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Review paper

Remote sensing of forest degradation in Southeast Asia—Aiming for a regional view through 5–30 m satellite data

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ABSTRACT

In this review paper we present geographical, ecological and historical aspects of Southeast Asia from the perspective of forest degradation monitoring and critically discuss available approaches for large area forest degradation monitoring with satellite remote sensing data at high to medium spatial resolution (5–30 m). Several authors have achieved promising results in geographically limited areas within Southeast Asia using automated detection algorithms. However, the application of automated methods to large area assessments remains a major challenge. To-date, nearly all large area assessments of forest degradation in the region have included a strong visual interpretation component. We conclude that due to the variety of forest types and forest disturbance levels, as well as the variable image acquisition conditions in Southeast Asia, it is unlikely that forest degradation monitoring can be conducted throughout the region using a single automated approach with currently available remote sensing data. The provision of regionally consistent information on forest degradation from satellite remote sensing data remains therefore challenging. However, the expected increase in observation frequency in the near future (due to Landsat 8 and Sentinel-2 satellites) may lead to the desired improvement in data availability and enable consistent and robust regional forest degradation monitoring in Southeast Asia.

Contents

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1. Introduction

Over the past decade, assessment of forest degradation has become one of the main targets of tropical forest monitoring. Information on the extent and level of forest degradation is required to support reporting obligations under international conventions, to design and implement forest-related policies and as input to potential payment mechanisms and incentive schemes (FAO, 2011a). Forest degradation can be generally defined as: *the reduction of the capacity of a forest to provide goods and services* (FAO, 2010a). However, this general definition can be interpreted in numerous and potentially rather contradicting ways. Depending on the scope of the analysis, the evaluation of degradation in a given forest area can be based e.g. on (1) biological diversity; (2) forest health and vitality; (3) productive functions of forest resources; (4) protective functions of forest resources; and (5) socio-economic functions of forests (FAO, 2011a). Due to the recent prominence of carbon issues in international forestry discussion, most particularly in the context of the Reduction of Emissions from Deforestation and Forest Degradation (REDD+) scheme under the United Nations Framework Convention on Climate Change (UNFCCC), the long-term reduction of forest biomass is nowadays perhaps the most widely discussed aspect of forest degradation (GOFC-GOLD, 2014), although changes in forest biomass do not necessarily provide any information on several other aspects of forest degradation.

Different drivers of tropical forest degradation (e.g. unsustainable logging or shifting cultivation) cause varying effects in forest ecosystems, ranging from structural changes such as canopy cover and biomass reduction to more subtle effects including e.g. minor alterations in ecosystem services. Furthermore, different types of forests (e.g. humid evergreen and dry deciduous forests) respond differently to the numerous types of activities taking place in tropical forest areas. Therefore, optimal approaches for monitoring forest degradation by remote sensing are likely to vary considerably depending on the driver of degradation, the type of forest concerned, the intensity of the impact as well as on the geographical location, and combined use of different data sources and methods may be required (De Sy et al., 2012).

In this review paper we first discuss the geographical, ecological and historical differences between sub-regions within Southeast Asia from the perspective of remote sensing based forest degradation monitoring. We will then contrast the most commonly used remote sensing approaches to the characteristics of the region and analyse their usability for monitoring forest degradation in Southeast Asia. We mainly concentrate on degradation processes caused by selective logging, shifting cultivation and fire, which all may cause reduction in canopy cover and can lead to reduction of forest biomass. Our main focus will be on approaches that would allow large area assessments utilizing satellite data with spatial resolution typically in the range of 5–30 m.

2. Geography of Southeast Asia

Southeast Asia is defined in this paper as the area covered by the Association of Southeast Asian Nations (ASEAN) countries, along with Timor Leste and Papua New Guinea, stretching between 92° E and 155° E longitude and 10° S and 28° N latitude. The region covers around 5 million km^2 of land areas (Fig. 1(a)) and can be divided into two distinctively different parts: (1) continental Southeast Asia (2.2 million km^2) and (2) insular (i.e. archipelagic) Southeast Asia (2.7 million km^2). The continental part includes Cambodia, Lao PDR, Myanmar, Thailand and Viet Nam. In addition, we include the Philippines in continental Southeast Asia in this paper, due to climatic similarities. Insular Southeast Asia is shared by Brunei, Indonesia, Malaysia, Papua New Guinea and Timor Leste. Thus, the border between the seasonally dry continental and the per-humid insular parts of the region can be drawn at around 7° N latitude.

Apart from the large archipelago, another distinct feature of Southeast Asian geography is the high number of mountain ranges and steep landscapes, in many ways affecting both the current distribution of forest areas as well as the degradation level of the remaining forests. Major mountain ranges in the region include e.g. the Arakan and the Annamite Mountains in the continent as well as the string of volcanic peaks along the "ring of fire" in Indonesia and the highlands in the central parts of Borneo, Sulawesi and New Guinea Islands. Maybe even more than the elevation (which generally reduces the availability of cloud free data in mountainous areas), it is the steepness of the landscape that affects any remote sensing based forest monitoring system widely over the region by introducing considerable topographic effects (due to varying steepness and aspect) into the satellite data (Fig. 1(a) and (b)).

There is a striking difference in climate between continental and insular Southeast Asia, leading to marked differences in forest types and their appearance on satellite data, and thereby affecting the suitability of remote sensing data and of monitoring methodologies. Continental Southeast Asia has a distinct monsoonal (i.e. seasonal wet/dry) climate. In this area, drought limits plant growth in the dry season that typically stretches from November to April (Corlett, 2009). Evergreen, semi-evergreen and deciduous forest types intermingle with managed landscapes in this part of the region, with the evergreen forests typically in mountainous areas and on nutritious soils on lowlands, and the deciduous forests on poorer and dryer soils on lowlands and gently undulating landscapes. In the driest areas of continental Southeast Asia, the increase in anthropogenic fire activity over recent history has caused degradation of the deciduous tropical forests into savanna and grasslands (Stott, 1988; Corlett, 2009).

