the FIRMS team for historical analysis. However, one disadvantage of the MODAPS data is the time delay of approximately 2 months until the data are available due to the additional processing requirements. For the accuracy assessment, we used the MODIS Rapid Response (MRR) data, which include active fires in near-real time with a lag of approximately 2 to 4 hours between satellite overpass and data availability.

Caveats About the Active Fire Data

Cloud cover and smoke obstruct fire detection and may lead to high errors of omission (undetected fires, Roy *et al.* 2008). It is therefore probable that fire counts are underestimated, particularly in tropical regions (Giglio *et al.* 2006b; Schroeder *et al.* 2008). However, clouds are also indicative of rain when the fire probability is lower, which may reduce this bias somewhat (Aragao and Shimabukuro 2010). The fire season in Laos coincides with the dry

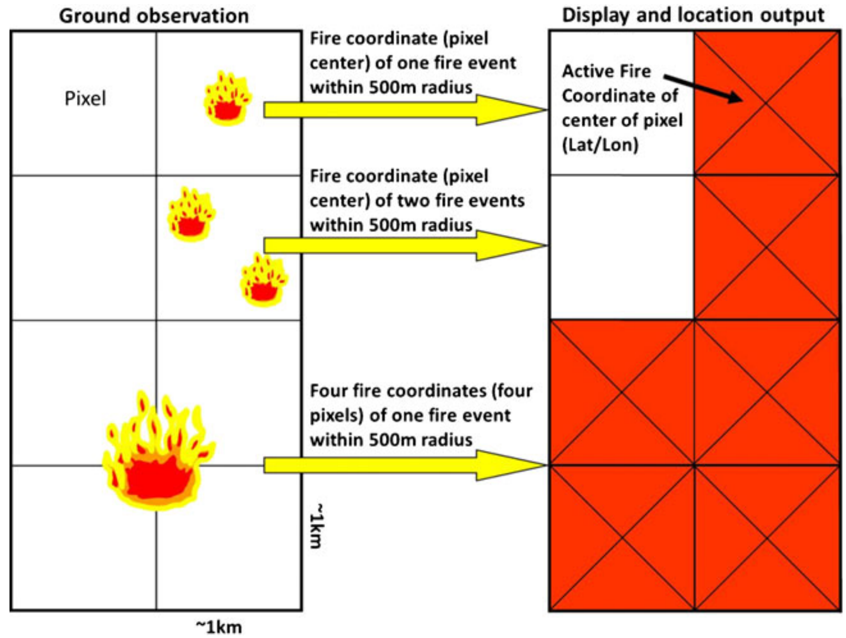

Fig. 1 Fire pixels. Source: Authors

season, when cloud cover is low (and rainfall negligible). Therefore, the potential bias in Laos due to cloud cover is most likely to be small for MODIS fire products. Moreover, false detections are observed in areas where the canopy cover exhibits strong differences in surface temperatures. These differences may occur if gaps in the forest canopy cover are present. Such gaps can be due to recent clearings (Schroeder *et al.* 2008). Another fraction of false detections may be related to recent burning activities, where homogenous areas of dark char cause errors of commission (Schroeder *et al.* 2008).

The size of a particular fire cannot be calculated from the active fire data. Although a direct relationship may exist between the number of fires detected in a specific area, the size of the area affected, the smoke emitted and the biomass burnt (Aragao and Shimabukuro 2010), the degree of these linkages is unclear from the active fire data (Balch *et al.* 2010). Moreover, the active fire data do not distinguish between one or more fires actively burning within a pixel at the same overpass (Fig. 1), yet it is often quite likely that multiple fires occur within a pixel during the burning season because of the coarse spatial resolution of the fire records (Giglio 2010). We concentrate our analysis on fire pixels. This approach makes our estimates more conservative because it underestimates the actual number of fires in the case of many sub-pixel fires. In contrast, larger fires or a fire front may saturate more than one pixel, but it is probable that such fires are rare in Laos. The number of fire pixels is therefore expected to be considerably lower than the actual number of fires because of overpass gaps and frequent sub-pixel fires in small-scale agriculturally used areas. These circumstances will cause the actual fire density to be underestimated. A related shortcoming is that the exact location of a fire within the pixel is unknown. This consideration is particularly important for the assessment of accuracy because it is difficult to associate the detected fire with a specific land-use patch within a pixel.

Existing Accuracy Assessments of the Active Fire Data

We rely on evidence from the literature, our own accuracy assessment and communications with experts to assess the accuracy of MODIS fire products to proxy small-scale vegetation fires in shifting-cultivation landscapes. In Laos, the slashed and dried vegetation on agricultural plots provides high fuel loads because of the biomass accumulated during the fallow period. These factors produce a longer burning time, more combustion and thus larger and hotter fires compared to fires in primary forests, thereby increasing the likelihood of detection, because hotter fires are more likely to be detected (Schroeder *et al.* 2008; Langner and Siegert 2009). However, the affected areas are fairly small in Laos. Hence, the absolute burning time per fire may be smaller than that for large fires.

The MODIS fire team frequently detected shifting cultivation, for example, in the Congo Basin (C. Justice, pers. comm.). However, fire detection in Laos may be negatively affected by the rougher topography, which indirectly influences fire detection because of overall cooler temperatures. Extreme care is required, particularly for the examination of interannual variation, because of incomplete sampling caused by gaps in the overpass timing and the uneven data quality returned by the sensor (C. Justice, pers. comm.).

