Remote sensing of forest degradation: a review

Yan Gao, Margaret Skutsch, Jaime Paneque-Gálvez and Adrian Ghilardi
Centro de Investigaciones en Geografía Ambiental, Universidad Nacional Autónoma de México, Morelia, México
E-mail: ygao@ciga.unam.mx
Keywords: forest disturbance, illegal logging, forest fires, shifting cultivation, fuelwood collection, pests, hurricanes, tsunamis, over-hunting, time series analysis, spectral mixture analysis, satellite images

Abstract
Forest degradation affects forest structure, composition and diversity, carbon stocks, functionality and ecosystem processes. It is known to contribute significantly to global carbon emissions, but there is uncertainty about the relative size of these emissions. This is largely because while deforestation, or long-term forest clearance, has been successfully monitored using remote sensing (RS) technology, there are more difficulties in using RS to quantify forest degradation, in which the area remains as forest, but with an altered structure, composition and function. A major challenge in estimating emissions from forest degradation is that in addition to identifying the areas affected, the amount of biomass loss over time in a given area must be estimated. Contributory challenges to mapping, monitoring and quantifying forest degradation include the complexity of the concept of degradation, limitations in the spatial and temporal resolution of RS sensors, and the inherent complexity of detecting degradation caused by different disturbance processes and forest uses. We take the innovative approach of dividing the studies reviewed by the specific type of forest disturbance that is being monitored (selective logging, fires, shifting cultivation and fuelwood extraction etc.), since these different activities will result in different signatures in the canopy and thus may determine the type of RS technology that may best be applied.

1. Introduction
Both deforestation and forest degradation contribute to global carbon emissions, and reporting on both are required by the United Nations Framework Convention on Climate Change (UNFCCC). Forest degradation is broadly understood as disturbance caused by human actions in a forested landscape and is generally defined by FAO as a reduction of the capacity of the forest to provide goods and services (FAO, 2010). In the context of climate change, forest degradation is considered a process that results in carbon emissions from forest but not in a change in land cover type (GOFI, 2016, p. 19). In addition to the removal of some standing trees e.g. for selective timber extraction, it can include extraction of biomass below the canopy cover, for example by cattle browsing freely or where there is cyclical use of forest for shifting cultivation. Forest degradation is usually a gradual process—though it may be induced by quick, single events like hurricanes—and it may involve long-term and severe environmental changes (Thompson et al 2013, Mietinnen et al 2014).

Global estimations of the carbon emissions originating from forest degradation range from 40%–212% of those from deforestation (Baccini et al 2017, Pearson et al 2017). The large uncertainty about emissions from forest degradation is mainly due to the difficulty of monitoring forest degradation over large areas. While monitoring deforestation requires only an estimate of the area cleared plus a default figure representing the average carbon content per hectare of the given forest type, for degradation two variables are needed: the area affected, and the quantity of biomass lost in any given area over a given time, which will vary with the intensity of the degradation as well as with the natural biophysical characteristics of the forest (Goetz et al 2015). Given that 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 2011), it is crucial that efficient and reliable methods to measure degradation are developed.

Most studies on remote sensing (RS) of forest degradation have focused on selective logging and fires in humid tropical forests (Asner et al 2005, 2009, Souza et al 2005a, Souza et al 2005b, 2013), although there is increasing attention to low intensity disturbances such as shifting cultivation, fuelwood collection, and cattle grazing (Hett et al 2012, Ryan et al 2012, 2014). Given the importance of mapping, monitoring and quantifying forest degradation in the context of climate change research and the challenges involved with RS technology, we consider that a research review on forest degradation using RS technology is highly relevant. Among the few previous review papers, Goetz et al (2015) include a short section on the use of RS for monitoring degradation, though most of the article is dedicated to deforestation. They discuss the potential of high resolution optical imagery for this purpose, but suggest that it may be easier to use indirect proxy data, given the difficulties involved with RS. Since that time, however, there have been important developments in RS technology. Hirschmugl et al (2017) focus on high spatial resolution optical data with a limited range of RS methods including only a two-time comparison change detection and time series analysis. Mitchell et al (2017) address two approaches, namely the detection of changes in canopy cover or proxies and the quantification of loss (or gain) in aboveground biomass; however, they focus only on sub/tropical forests and the specific data needs of Reduced Emissions from Deforestation and forest Degradation (REDD+) policy. Similarly, the review published by Dupuis et al (2020) is limited in that they focus solely on tropical moist forest, leaving aside dry tropical forests which form more than half of all tropical forests and which are arguably more subject to degradation than moist forest, moreover they look only at questions of spatial resolution. None of these otherwise excellent papers look at the potential of RS data and methods to distinguish the signatures of different kinds of degradation caused by different forest uses. Only Mitchell et al (2017) address the three-dimensional aspect of measuring degradation, though they do not include the current potential of drones. Our paper reviews forest degradation by different causes such as unsustainable logging, fires, forest agriculture practices, fuelwood extraction, hurricanes and pests. It discusses what detectable patterns these might leave on the structure of forest, and what the possibilities of measuring aboveground biomass loss over time in a given location may be. In addition, we review not only optical RS systems but also LiDAR, radar and the potential for various systems mounted on drones.