In insular Southeast Asia, different variations of humid tropical evergreen forests dominate the lowland vegetation in natural conditions. These forests are considered to contain the highest biodiversity of all regions in the world (Whitmore, 1984; Corlett, 2009). Perhaps the most special feature of this region is the vast extent of tropical peat swamp forests growing on up to 15 m thick peat deposits that have formed over thousands of years through the accumulation of organic material

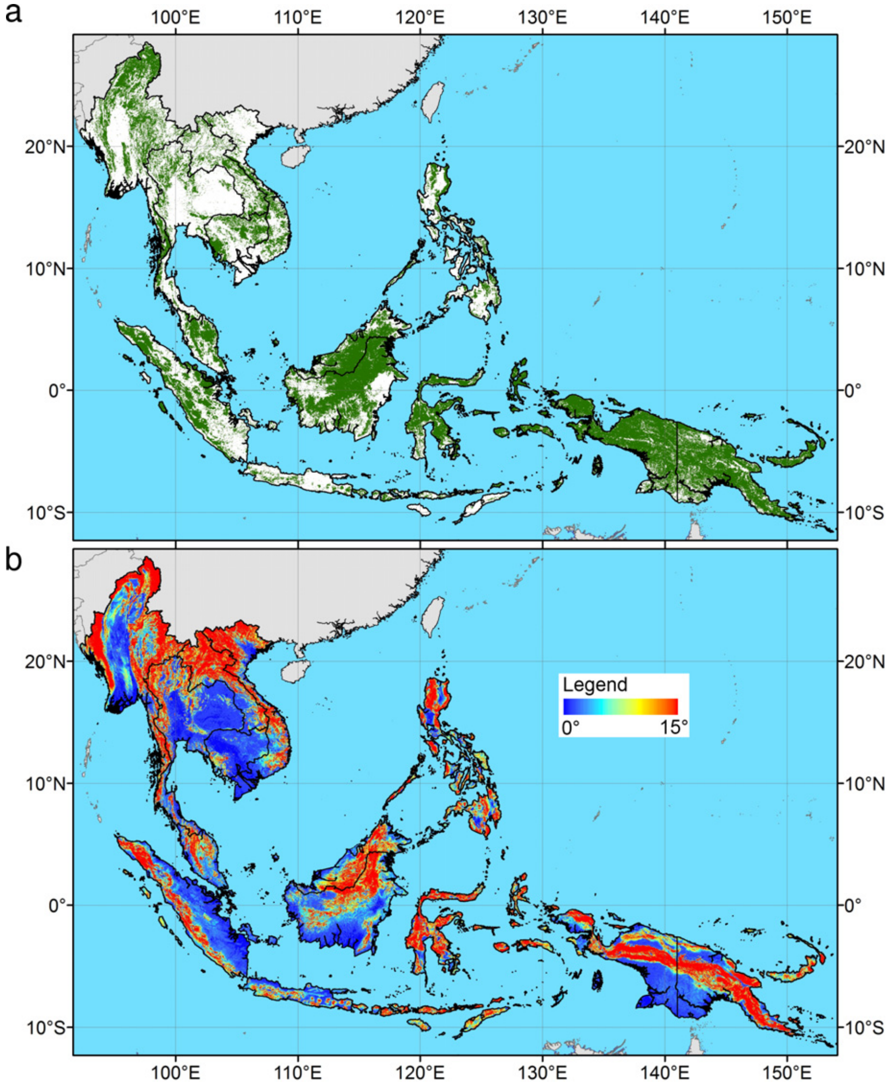

Fig. 1. Geography of Southeast Asia. (a) Extent of forest cover in 2000 (in green colour; Stibig et al., 2007a) and (b) steepness of the terrain with areas steeper than 15° gradient in red colour (derived from 90 m SRTM product; Jarvis et al., 2008). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

in waterlogged conditions (Rieley and Page, 2005). Several other vegetation types exist in smaller extent on special soil or hydrological conditions and in higher elevations (see e.g. Corlett, 2009 for more details).

The Southeast Asian region has experienced a 2.8 fold population increase over the past 50 years, reaching a total population of over 600 million people by 2010 (UN, 2013). Over the past 70 years, much of the region has also experienced a politically turbulent transformation from colonial territories into sovereign states. This instability has unavoidably affected the design and enforcement of natural resource policies. Furthermore, during the past two decades the economic growth in the region has been very rapid. Several countries, like Lao PDR, Malaysia, Singapore, Thailand and Viet Nam, have more than doubled their per capita Gross Domestic Product (GDP) since 1990 (World Bank, 2014). The rural/agricultural sector is one of the most affected by these demographic, political and economic changes, as it has simultaneously been going through transformation from traditional subsistence farming to modern agricultural practices favouring cash crops like oil palm, rubber, tea and coffee (Fox et al., 2009). This has profoundly affected the entire rural landscape including both agricultural and forest areas.

The majority of the original extent of natural forest areas in Southeast Asia have by now been either logged with varying intensity, have been reduced to degraded savanna and grassland, or have been converted into managed land cover types while environmental degradation and land cover changes continue to take place (Kauppi et al., 2006; Hansen et al., 2009; Miettinen et al., 2011a,b, 2012; Stibig et al., 2014). As the pressure on the remaining forests is expected to remain high in the near future, operational monitoring methods for forest degradation are urgently needed.

3. Forest degradation in Southeast Asia

3.1. Definition of the scope of this paper

There are several drivers of forest degradation in Southeast Asia including unsustainable selective logging (legal and illegal), shifting cultivation, small-holder forest encroachments, fuel wood collection, wood extraction for charcoal production, overgrazing, fires and even changes of natural water regimes. In this paper, we concentrate on the most dominant and physically destructive forms of forest disturbances that are in principle detectable on 5–30 m resolution remotely sensed data. From the categories outlined by Hosonuma et al. (2012) in an analysis of drivers of degradation in tropical forests, we discuss here selective logging and uncontrolled fires as main causes of forest degradation. We also include fuelwood and charcoal collection as potential causes of noticeable forest canopy changes. We do not look into livestock grazing, as it is merely a marginal degradation driver in Southeast Asia (Hosonuma et al., 2012; Kissinger et al., 2012). However, we include shifting cultivation in our analysis, although some authors (e.g. Hosonuma et al., 2012) consider it purely as a driver for deforestation rather than for forest degradation. The three main types of disturbances included in the analysis in this paper (selective logging, shifting cultivation and fire) account for the majority of degradation in the forests of Southeast Asia (Stibig et al., 2007b).