Therefore, stringent accuracy assessments with independent reference data are required to obtain an estimate of the validity of the MODIS active fire data. Most existing assessments validate the accuracy of active fire data with auxiliary satellite imagery. These assessments include Schroeder *et al.* (2008) in Amazonia, Morisette *et al.* (2005) in South Africa, Csiszar *et al.* (2006) in Northern Eurasia and Hawbaker *et al.* (2008) in the United States. Their results suggest that omission errors are relatively frequent whereas commission errors are comparatively rare, particularly for smaller fires. Tansey *et al.* (2008) studied Indonesian peat fires in Kalimantan and concluded that the quality of active fire data depends crucially on vegetation type and function, again with high omission errors. Another study of Kalimantan peatlands validated the active fires with 20 m SPOT imagery and found 27 % false alarms, mainly attributed to hot surfaces after fires, and 34 % undetected fires, particularly in dense vegetation (Liew *et al.* [2003] cited in Miettinen *et al.* 2007). To the best of our knowledge, only the accuracy assessment by Tanpipat *et al.* (2009) investigates the usefulness of the active fire locations for assessing the occurrence of small forest fires. For three study sites in Thailand, the authors validated fire pixels with field observations within a 500 m radius of the pixel center (covering 79 % of the pixel area). A fire detected by MODIS was labeled as an accurate detection if a burned area of at least 50 by 50 m was present. The detected burned areas were between 0.16 ha and 192 ha. The mean overall accuracy of detection was 92 % for all three sites, and it even reached 98 % for northern Thailand, which is relatively similar to northern Laos in land use and ecoregional characteristics. This study therefore suggests that active fire data may indeed be useful for monitoring vegetation fires in Laos.

Methods

Processing of Active Fire Data

For our historical analysis of the location, seasonality and interannual variation of fire records in Laos, we used the active fire data (MCD14ML, collection 5.1). We selected all available fire records from 4 July 2002 to 30 June 2010 from both the Terra and Aqua satellites, because it is probable that the detection rates are greater if both sensors are used (Hawbaker *et al.* 2008). However, the detection rates of Aqua tend to be greater in the tropics because the overpass at approximately 1:30 pm occurs at a time close to that of the peak fire activity (Giglio *et al.* 2006a). From these data, we defined a fire pixel as one that contained one or more fires per day. Fires in Laos rarely burn longer than 1 day because the dry vegetation combusts quickly.

Biomass burning in the tropics is concentrated in a burning season that typically extends from January through March in the Northern Hemisphere and from July through September in the Southern Hemisphere (Crutzen and Andreae 1990; Giglio *et al.* 2006a). In Laos, fire occurrences are strongly clustered in the dry season, from February through early April. Hence, we derived fire years and fire seasons to account for the distinct seasonal patterns of fire occurrences and to improve interannual comparisons (Koren *et al.* 2007; Giglio *et al.* 2006a; Boschetti and Roy 2008). This approach also reduced errors of commission in the data, as the selected fire records are limited to the subset of fires most likely caused by agricultural practices such as shifting cultivation and by forest clearing activities.

To define the start of the fire year, we searched for the day(s) within each calendar year for which the maximum number of fire events had been recorded. We then defined a fire year as the period half a year (182 days) before and after the day with the maximum fire occurrences. Thus, all fire years last for 365 days, and we ignored leap years for simplicity. For example, we refer to the fire year of 2003 when the peak fire season (February to April) was in 2003, although this particular fire year had already commenced in September 2002. In the next step, we defined the fire season as the shortest period within each fire year that contained 90 % of all fires. The fire seasons had various lengths for the different years as well as various start and end points. This approach avoided overlaps and thus avoided double counting. The definition of distinct fire seasons better reflects the effect of short-term weather fluctuations on fire patterns because farmers will immediately respond to changing conditions, for example, by postponing biomass burning if the vegetation still contains too much humidity. In years with excessive rainfall, the period allowed for the slashed vegetation to dry will be longer than in drier years. Hence, burning will be postponed. To account for probable variations in the seasonality of burning among different regions, we calculated fire years and fire seasons separately for ecoregions because ecoregional characteristics capture distinct patterns of climate and vegetation. We used the Global 200 ecoregions from the World Wide Fund for Nature (WWF) to stratify the fire data by ecoregion (Fig. 2). The final subset of fire records reduces commission errors of fires related to agricultural practices in the study region because the selection better matches the cyclical pattern of farming systems.

Identification of Fire Density

To visualize the spatial clusters of fire occurrence for Laos, we used preselected fire records from the previous section to produce maps of fire density for all fire seasons from 2003 to 2010. The maps describe fire counts per unit area, and they allow the distinguishing of hotspots (with high fire-occurrence density) and coldspots (with low fire-occurrence density). We used nonparametric kernel density estimation (Diggle 1985) with a fixed bandwidth of 45 km to produce continuous fire intensity surfaces from the active fire data.

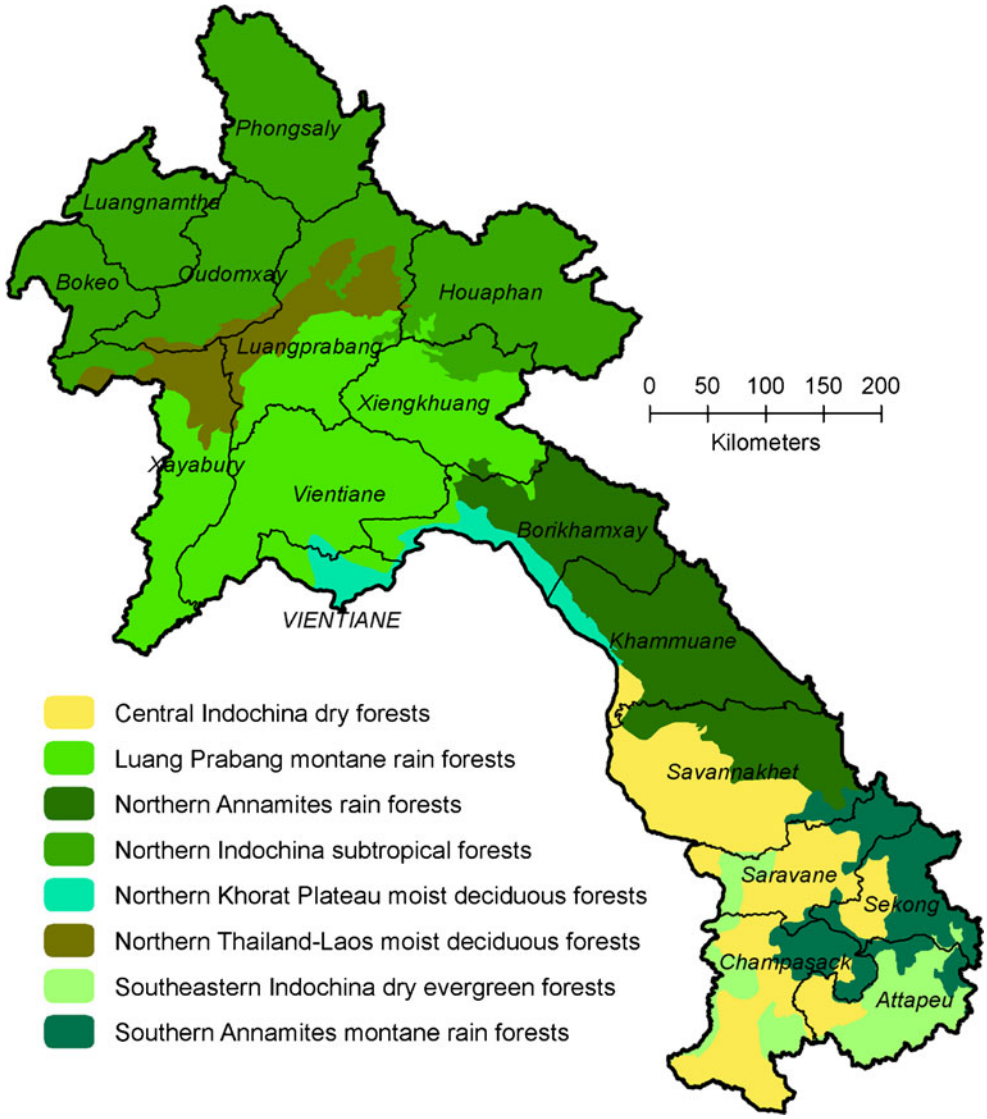

Fig. 2 Ecoregions and provincial boundaries in Laos. Source: Authors, data from http://www.worldwildlife.org/wildplaces/about.cfm

Accuracy Assessments

A quantitative accuracy assessment of the active fire data is a challenge because of the difference in spatial resolution between the fire data and the size of a typical vegetation fire in Laos. It is problematic to conclude with certainty whether a location within a 1 km^2 pixel was affected by fire because the sub-pixel location of the fire is unknown. Nevertheless, we derived qualitative and quantitative inferences about the validity of the active fire data by comparing them with three independent data sources. First, we assessed the accuracy of the active fire data with fire locations that we geolocated in the field during the 2010 fire season. Second, we compared the active fire data with digitized shifting cultivation plots that were preceded by clearing with fire. Third, we used very-high-resolution satellite imagery available in Google Earth to visually compare burned areas with the active fire data.

Results

Accuracy Assessments

GPS-Supported Field Verification

Field verifications of the MRR active fires were conducted from March 29 to 31, 2010 by locating the active fires and recently burned areas in the field using GPS receivers. However, this approach posed two problems. First, most of the areas burned are not connected to the road network, and reaching the detected fire was often difficult because of the thick vegetation dominated by bamboo. Second, the spatial resolution of the MODIS fire pixels renders it impossible to state with certainty whether a burned area on the ground was the result of a detected fire. In most cases, the entire pixel could not be overseen in the field, and a degree of uncertainty always remained. Nevertheless, 12 fires were assessed, and ten of these (83 %) contained a fire on the ground within the potential area affected. In addition, 17 recent vegetation fires, all larger than 10 ha, were detected along the road. These fires did not have a corresponding active fire record, possibly because of a mismatch between the overpass and the fire activity or because of smoke. Errors of omission thus seem considerably higher than errors of commission in this small sample.

We also analyzed 151 GPS points of burned areas in Bokeo province in northwestern Laos (cf. Fig. 2). All GPS points were taken during the peak of the fire season between 29 March and 18 April 2010. We evaluated these with corresponding ground photographs that recorded all burned areas containing an active fire within 2 weeks before the acquisition of the GPS data. We therefore selected these 2 weeks from the MODAPS active fire data and labeled a GPS point as a positive detection if it fell inside a 1 km^2 fire pixel. The results showed that 58 % of the GPS records were captured by the active fire data.