3.2. Selective logging

In continental Southeast Asia large scale selective logging has been practiced since the mid of the 19th century, when Sir Dietrich Brandis, often considered the 'father of tropical forestry', set the foundation for modern forestry approaches and sustainable logging systems in Myanmar (Schlich, 1907). In the year 2000, the extent of 'intact forest landscapes' in continental Southeast Asia was estimated at only 110 000 km^2 (Potapov et al., 2008), corresponding to 12% of the remaining forest area (FAO, 2010b). However, it is important to point out that when practiced in a sustainable way respecting the allowable cut limits, selective logging does not necessarily render the forest 'degraded'. For instance, some areas in Myanmar have been logged using the Myanmar Selection System continuously since 1856 without causing forest degradation, i.e. without causing long-term reduction of forest biomass or changes in forest types (Mon et al., 2012a).

Selective logging with high temporal frequency or logging intensity (i.e. unsustainable logging), on the other hand, does lead to forest degradation (Mon et al., 2012a) and is considered to be the most dominant driver of degradation in Southeast Asia (Kissinger et al., 2012). Although, due to higher profitability of agricultural crops and increasing importance of plantation forests, the peak of timber extraction from natural forests in continental Southeast Asia has most likely already been passed, both legal and illegal logging operations continue to take place in the sub-region (FAO, 2011b; EU FLEGT Facility, 2011a). Whilst for instance Thailand imposed a logging ban in 1989 (EU FLEGT Facility, 2011b), in some countries (e.g. Lao PDR) the number of logging operations continues to rise (EU FLEGT Facility, 2011c), most likely including unsustainable logging.

In insular Southeast Asia the history of logging is rather different from the continent. The escalation of timber extraction in the humid tropical forests of insular Southeast Asia is well described by Kaur (1998), using the Sarawak state in Borneo Island as an example. He highlights the slow increase in logging activities between the World Wars and the dramatic change in policies after the Second World War when logging became an integral source of revenue for Southeast Asian governments. Finally, in the 1960's the development in technology and machinery for both road making and timber handling enabled heavy exploitation of tropical forests in often difficult working conditions (e.g. in peatlands or steep slopes) of insular Southeast Asia (Fig. 2(a)).

Due to the high number of commercially valuable timber trees and poor adoption of Reduced Impact Logging (RIL) practices (FAO, 2011b) selective logging in insular Southeast Asia tends to be significantly more intensive than in other humid tropical areas. In an analysis including several studies Putz et al. (2008) estimated harvesting intensities in insular Southeast Asia (Sabah) to be 80–120 m^3/ha, compared to only 5–30 m^3/ha in Latin America and Africa. In addition, the damage to remaining vegetation is often significant, causing further biomass loss and decrease in canopy cover (Pinard and Putz, 1996; Pearson et al., 2014). This, together with the short repeat period, has commonly led to unsustainable logging practices with a cycle of biomass reduction. Rotational times as short as 20 years are sometimes used in insular Southeast Asia (Wilcove et al., 2013), at which point the forest carbon stock may be less than two-thirds of what it was before the previous logging (Putz et al., 2008). Carbon emissions from tropical forest degradation caused by logging have been estimated at 6.0 and 27.5 Tg C yr^{-1} in Indonesia and Malaysia respectively, representing 6% and 68% of emissions from deforestation in these two countries for year 2005 (Pearson et al., 2014). A cycle of degradation initiated by logging and further exacerbated by fire (which is rare in undisturbed humid tropical forests) has been particularly damaging in the peatlands of the region (Miettinen et al., 2011b), but is by no means restricted to peatland areas (Goldammer, 1999; Cochrane, 2003). At the dawn of the new millennium, only around 620 000 km^2 or 38% of the remaining forest areas in insular Southeast Asia were estimated to remain 'intact' (Potapov et al., 2008; FAO, 2010b), mostly concentrated in the island of New Guinea and in the Indonesian part of Borneo Island.

3.3. Shifting cultivation and other small-holder activities

The history of shifting cultivation in Southeast Asia goes back for thousands of years (Maxwell, 2004). This agricultural system can be considered sustainable in low population densities. However, this is not the case where population densities

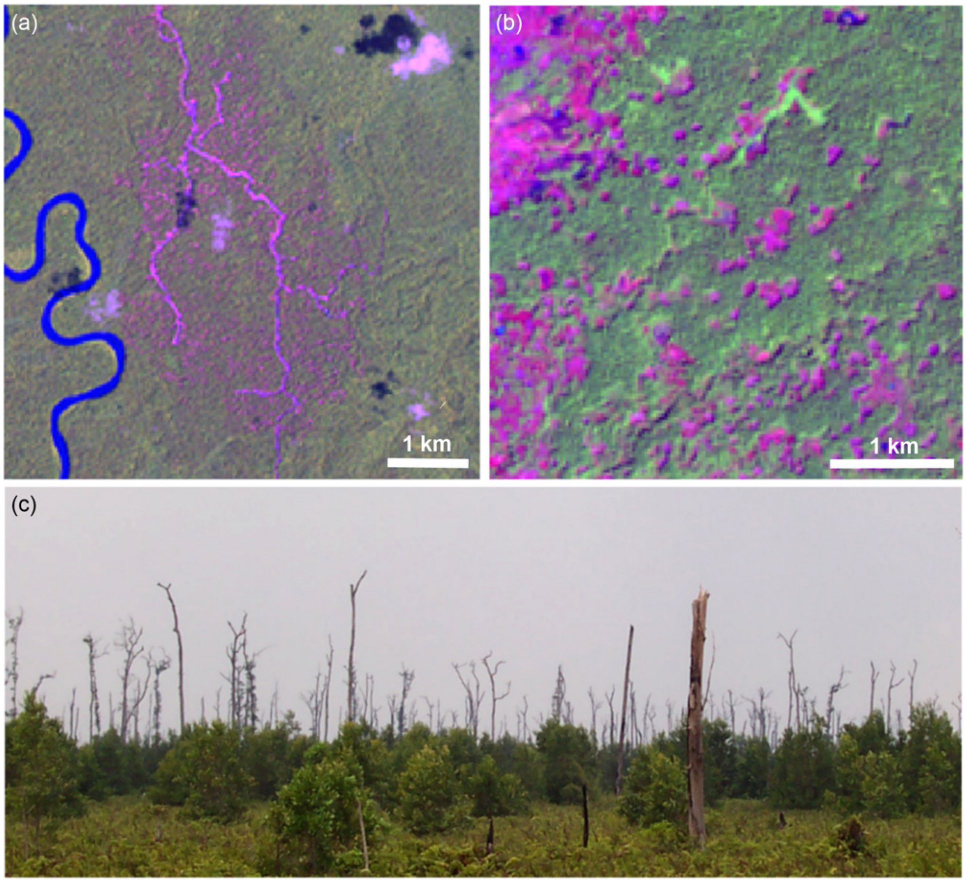

Fig. 2. Examples of different types of potential forest degradation. (a) Selective logging in Indonesia, New Guinea Island (note that the sustainability of the operation cannot be evaluated from this image), (b) shifting cultivation area in Lao PDR and (c) repeatedly burnt and extremely degraded peatland area in Borneo Island. Photo by Jukka Miettinen.