Comparison with Very-High-Resolution Imagery from Google Earth

We assessed the accuracy of the fire locations with very-high-resolution imagery (VHRI) available from Google Earth (mainly true color composites of QuickBird and IKONOS) by summer 2010. We digitized the extent of the 66 available tiles of VHRI in Laos, which covered approximately 20 % of the country. All acquisition dates were between January 2003 and April 2009. We selected all active fire records that were recorded within 14 days before the image acquisition, and we placed a 1 km square around each fire location. The resulting 24 fire records that matched the imagery in space and time allowed a visual comparison between the size of a fire pixel

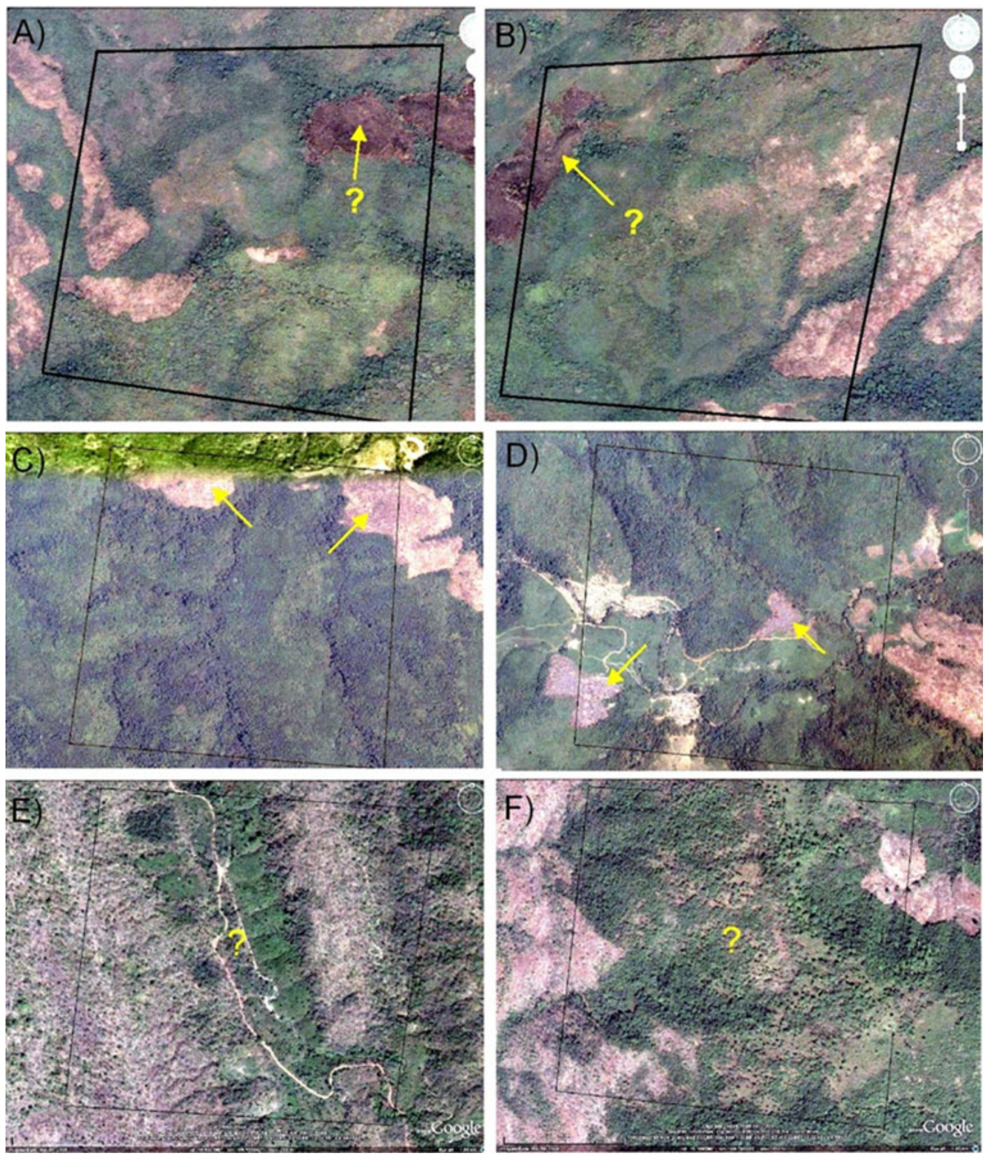

Fig. 3 MODIS fire pixels and successional land cover. Source: Authors. Note: *All rectangles* indicate fire pixels, and the *yellow arrows* point to probable burn scars. All fires were recorded within 2 weeks before image acquisition

Table 1 Number and area of shifting cultivation plots intersected by fire pixels

Year	Total	Inside fire pixel	% inside fire pixel
Plots (number)			
2005	96	47	49 %
2006	89	30	34 %
2007	95	76	80 %
2008	120	22	18 %
Sum	400	175	44 %
Area (hectares)			
2005	143.7	83.4	58 %
2006	102.8	39.9	39 %
2007	103.5	84.6	82 %
2008	135.6	30.3	22 %
Sum	485.5	238.1	49 %

and the burned area visible in the imagery of the subsequent 2 weeks.

In most cases, we were unable to conclude whether a fire event was correctly recorded by MODIS. The 1 km resolution of the active fire data complicates a consistent accuracy assessment because the location within a pixel of detected fires with sub-pixel size is unknown. Moreover, making a definite decision regarding whether a burned area was present in an image was often not possible. Therefore, the conclusion that pixels potentially contained a burned area remained subjective. Figure 3 gives an example of this spatial mismatch and shows six fire pixels detected with high confidence. We inferred the probable burn scars in the imagery on the basis of our own visual interpretation. In examples A) and B), we indicate the potential burn scars with yellow arrows. Both examples demonstrate the capability of the detection algorithm to detect fires of sub-pixel size. Examples C) and D) contain probable burn scars that may have been caused by fire. In examples E) and F), we were unable to detect burned areas or burn scars using visual interpretation; these pixels may thus represent false alarms. In conclusion, the evidence from this assessment is mixed, and Fig. 3 demonstrates the difficulty of validating the active fire data using Google Earth.