are high and fallow periods too short. Due to the very long history of shifting cultivation it can be asked whether there is much 'primary' forest left in continental Southeast Asia (Fox, 2000). In insular Southeast Asia the situation is very different. Until recently, the forested inner parts of the major islands remained primarily habited by hunter and gatherer societies conducting very minor shifting cultivation activities (Kaur, 1998). This was followed by rapid shift to permanent agricultural practices. Therefore, shifting cultivation is not considered to be a significant driver of forest degradation in the insular part of the region (Stibig et al., 2007b).

For the analysis of forest degradation, shifting cultivation is a complex issue. The temporal and spatial scales of the analysis, the definition of forest and the definition of degradation define whether, or for how long, shifting cultivation areas should be considered 'degraded forest', or even deforested land (Fig. 2(b)). In continental Southeast Asia biomass values may remain reduced up to 50 years after the abandonment of the fields, particularly after cultivation of certain crops (e.g. poppy), while other crops (e.g. upland rice) may allow faster recovery (Fukushima et al., 2008). Regardless of the definitions of degradation, monitoring the extent and effects of shifting cultivation is challenging since the disturbances are spatially limited (i.e. more difficult to identify) and temporally dynamic (i.e. need to use time series with high frequency), and the long-term impacts on biomass are very complex (Kissinger et al., 2012; Mertz et al., 2012).

Largely as a result of socio-economic policies favouring permanent agriculture, shifting cultivation practices are progressively disappearing in Southeast Asia (Fox et al., 2009). However, this does not mean that the effect of small-holder farmer activities leading to forest degradation would necessarily be diminishing. Due to continuing population growth, the rural population is constantly encroaching into new forest areas throughout Southeast Asia. This often starts with collection of fuel wood or charcoal production, and may later lead to deforestation and conversion of land use. The combination of policy support for permanent agriculture and continuing population growth also increases available labour force in rural areas, which can further support unsustainable exploitation of forest products like fuel wood and non-timber forest products (Davidar et al., 2010). In Myanmar, fuel wood collection and marginalization of sustainable forest management systems have been witnessed to build up pressure on forests near populated areas (Leimgruber et al., 2005; EU FLEGT Facility, 2011d). Charcoal production can be particularly destructive for certain ecosystems (e.g. mangrove). Where available, mangrove tree species are favoured for charcoal, which puts high pressure on the already depleted Southeast Asian mangrove areas (Spalding et al., 2010).

3.4. Fire

Forest fires are strongly connected to the selective logging and small-holder activities presented above but they deserve to be highlighted separately when discussing forest degradation, particularly if the reduction of biomass is of interest, as is the case e.g. in the REDD+ context (Barlow et al., 2012). In Southeast Asia, nearly all vegetation fires are nowadays of anthropogenic origin. Fire is widely used throughout the region for numerous purposes, but the fire regimes and the effects of fires vary significantly between the continental and insular parts of the region.

In the seasonally dry continental Southeast Asia, anthropogenic vegetation fires have been an essential part of the ecosystem dynamics for thousands of years (Maxwell, 2004). In these areas forest ecosystems are nowadays often fire tolerant and repeated fires do not lead to degradation in short term. However, it is likely that over the past thousands of years, the increased anthropogenic fire frequency has caused changes in vegetation types favouring more fire tolerant vegetation (Stott, 1988; Corlett, 2009). Fires are mainly used for either preparation of shifting cultivation fields in denser forests or clearance of ground layer vegetation in open forests (Maxwell, 2004).

The humid tropical forests of insular Southeast Asia, on the other hand, very rarely experienced fire in natural conditions (Goldammer, 2006). Undisturbed humid tropical forests are highly resistant to fire but selective logging and other human activities tend to open the canopy, make the microclimate dryer and increase the amount of dry fuel, thereby increasing fire vulnerability remarkably (Cochrane, 2003). This raises the risk of wildfires greatly and causes them to become more severe and more destructive (Siegert et al., 2001). In the worst case this may lead to repeated wildfires each time further degrading the area and finally leading to the replacement of the forest ecosystem with grassland (Goldammer, 1999). Fire is nowadays widely used in insular Southeast Asia for land clearance and preparation by both small-holder farmers as well as large scale plantation developers, often resulting in uncontrolled wild fires (Miettinen and Liew, 2009). Over the past 20–30 years fire driven forest degradation has become a serious problem particularly in selectively logged lowland forests as well as in drained and degraded peatlands (Siegert et al., 2001; Langner and Siegert, 2009; Miettinen et al., 2011b; Fig. 2(c)).

4. Degradation monitoring methodology review

4.1. Definition of the approaches included in the analysis

The different forest degradation processes discussed above (apart from fires in fire-tolerant forests in continental Southeast Asia) cause physical destruction in the forest and usually lead to a significant reduction of canopy cover which can be assessed using high to medium spatial resolution (5–30 m) satellite data. Subsequently, spatial patterns and context from the satellite data, as well as auxiliary information sources can be used to determine the type of the disturbance. However, in reality, even the detection of the main types of forest disturbance may not be a simple task. The remote sensing conditions (both ground and data characteristics), intensity of the disturbance and type of the ecosystem all affect the feasibility of forest degradation monitoring by remote sensing.

To further complicate the matter, the detected disturbance in the forest should ideally be evaluated against a desired baseline (corresponding to 'intact' forest) in order to determine the level of degradation, taking into account the duration of the detected effects and the natural variation of the forest (Thompson et al., 2013). Available remote sensing data often do not cover long enough historical time-frame to properly monitor the full duration of the effects. Therefore, although the aspect of duration is discussed at some points in the following sections, it is important to emphasize that we primarily look at indicators of forest degradation which can be derived from remote sensing data. In other words, we look at methods which can identify areas of "potential recent forest degradation", using a single date or time series of satellite datasets. For practical applications, these potential signs of degradation derived from high to medium resolution satellite data need to be verified and potentially calibrated with auxiliary information (e.g. field data or very high resolution satellite sampling).

Currently available remote sensing methods for forest degradation monitoring can be coarsely grouped into four categories: (1) detection of direct degradation indicators (e.g. canopy cover percentage) on single date or composite image (e.g. Souza et al., 2003); (2) detection of direct degradation indicators by time series analysis (e.g. Healey et al., 2005); (3) mapping of secondary indicators (e.g. logging roads, log landings, villages) and assuming certain degradation buffers around them (e.g. Potapov et al., 2008); and (4) direct estimation of forest parameters (e.g. stem volume and biomass), nowadays most typically performed with radar or LiDAR systems in tropical forests (e.g. Jubanski et al., 2013). We describe and analyse the current status of know-how in each of these four categories from the perspective of Southeast Asia. Note that, the category 4 methods are not particularly designed for degradation monitoring. Therefore, we do not attempt to comprehensively cover this category, but merely highlight some of the latest developments which may be of interest from the perspective of forest degradation monitoring.

4.2. Continental Southeast Asia

In view of monitoring forest degradation in continental Southeast Asia the following conclusions may be drawn from Section 3. First, due to the long historical human impact in the form of both selective logging and shifting cultivation, accompanied with anthropogenic fire activity, it is difficult to identify areas of remaining intact forests and, consequently, to produce or agree on a single standard definition of what should be considered as non-degraded forest in this sub-region. Second, large variation exists in the physical structure of natural forest types, ranging from evergreen and semi-evergreen (with some seasonality) closed canopy forests to open canopy dry deciduous savanna type forests. The variation in physical forest structure characteristics (e.g. canopy openness) caused by these two points may not be easily distinguished from the effects caused by recent disturbances (e.g. selective logging or shifting cultivation). This potential confusion profoundly affects the suitability of various remote sensing approaches for forest degradation monitoring in continental Southeast Asia.

Among the set of available remote sensing approaches, the first category deals with detection of direct degradation indicators on a single image. It is indeed possible to assess the current status of a forest area by analysing a single image with a choice of numerous existing methods and satellite datasets. The Forest Canopy Density mapper (Rikimaru et al., 2002), which utilizes a semi-automated approach combining a set of vegetation indices, allowed to map canopy cover in semi-evergreen forests in Myanmar with nearly 70% overall accuracy (Mon et al., 2012b). Similarly, Joshi et al. (2006) and Panta et al. (2008) showed that artificial neural network can be used to map forest canopy cover percentage from Landsat imagery at 30 m resolution with 60%–80% overall accuracy. These two previous studies were conducted in semi-evergreen forests in India and Nepal in conditions comparable to those in continental Southeast Asia. And finally, Hame et al. (2013a) used unsupervised fuzzy classification methods applied to a combination of optical and radar data to produce a forest map in Savannakhet Province (Lao PDR) including disturbed forest classes.

However, a single date mapping of canopy cover (or other degradation indicators) in continental Southeast Asia is not meaningful for the assessment of forest degradation without longer time-frame or detailed information on forest characteristics on the specific site in 'intact' conditions. Mon et al. (2012a) in Myanmar and Hett et al. (2012) in Lao PDR needed to perform assessments of forest canopy cover percentage and shifting cultivation area (respectively) at several time slices in their study sites to investigate the factors affecting forest degradation. Similarly, Panta et al. (2008) performed repeated canopy cover assessment for forest degradation analyses in one study area in Nepal. The historical time-frame enabled these authors to derive information on the status of forests (disturbed/degraded versus intact) based on the analysis of the changes in the extent of different forest types and the development of canopy cover percentages over their study period. Therefore, time series analysis has been strongly advocated for degradation monitoring in open canopy tropical forests (Lambin, 1999), representing the second category of remote sensing approaches listed above. The recent increase in the availability of high to medium spatial resolution (5–30 m) satellite data (mainly due to the opening of the Landsat archive and the recent RapidEye and Landsat 8 satellites) and the anticipation of the upcoming Sentinel-2 mission, have sparked increasing amount of interest in time series analyses conducted at unprecedented spatial and temporal scales. Several research groups have developed automated or semi-automated approaches utilizing large numbers of satellite scenes and taking advantage of time series data (see e.g. Healey et al., 2005; Masek et al., 2008; Huang et al., 2010; Kennedy et al., 2010; Hansen et al., 2013). However, not only have these methodologies mainly been developed for boreal and temperate areas, but they also typically concentrate on the assessment of two land cover classes only: forest and non-forest. To date, to our knowledge, no automatic time series analysis method has yet been implemented for forest degradation assessment in seasonal tropical forests.

The most extensive forest degradation mapping effort to-date, covering also continental Southeast Asia, has been produced by Potapov et al. (2008) through mapping of secondary indicators of degradation (third category of remote sensing approaches listed above). The global coverage Potapov et al. (2008) map is based on the concept of intact/non-intact forest areas, which has recently been suggested to be utilized also in the framework of REDD+ (Bucki et al., 2012), using a spatial morphological pattern tool (Riitters et al., 2009) as a proxy to identify non-intact forests. Through visual interpretation of Landsat imagery and utilization of auxiliary GIS datasets Potapov et al. (2008) mapped and buffered potential indicators of human disturbance (e.g. logging roads, power lines, burnt areas and waterways) to exclude such areas from a forest map of year 2000. The remaining forest areas were considered as intact forest landscapes. In a more automated approach, Messerli et al. (2009) derived information on the extent and intensity of shifting cultivation in Lao PDR by analysing local spatial statistics of land cover distribution on remote sensing based land cover maps. Although potentially a powerful tool for monitoring forest degradation driven by shifting cultivation, this type of higher level land cover mosaic analysis is vulnerable to the quality and scale of the input land cover maps. Moreover, similar set of parameters may not produce optimal results throughout large areas (e.g. in sub-regional level analysis), but parameters may need to be tuned locally based on variations e.g. in land cover regimes and map specifications.