Validation with Digitized Shifting Cultivation Plots

We analyzed digitized plots of shifting cultivation areas for a village in the Viengkham District of Luangprabang Province. The data were recorded yearly during the cropping seasons of 2005 to 2008 and include only cultivated plots. Before the first year of cultivation, each plot was cleared with fire. We deleted all plots that were cultivated for the second or third consecutive year because there was no associated clearing with fire. The remaining data consisted of 400 polygons for the 4 years. We compared these with all active fires from the fire season of

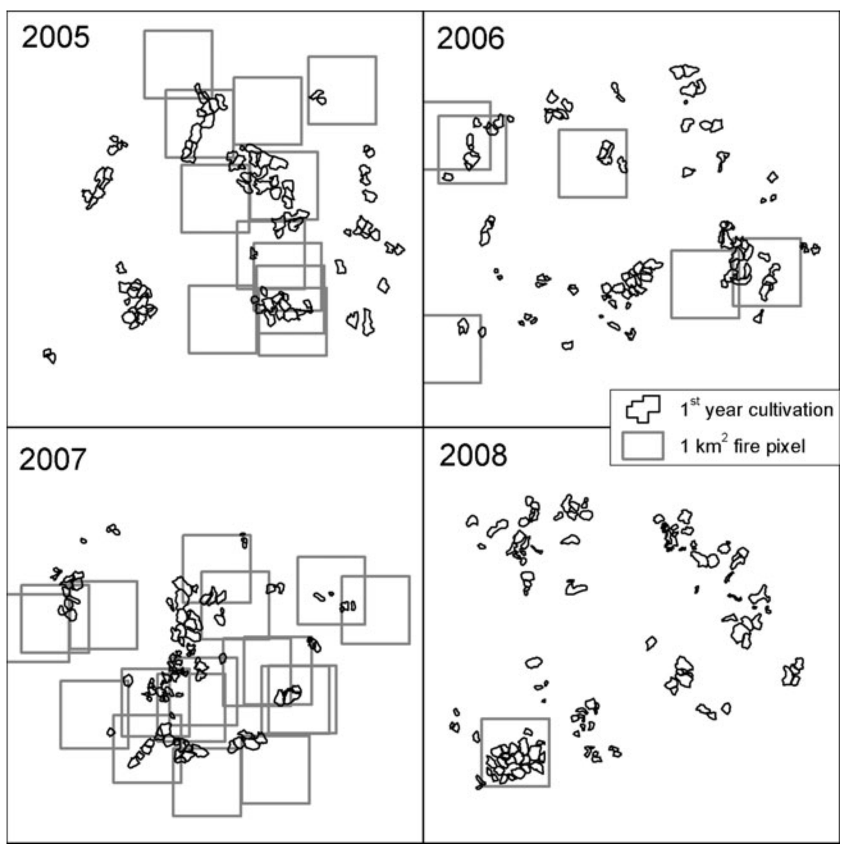

Fig. 4 Overlay of shifting cultivation plots and fire pixels. Source: Authors. Note: Each map contains shifting cultivation plots and fire pixels of the respective year. Only plots from the first year of the cropping cycle were included along with all fires from the particular fire season irrespective of the detection confidence

the same year, irrespective of confidence classes. Of the 400 recorded plots of shifting cultivation, 175 (44 %) fell completely within or intersected a 1 km^2 area that was potentially affected by a fire (Table 1). The performance of the fire records varies over the years from a meager 18 % in 2008 to 80 % in 2007. The large variation may have been due in part to the El Niño years 2006 and 2007, which were associated with little cloud coverage in Laos. It is probable that this situation improved the detection accuracy. This period was followed by a La Niña year in 2008. The accompanying clouds and excessive rainfall may have decreased the number of detections.

Figure 4 visualizes the overlay of the shifting cultivation plots with the 1 km^2 pixels of the respective year. The spatial mismatch between the size of a plot and the size of the pixel that contains the fire is evident. Fires in shifting cultivation areas are underestimated by the MODIS active fires (high omission errors). But Fig. 4 demonstrates that commission errors are very low and only in 2005 one MODIS pixel was a false positive detection (commission error). In conclusion, this assessment does not substantiate the use of the MODIS active fire data as a component for MRV with the aim of monitoring changes in shifting cultivation systems at the plot and village level (Tier 3).

Spatial and Temporal Patterns of Fire Activity

Overpass Time

The satellite overpass time is crucial for the detection algorithm, which relies on the size and temperature of fires at the time of overpass (Giglio *et al.* 2003; Schroeder *et al.* 2005). Overpasses at peak fire activity are most likely to produce a large number of successful detections. Fire activity remains undetected if it does not coincide with the satellite overpass time. In Laos, the burning of vegetation typically occurs during the hotter hours of the day, when the slashed vegetation is dry after the night's moisture (Van Gansberghe 2005). A number of experts on Laos set the timing of the local fire activity from 12:30 pm until after 5 pm. If fields are very close to villages, the clearing fires may even be lit after sunset to pinpoint flying sparks against a background of darkness because sparks can set fire to thatched roofs (O. Ducourtieux, pers. comm.).