The fourth category of approaches for forest degradation monitoring consists in using more direct forest inventory approach, concentrating on forest parameters like stem volume, basal area or biomass. The changes in these parameters over consecutive inventories can then be used as potential signs of degradation (e.g. decrease of forest biomass) warranting further investigation on the matter. Combinations of optical and radar satellite data, as well as airborne datasets, have been tested in continental Southeast Asia to estimate basal area, stem volume and biomass, resulting in RMSE of the means at $\sim$40%–50% (e.g. Hou et al., 2011; Hame et al., 2013b). In comparable climatic conditions in forest-savanna landscape in Africa, L-band Synthetic Aperture Radar (SAR) data has been used to monitor biomass over time with $r^2 = 0.49$–0.86 (Mitchard et al., 2011; Ryan et al., 2012). Such methods for direct estimations of forest parameters may offer tools for biomass inventories in seasonal tropical areas where forest biomass is low and the issue of saturation of the radar signal (see e.g. Morel et al., 2011) is not as crucial as in humid tropical forests of high standing stock. However, the suitability of such radar based biomass estimation methods for continental Southeast is yet to be tested and it may be seriously reduced by the vulnerability of radar data to steep landscape features which are common in much of the remaining forest areas in the sub-region.

4.3. Insular Southeast Asia

Apart from a few special landscapes, which altogether cover only a marginal area (e.g. in high elevation), all forest types in insular Southeast Asia have closed canopy in natural undisturbed state. This, in theory, simplifies greatly the task of forest degradation monitoring as any sign of canopy gaps and areas with reduced canopy cover can be considered as potential indicator of degradation. Moreover, due to the per-humid climate conditions, intra-annual variation in forest characteristics is minimal. Unfortunately the per-humid climate conditions seriously complicate remote sensing in the region by reducing the number of available cloud-free optical satellite images. Furthermore, even the few acceptable scenes (with limited cloud cover) are rarely free of remaining atmospheric disturbances (e.g. small clouds and haze). This reduces greatly the number of valid observations for any given area. Together the abovementioned factors create a very different environment for remote sensing based forest degradation monitoring compared to the continental part of the region.

The generally closed canopy of natural forest enables the effective use of canopy openness as an indicator of forest degradation, even if measured only from a single scene without any time series analysis. This type of single date analysis has been used in insular Southeast Asia with Landsat images e.g. by Langner et al. (2012) who developed a degradation index based on Short Wave Infrared (SWIR) reflectance which showed to be correlated with biomass in Dipterocarp forests in Sabah ($r^2 = 0.66$), as well as by Wijedasa et al. (2012), who used simple maximum likelihood classification approach to classify disturbed and primary peat swamp forests (with 53%–88% user's accuracies depending on site). In addition, a number of methods developed in the Amazon basin are potentially useable also in insular Southeast Asia. Two separate research groups working with logging and fire induced forest degradation found the Modified Soil Adjusted Vegetation Index (MSAVI) to correlate strongly ($r^2 \sim 0.80$) with forest canopy cover percentage (Wang et al., 2005; Matricardi et al., 2010). Pithon et al. (2013) developed a segmentation based automated statistical method to detect canopy gaps caused by logging with ~90% accuracy. However, the majority of studies conducted in South America have been based on Spectral Mixture Analysis (SMA). This approach has been used with both SPOT satellite data (Souza et al., 2003) and Landsat data (Asner et al., 2005; Souza et al., 2005; Negron-Juarez et al., 2011) with varying success for purposes ranging from canopy gap detection and biomass estimation to delineation of logged areas. Souza et al. (2005) further developed a single index called Normalized Difference Fraction Index (NDFI) to combine the information from SMA significant for forest degradation monitoring into one band and reached 94% accuracy in detecting forest areas with canopy damage.

Initial attempts to apply the SMA approach for forest degradation monitoring in the conditions of insular Southeast Asia have encountered some problems. Franke et al. (2012) tested the SMA approach in a flat and rather homogeneous peat swamp forest area in Central Kalimantan to map degradation caused by logging and fire using RapidEye satellite data. The results were generally positive, allowing e.g. extraction of logging trails with 98% accuracy, and thereby indicating a great potential of this approach. However, their study also revealed important limitations, most notably the fact that the end-member selection for the SMA approach would have to take into account the variation in spectral reflectance caused by topography and atmospheric conditions. Such limitations greatly complicate the use of SMA for analyses over large areas (typically more than one satellite scene) in the difficult climatic and topographic conditions of insular Southeast Asia. Bryan et al. (2013) used the CLASlite software (Asner et al., 2009) to apply the SMA approach with Landsat data in their study in Sarawak for a basic tree/palm vegetation classification, but visual interpretation was needed to separate natural forests from plantations, and subsequently they resorted to visual secondary indicator (i.e. logging road) mapping to estimate the extent of degradation. Carlson et al. (2013), likewise using CLASlite, applied the SMA approach followed by a decision tree classification step for land cover mapping, in a study focusing on oil palm conversion over the entire Kalimantan (i.e. Indonesian part of Borneo Island). By excluding areas with atmospheric disturbances and masking out slopes $>15°$ (to avoid issues related to topography) they managed to obtain ~60% coverage of Kalimantan using ±4 years of Landsat data around their target years. They took into account the remaining atmospheric and topographic effects as well as variation of vegetation conditions over Kalimantan in the design of the decision tree classification. The approach resulted in the mapping of two basic forest classes of 'intact' and 'logged' forests (in addition to two non-forest classes) with 77% overall accuracy. This information was considered sufficient to produce meaningful results for the areas subjected to conversion to oil palm, i.e. areas almost entirely concentrated on elevation <100 m above sea level. Then again, this study highlights very well the obstacles in implementing automatic classification approaches for forest degradation monitoring in the insular Southeast Asian conditions, especially as most of the remaining forests are concentrated in mountainous inland areas (Fig. 1(a)), which do not only have generally steep landscape features (Fig. 1(b)) but are also very prone to persistent cloud cover.

Due to the minimal seasonal changes in insular Southeast Asia, on the one hand, and the extremely limited availability of cloud free observation, on the other, the feasibility and potential benefits of time series analysis for forest monitoring can be debated. It is a fact that the initial signs of logging visible from satellite data (i.e. the soil spectral signature corresponding to logging roads and gaps from logged trees) disappear in the humid tropics very fast due to fast regrowth of secondary vegetation. This would promote the importance of frequent monitoring to follow closely the temporal dynamics of reflectance signatures. However, it is also true that the vigorous regrowth vegetation that covers the scars in the canopy is also detectable in satellite data, prolonging the available time for degradation monitoring. Moreover, due to the atmospheric conditions, it has been impossible to obtain continuous time series with high to medium resolution data until very recently. Several authors (e.g. Broich et al., 2011a; Bryan et al., 2013; Carlson et al., 2013) have shown that the entire Landsat archive is not sufficient to create even annual gap free maps in the region. Broich et al. (2011b) and Margono et al. (2012, 2014) were able to produce results on the spatio-temporal distribution of deforestation in Indonesia using a long time series of

Landsat data. But they were not able to derive information on forest degradation using time series analysis. Comparing to the conditions in the Amazon, a study conducted in Mato Grosso state of Brazil, showed that annual mean values of selected parameters derived from spectral channels of Landsat imagery (e.g. green vegetation fraction) could be used for monitoring logging and fire induced degradation through long-term time series analysis (Morton et al., 2011). However, Mato Grosso has somewhat more seasonal climate (with a short dry season around July–August) and less persistent cloud cover than most of insular Southeast Asian forest areas, which likely increases the availability of satellite images.

Until now, nearly all large scale forest degradation estimates in insular Southeast Asia have been derived by visually mapping either primary or secondary indicators of forest degradation (e.g. canopy openness, logging roads, villages, waterways, power lines). The global study by Potapov et al. (2008) already presented above covered the entire insular Southeast Asia and provided valuable information on the general distribution of the major intact forest landscapes. Margono et al. (2012, 2014) later utilized this approach in their Indonesian deforestation studies to derive information on forest degradation at 5-year intervals. Miettinen and Liew (2010) used visual interpretation of SPOT 4 and 5 images to delineate areas of peat swamp forest with visible signs of degradation including e.g. canopy openness, fire scars, small-holder encroachment and logging canals. They classified all remaining peat swamp forests into four categories including intact forest and three intensities of degradation. Several authors utilizing visual interpretation have concentrated specifically on selective logging. Shearman et al. (2009) incorporated visual delineation of logging roads on SPOT and Landsat images into their forest and land cover mapping scheme in Papua New Guinea and visually defined a timber extraction radius (100–500 m) around them. In the Sarawak study already mentioned above, Bryan et al. (2013) mapped and buffered all logging roads with a 350 m buffer using Landsat images acquired since 1990 to estimate the extent and 'intensity' (i.e. frequency of repetition) of logging induced disturbance. And most recently, Gaveau et al. (2014) published forest cover change results for Borneo Island 1973–2010 with the extent of selectively logged forests derived by visually mapping logging roads on Landsat data. They defined the width of the buffer around logging roads (700 m) by analysing tree cover percentages derived from MODIS data.

Due to the closed dense canopy with multiple layers, the direct estimation of forest parameters (e.g. basal area, biomass) is generally not considered feasible in the humid evergreen forests of insular Southeast Asia using optical remote sensing data. As a result of its cloud and canopy penetrating characteristics, radar data offer tempting possibilities for biomass estimation in the humid tropical forests. However, low saturation levels of above ground biomass (AGB) estimates due to the inadequate depth of canopy penetration even with the longest currently available space-borne radar wavelength (L-band) essentially prohibits large scale usage of radar data in humid tropical forests (Mitchard et al., 2009; Morel et al., 2011). According to a study performed on Central Kalimantan peatlands, the saturation level can be somewhat raised (up to $\sim$300 t/ha AGB) on flat terrain with a combined used of L-band and X-band radar data (Englhart et al., 2011). Adding to the saturation problems is the fact that the remaining forests can largely be found on mountainous and often steep landscape in insular Southeast Asia (Fig. 1(a) and (b)), leading to associated issues with topography, including e.g. hill shadows. Thereby, it is unlikely that spaceborne radar data could be successfully used for large area biomass or degradation monitoring in the region with the currently available datasets in the near future. A new satellite with a P-band radar sensor is planned to be launched in 2020 as ESA Earth Explorer Core mission: the BIOMASS mission is aimed at mapping and monitoring the distribution of forest biomass globally (Le Toan et al., 2011) and will thereby possibly offer means for forest degradation monitoring as well.

Recently, airborne LiDAR measurements have shown high potential for biomass estimation in insular Southeast Asia, in some cases reaching r^2 close to 0.90 (Kronseder et al., 2012; Jubanski et al., 2013). However, due to the limited coverage and high associated costs, airborne LiDAR data alone cannot be expected to be used for large scale mapping. In South America, LiDAR sampling has been used in combination with wall-to-wall datasets to derive large scale estimations of biomass (Asner et al., 2012). Repetition of these types of assessments in suitable time intervals would allow monitoring of the development of biomass levels.

5. Synthesis and conclusion

In the preceding sections we have outlined the main geographical, ecological and historical issues affecting remote sensing based forest degradation monitoring in Southeast Asia and contrasted these regional characteristics to the available monitoring approaches utilizing high to medium resolution satellite data. The differences in the characteristics of the continental and insular parts of the region cause to some extent different types of challenges for remote sensing based forest degradation monitoring. In the seasonally dry continental Southeast Asia specific difficulties are mainly related to (1) the variety of natural forest types (e.g. in the openness of canopy) and (2) the intra-annual variability of radiometric reflectance in the satellite data related to the seasonality of vegetation. In the per-humid Southeast Asia the limited availability of cloud free images combined with issues related to the variability of reflectance values due to remaining atmospheric effects has largely directed the development of methodologies until now. Throughout the region, steepness of the landscape complicates forest degradation monitoring by remote sensing.

Regardless of these difficulties, several authors have achieved promising results on single date image analysis on forest disturbance using automated or semi-automated methods. However, the majority of such studies have been geographically limited, allowing the authors to fine tune their image processing and analysis tools for the specific dataset and area (Table 1). Furthermore, a number of limitations have been documented (e.g. Franke et al., 2012; Langner et al., 2012; Mon et al., 2012b; Carlson et al., 2013): (1) the extent of natural forest area should be known, or should be first reliably mapped, in order to put any subsequent findings in a focused context. This information alone can be difficult to produce in some parts of the

Table 1
Comparison of category 1 and 3 studies (i.e. 1. detection of direct degradation indicators on a single date or composite image and 3. mapping of secondary indicators) conducted in Southeast Asia. The studies have been ordered according to increasing size of study area. Note that we are not aware of any studies using time series analysis to detect degradation (i.e. category 2) in the region to-date and studies on direct estimation of forest parameters (i.e. category 4) are not listed as they do not particularly concern with forest degradation analysis, although their results may be useful for this purpose if repeated regularly.