The most frequent time at which clearing fires occur in Laos coincides particularly well with the afternoon overpass of the Aqua satellite, extending from 12:30 pm to 2:30 pm (the average overpass time is 1:29 pm). Because fire activity is high after noon, 87 % of all detected fires in Laos since May 2002 (the onset of Aqua) were detected by the afternoon overpass of Aqua (Fig. 5, cf. Giglio *et al.* 2006a, b). This trend is typical for the tropics, where small fires follow diurnal variations and the fire activity is highest in the early afternoon (Giglio *et al.* 2006a). The morning overpass from

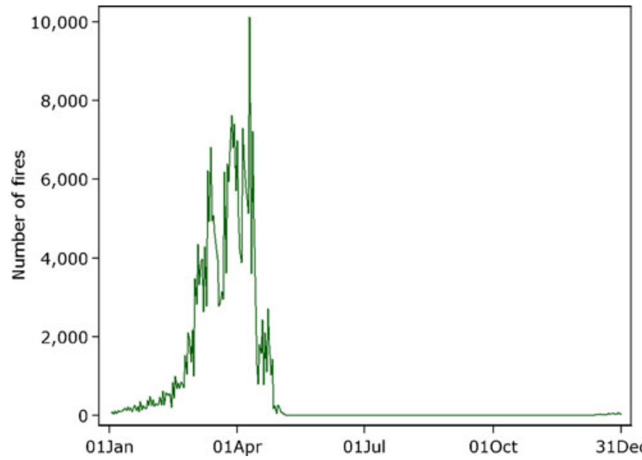

Fig. 6 Fire seasonality in Laos from 2003 to 2010. Source: Authors. Note: Fires from 2003 to 2010 included regardless of confidence class

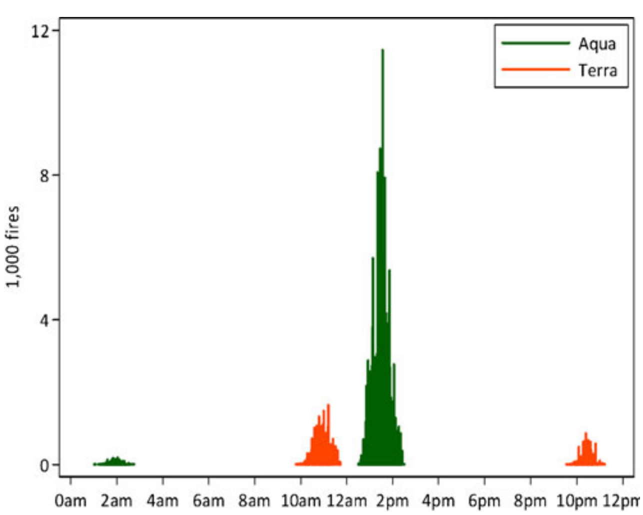

Fig. 5 Overpass time of detected fires. Source: Authors. Note: Fires from 2003 to 2010 included regardless of confidence class

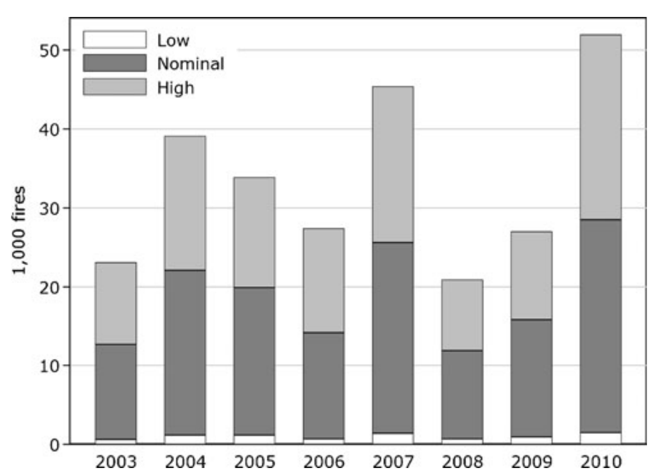

Fig. 7 Interannual fire activity in Laos. Source: Authors

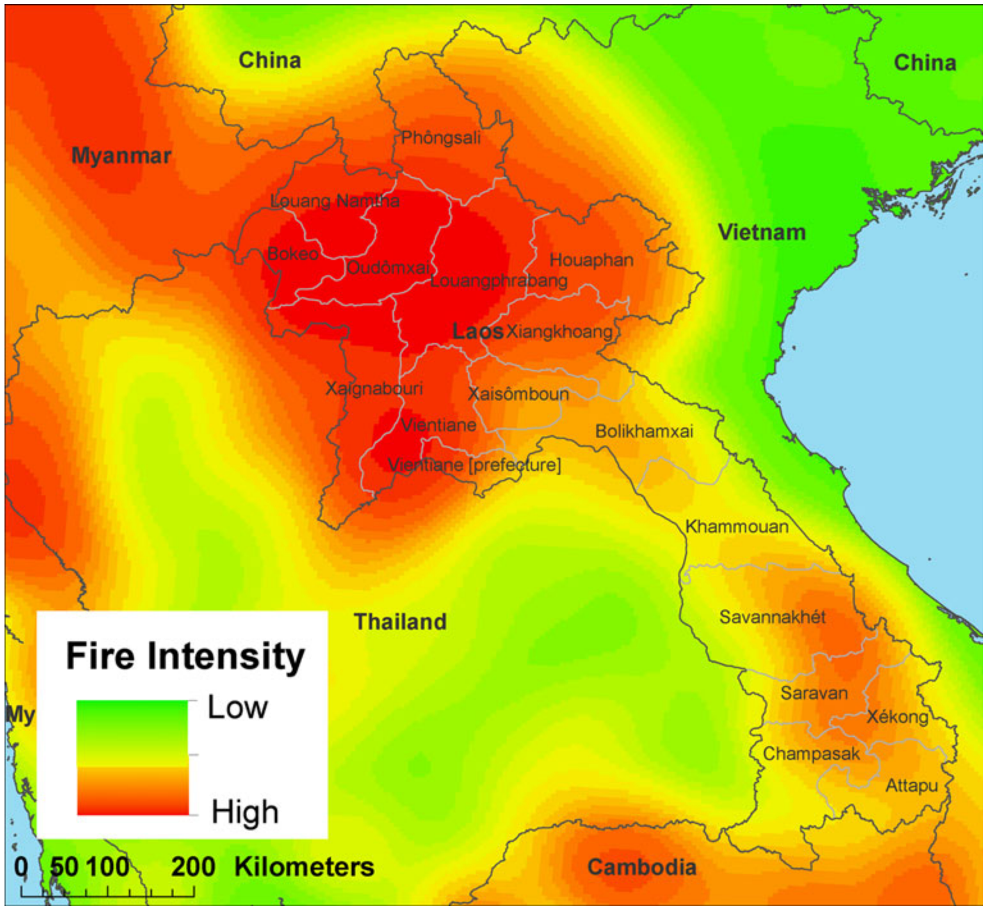

Fig. 8 Fire density map for 2003–2010. Source: Authors. Note: The map was created with a kernel density estimate from high-confidence fires using a bandwidth of 45 km, and it shows the density of fire activity in 5 % steps on a 5 km grid

Terra between 9:47 am and 11:43 am adds another 9 % of detected fires (the average overpass time is 10:54 am). Thus, 96 % of all detected fires fall between 9:47 am and 2:30 pm. Few fires were detected by the night-time overpasses between 21:33 pm and 23:13 pm for Terra and between 1:01 am and 2:44 am for Aqua. The gap between the Aqua and Terra overpasses around midday, particularly the lack of overpasses after 2:30 pm to 5 pm, arguably led to many errors of omission. We hypothesize that a considerable number of vegetation fires did not develop sufficient radiative power to be detectable during the Aqua afternoon overpass and that this situation negatively affected the detection rates (Schroeder *et al.* 2005).

Seasonal and Interannual Variation

Figure 6 illustrates the strong seasonality of the detected fires and the peak fire activity occurring from February through April.[1] On average, the maximum number of fires between 2003 and 2010 was detected on April 10, just before the start of the Lao New Year.

Figure 7 shows the interannual variation of fires by detection confidence. However, interannual variation should be interpreted with great care because of the shortcomings mentioned in "Caveats about the Active Fire Data". No clear trend indicating a change in fire densities is discernible. The fewest fires were detected in 2003 and 2008, with slightly more than 20,000 fires per year. The low fire incidences in 2008 were likely caused by the La Niña anomaly, which brought colder temperatures and more rainfall to Southeast Asia (cf. "Validation with Digitized Shifting Cultivation Plots"). Most fires were recorded in 2010, an El Niño year, with more than 50,000 fires, followed by 2007 and 2004, both years of El Niño anomalies (cf. Hompangna *et al.* [2000], cited in Douangboupha *et al.* (2002), and London (2003) for evidence about the association of the El Niño drought in 1998 and the subsequent increase in fires).[2] Consistently, few fires were assigned to the low confidence class, and a similar number of fires have nominal and high detection confidence.

[1] Because of the data gaps, all calculations conservatively approximate fire patterns and should not be interpreted as comprehensive fire counts.

[2] See http://www.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ensoyears.shtml

Fire Density

Maps of fire density were produced at a 5 km spatial resolution. We prepared the density maps for each fire season from 2003 to 2010. Figure 8 shows the mean fire density for all high-confidence fires from the fire seasons of 2003 to 2010. A low fire density is found in the southern parts of Laos whereas northeastern Laos appears as the expected fire hotspot because of the dominance of shifting cultivation systems. These patterns also compare well with the results of Hurni *et al.* (this issue). The fire density map also captures the shifting cultivation in other areas surrounding Laos toward the subtropical forests of northern Indochina, such as the northern uplands of Vietnam, the Xishuangbanna prefecture of Yunnan province and southeastern Myanmar. According to the fire data, the greatest number of fires on the Southeast Asian mainland occurred in the ecoregion of the northern Indochina subtropical forests (cf. Fig. 2).

Conclusions

We investigated the suitability of MODIS active fire data as input into a REDD+ MRV system in Laos to monitor vegetation fires that were largely caused by shifting cultivation. Unfortunately, representative data for ground validation of the extent of shifting cultivation in Laos are lacking. Moreover, a consistent and independent accuracy assessment of the active fire data was complicated by the spatial mismatch between burned areas of sub-pixel size and the size of fire pixels. Our accuracy assessment with GPS verification, project-level field data and Google Earth at Tier 3 (sub-national) failed to yield convincing quantitative evidence of the validity of the active fires at the local level. Errors of omission (non-detected fires) were particularly large whereas we observed relatively fewer errors of commission (false alarms).

We see several reasons for these results. First, active fires suffer from incomplete data records because of gaps in the overpass timing and multiple fires within one fire pixel. The partial mismatch between fire activity and satellite overpass time leads to a substantial underestimation of fire activity, and a slight deferral of burning activities may grossly affect the detection rates. Second, the detection accuracy is affected by a variety of additional factors, such as the satellite viewing angle, cloud cover and smoke at the time of overpass, and the transient response of the sensor due to data transmission problems. These problems increase errors of omission and result in a significant underestimation of the number of fires in Laos. It is probable that both omission errors and commission errors are spatially clustered because the data shortcomings of the sensor are not uniform across space, thus inducing spatial biases in the detected fires. In sum, the active fire data are not adequate for site-specific monitoring at Tier 3. We also advise against using the active fire data for the detection of the interannual changes in vegetation fires at the local level.