Sub-region	Authors	Category		Primary dataset	Coverage (km^2)	Methodology used in degradation analysis	Forest type
		1	3				
Continental Southeast Asia	(Mon et al., 2012b)	X		Landsat ETM+	~2700	Comparison of three semi-automated classification methods to derive canopy cover percentage.	Deciduous
	(Hame et al., 2013a)	X		ALOS AVNIR and PALSAR	~22 000	Unsupervised fuzzy classification with a sample of very high resolution data (2–4 m) to support medium resolution mapping.	Evergreen to deciduous
	(Messerli et al., 2009)		X	Existing land cover maps	~237 000	Land cover mosaic analysis to detect the extent and intensity of shifting cultivation.	Evergreen to deciduous
	(Potapov et al., 2008)		X	Landsat TM and ETM+	~2 200 000 (entire sub-region)	Visual analysis of signs of anthropogenic disturbance combined with GIS analysis of auxiliary datasets (e.g. roads).	Evergreen to deciduous
Insular Southeast Asia	(Langner et al., 2012)	X		Landsat ETM+	~830	Degradation index taking advantage of SWIR reflectance.	Evergreen
	(Franke et al., 2012)	X		RapidEye	~4700	Spectral mixture analysis followed by decision tree classification.	Evergreen
	(Miettinen and Liew, 2010)		X	SPOT 4 and 5	~130 000	Visual detection of signs of anthropogenic disturbance.	Evergreen (peat swamp forest)
	(Wijedasa et al., 2012)	X		Landsat TM and ETM+	~200 000 (flat peatlands)	Maximum likelihood classification with post classification compositing.	Evergreen (peat swamp forest)
	(Bryan et al., 2013)		X	Landsat TM and ETM+	~200 000	Buffering of visually detected logging roads.	Evergreen
	(Carlson et al., 2013)	X		Landsat TM and ETM+	~320 000 (excl. steep landscapes)	Spectral mixture analysis followed by decision tree classification.	Evergreen
	(Margono et al., 2012)		X	Landsat ETM+	~450 000	Visual analysis of signs of anthropogenic disturbance combined with GIS analysis of auxiliary datasets (e.g. roads).	Evergreen
	(Shearman et al., 2009)		X	Landsat and SPOT	~460 000	Buffering of visually detected logging roads.	Evergreen
	(Gaveau et al., 2014)		X	Landsat MSS, TM and ETM+	~740 000	Buffering of visually detected logging roads.	Evergreen
	(Margono et al., 2014)		X	Landsat ETM+	~1 900 000	Visual analysis of signs of anthropogenic disturbance combined with GIS analysis of auxiliary datasets (e.g. roads).	Evergreen
	(Potapov et al., 2008)		X	Landsat TM and ETM+	~2 700 000 (entire sub-region)	Visual analysis of signs of anthropogenic disturbance combined with GIS analysis of auxiliary datasets (e.g. roads).	Evergreen

region due to the challenges in mapping seasonal forest cover and coping with other effects (e.g. topography); (2) current approaches most often need an image-by-image sample area/end-member collection, jeopardizing the consistency of the analysis over large areas; (3) most of the successful studies have been performed on relatively flat and homogeneous forest areas, avoiding topographic issues and therefore not reflecting the reality in the vast majority of the remaining forest areas in Southeast Asia; (4) empirically defined thresholds of parameters/indicators have been used to define categories for degradation, thereby putting extreme pressure on the radiometric calibration of large datasets; (5) automatic filtering or manual clean-up of the results has often been used, potentially reducing the reliability of comparisons to subsequent assessments. Finally, it is worth noting that to our knowledge no studies conducted in Southeast Asia so far has been able to apply multi-temporal time series analysis to forest degradation monitoring, although it has been used in deforestation monitoring (Broich et al., 2011b; Margono et al., 2012, 2014).

With such a list of limitations, it is very difficult to implement locally developed methodologies into large area assessments. The propagation of automated approaches over large areas, often with a limited set of generally poor quality satellite data (affected by both atmospheric and topographic issues) has proven nearly impossible until now. Satellite data quality problems may have been further exacerbated by changing viewing angles and compatibility issues when using data from different satellite sensors to obtain large area image coverage (e.g. the SPOT satellite series and RapidEye). Consequently, nearly all forest degradation mapping efforts over large areas in the region to-date have been performed using visual interpretation (Table 1). These assessments have provided valuable information on the extent and distribution of potentially degraded forest areas over the region. However, the unavoidably subjective nature of visual interpretation as well as the slowness and laboriousness of the effort greatly complicate the use of visual interpretation in operational forest degradation monitoring over large areas.

It is evident from the literature review that the implementation of the knowledge obtained in local small scale studies into large area assessments of forest degradation is currently the most important research gap and obstacle for operational forest degradation monitoring in the region. This is partially a scientific problem (i.e. finding the most suitable methodologies, coping with topographic and atmospheric effects) but also largely a technical problem (i.e. obtaining a high quality set of satellite data). As far as the latter is concerned, the expected dramatic increase in high to medium resolution satellite data observation frequency enabled by the upcoming Sentinel-2 twin satellites (10–20 m) and the already functioning Landsat 8 (30 m spatial resolution) may prove to be a crucial step forward. These two satellite systems together will provide the systematic coverage of all land areas in the region in <5 day observation frequency with fixed viewing angles and image acquisition times. This type of data should allow implementation of time series analysis in high spatial and temporal detail and derivation of full coverage cloud free datasets in unprecedented intervals. The scientific challenge in the next few years will be to develop operational approaches for forest degradation monitoring, fine-tuned for the continental and insular Southeast Asian conditions, taking advantage of the body of knowledge accumulated by the small scale studies and the increased amount of high to medium resolution satellite data provided by the new satellite systems.

We conclude that the range of characteristics of forest types and remote sensing conditions in Southeast Asia is so large that a single forest degradation monitoring approach is unlikely to work adequately throughout the region. Locally developed approaches allow case-by-case assessments of the level of degradation in small target areas, but do not enable production/derivation of regional level syntheses. The results achieved in different parts of the region with a range of locally fitted methods are currently not fully comparable to each other. Therefore, regionally robust and consistent approaches to assess and operationally monitor forest degradation throughout the region are urgently needed for the upcoming REDD+ era. The near future will tell whether the highly anticipated increase in the observation frequency of high to medium spatial resolution satellite imagery will allow a crucial improvement of existing methods and enable monitoring of forest degradation consistently and accurately in the whole region of Southeast Asia.

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