The active fire data only convey information about fire events, not the size of burned areas. Unfortunately, the MODIS-based burned-area products (or any other readily available burned-area product) fail to capture the predominantly small vegetation fires because the minimum mapping unit of burned-area products is considerably larger than the fire-affected areas of most vegetation fires found in Laos. Therefore, the majority of detected fires did not translate into burned areas at the resolution of MODIS (own observation, map available upon request). The estimation of land-use emissions at the national, sub-national and local level requires the mapping of burned areas from sensors with higher spatial resolution than MODIS (e.g., ALOS, Landsat, or SPOT). For example, the spatial resolution of Landsat allows the delineation of burn scars as small as 5 ha (Ballhorn *et al.* 2009), which in turn permit fine-scale comparisons of fire locations with burned areas. Burned-area mapping at a high or very high resolution is particularly relevant for assessing the emissions associated with shifting cultivation systems. However, most satellite data are optical and are consequently subject to cloud cover. In addition, the data must be acquired soon after the fire event to be credibly attributed to the fire. Very-high-resolution imagery (IKONOS, QuickBird) could, for example, be used in a hierarchical sampling framework with Landsat and MODIS to obtain accurate estimates at Tier 2. RapidEye, another very-high-resolution sensor that includes the infrared channel necessary for fire detection and can provide up to two observations per year, may allow the delineation of burned areas, although at high acquisition and processing costs. In the long run, it is possible that the satellite remote sensing of forest biomass changes will move toward the use of sensors that actively emit radiation, such as the RAdio Detection And Ranging (RADAR) and the Light Detection And Ranging (LIDAR) systems. RADAR imagery can penetrate clouds, but its use is complex in landscapes with rough topography due to shadows (DeFries 2008). LIDAR allows the calculation of three-dimensional canopy structure and aboveground biomass, but its acquisition involves high costs (Asner *et al.* 2010; Ballhorn *et al.* 2009; DeFries 2008).

Nevertheless, the active fire data are valuable for understanding the spatial and temporal variation of fire activity for larger areas. The data describe well the expected spatial patterns of fire regimes in Laos. Preprocessing steps, such as the definition of a fire season and the selection of high-confidence fires, help to select active fires with lower false alarms and to improve the appropriateness of year-to-year comparisons. The identification of fire season and peak fire activity from the active fire data can also support the acquisition of additional data such as, for example, auxiliary imagery to detect burn scars and fire affected areas. In addition, the calibration of active fires with weather data, cloud masks and the location of fires in the satellite orbit track will enhance detection rates and improve intertemporal comparisons of fire density. Moreover, the evaluation of active fires will benefit from a consideration of their relationship with burned areas if the necessary information is available (Tansey *et al.* 2008). We hypothesize that such contextualization allows the use of active fire data as valuable input into the monitoring of vegetation fires at the national level (Tier 2) and possibly at the provincial or even district level; however, we are unable to prove this hypothesis because of a lack of validation data. Moreover, it will not be possible to attach the uncertainty estimates to active fire data that are requested by United Nations Framework Convention on Climate Change (UNFCCC) for country-level MRV at any Tier level because of a lack of validation data.

The use of active fire data requires considerable training, application experience and local knowledge to understand the possibilities and challenges inherent in the data. It is important that users of the data have ample experience with interpreting the quality of active fire data in combination with contextual information. For example, the combination of fire records with daily MODIS image subsets can provide valuable insights that are necessary to assess gaps in the coverage of active fires and in the quality of the coverage. Near-real-time access to MODIS image subsets for the areas of interest will facilitate the interpretation of fire locations in relation to contextual land-cover data. The transmission of such large quantities of data may be achieved with resources that are available in the region, specifically at the Geo-Informatics and Space Technology Development Agency (GISTDA), the national space agency of Thailand. In the future, data transmission will be enhanced by GEONETCast,[3] a near-real-time global network of satellite-based data dissemination systems that transmit satellite and in situ data, products and services from Earth observation satellites to users.

Analyses of year-to-year variations from MODIS fire products must be evaluated very cautiously and carefully. The lack of historical medium-resolution data, such as data on climatic variations and land cover, compromises a retrospective analysis of fire dynamics. Thus, the establishment of credible and verifiable historical baselines from active fire data will be challenging. However, fire records can provide an important covariate in estimation efforts and models to assess the causes and determinants of historical land-use changes at Tiers 2 and 3. Another promising application of the active fire data toward MRV is in contributing to the identification of leakage and permanence. Questions to be addressed in this context are whether fires occur in areas where they should not or if a reduction of fires in one place is accompanied by increasing fire activity in neighboring places. The analysis of permanence can be supported by examining the reduction of vegetation fires in a country over time, again in combination with auxiliary data. Another current line of research in estimating fire emissions is the derivation of the radiative energy of fires from satellite imagery, including MODIS (Vermote *et al.* 2009). Methodological advances along these lines may contribute to Tier 2 assessments of emission reductions.

Slight improvements in the detection of active fires are expected from the planned MODIS successor, the Visible Imaging Infrared Radiometer Suite (VIIRS) aboard the National Polar-orbiting Operational Environmental Satellite System (NPOESS). VIIRS was launched in fall 2011, and it records thermal data at a higher spatial resolution of 750 m. It is probable that this higher spatial resolution will increase the detection capability. The overpass timing of VIIRS will be similar to Aqua; thus, the afternoon overpass will most likely be crucial for fire detection. Finally, VIIRS has a larger swath of 3,000 km compared with 2,330 km for MODIS (Lee *et al.* 2006). It therefore offers modest improvements in spectral, radiometric and spatial resolution but no momentous breakthrough for the detection of small-scale vegetation fires. It is more important that the continuation of satellite-based fire detection at medium resolution appears to be secure. Research on more effective uses of these data for the MRV of REDD+ activities is therefore needed to improve our ability to estimating fire-related GHGs. This capability is particularly important for areas that are dominated by the use of fire, such as the shifting-cultivation landscapes of Laos.

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[3] http://www.earthobservations.org/geonetcast.shtml

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