2. Objective and article selection criteria

This review intends to bring the challenges of mapping, quantifying and monitoring degradation using RS to the attention of the broader community concerned with forest degradation (as opposed to deforestation) and particularly to the attention of non-RS specialists, including those working in the area of climate change and REDD+. Many such professionals have pinned high hopes on the ability of RS to provide solutions or assume that methods for measuring deforestation can be applied equally well for degradation, which is not the case.

We based the search for articles on the following keywords: selective logging, illegal logging, shifting cultivation, swidden agriculture, slash and burn agriculture, cattle grazing, fuelwood extraction, hurricanes, tsunamis, pests, and insects in a combination with the keywords RS, forest degradation and forest disturbance, using the search engines of Google Scholar and Scopus. In addition, we used a heuristic approach based on our knowledge on the topic and searched for all the relevant papers from well-established scientists within the field. We further found relevant articles after a careful inspection of the literature cited in such papers by key authors. Only peer-reviewed journal articles from 2000 to 2020 were considered (figure 1), and we selected for inclusion in the study only those which explicitly applied RS methods to the detection and/or monitoring and/or quantification of degradation and in which a given forest area was assessed for degradation over at least two dates, since degradation implies a process over time, and can only be quantified through comparison with a baseline condition (Thompson et al 2013). This filtering resulted in a total of 139 articles that were considered relevant in demonstrating the state of the art on the topic of concern. Most of the selected articles (82%) were published 2008–2020. The large number of articles in this period reflects growing needs for data on forest degradation in connection with the development of UNFCCC REDD+ policy, as well as technological developments in RS platforms, sensors, data and methods.

3. Challenges to operationalizing forest degradation using RS

There are many challenges and limitations in the measurement of forest degradation with RS, starting with the fact that definitions of forest and forest degradation vary. In addition, the spatial, spectral and temporal resolution of RS sensors may be insufficient to accurately detect degradation.
3.1. Definitions of forest and forest degradation

A clear definition of forest is important to determine forest cover change, and to define the areas in which forest degradation may occur. There are more than 50 definitions of forest reflecting biophysical differences in forest formation, perceptions, objectives (use/management) and values (FAO 2006, Putz and Redford 2010, Ghazoul and Chazdon 2015, Buetel et al 2017); many of these definitions are summarized in Morales-Barquero et al (2014). UNFCCC defines forest as land in which tree cover predominates with a threshold canopy cover of minimum 10%–30%, height (in situ) of minimum 2–5 m at maturity, and area of minimum 0.05–1.0 hectare, the specific choice of threshold values being made by each country (UNFCCC 2002). Before degradation was added into UNFCCC reporting requirements, various scholars (Mollicone et al 2007, Sasaki and Putz 2009) argued that the UNFCCC had set the threshold for canopy cover too low, as by this definition, woodland could be severely degraded under a logging regime but still be classified as a forest; the country would not have to report this as deforestation, so the emissions produced would not be accounted for. However, since reporting on degradation is now required, this should no longer be a problem (Goetz et al 2015). A further definitional question relates to the type of trees that should be considered as a forest formation, for example whether plantations of pine or eucalyptus, and plantations of tree crops, notably palm oil and avocado, should be considered ‘forest’. This has been a major area of dispute in the REDD + negotiations.

For the purposes of climate change reporting, forest degradation is defined as a human-induced loss of forest carbon stocks which are not already accounted for under deforestation (IPCC 2003). Forest degradation denotes thinning of the canopy and loss of carbon in remaining forest and within a clearly defined time window, where damage is not associated with a change in land use and where, if not hindered, the forest is may regrow, recovering the carbon and biomass but not necessarily all the goods and services it used to provide such as biodiversity. The definitions of forest degradation proposed by relevant international policy bodies however vary depending on whether the focus is on ecosystem services in general or specifically on carbon content (FAO 2011, Morales-Barquero et al 2014).

Some authors argue that a universal definition of forest degradation is not necessary for REDD + activities under the UNFCCC, and that the emphasis should be on monitoring persistent declines of carbon stock overtime and stratified for different activities that remove the carbon from the forest where there is no overall loss of forest cover (Guariguata et al 2009). The main challenge is to adequately define the baseline carbon stocks and monitor their change over time to assess the decline. These authors argue that RS can be used to measure timber harvest over large areas, but for the quantification of carbon stock loss from low-intensity timber harvest (Gaveau et al 2014), fuelwood collection, and understory thinning for example caused by cattle grazing we may have to rely on direct, ground level observation.
3.2. Limitations of spatial and temporal resolution of RS data

RS is widely recognized as an effective way of land use mapping and for land cover change analysis (Rogan et al 2004), for retrieval of land surface characteristics such as vegetation leaf area index (Ganguly et al 2008), for identifying areas of forest disturbance, and also for biomass estimation and carbon flux change studies (Frolking et al 2009, Griffiths et al 2014, Harris et al 2016). In the context of climate change, it is most commonly used to detect deforestation (Sanchez-Azofeifa et al 2001, Chowdhury 2006). However, as we have noted above it is more challenging to monitor forest degradation with RS, since degradation involves much more than just canopy cover change, and cannot simply be equated with this. Some types of degradation result in structural changes below the canopy which cannot easily be detected from above, and in any case biomass losses do not necessarily correlate well with canopy cover change. Moreover, degradation often occurs at spatial temporal scales often below the detection capabilities of most RS technologies, especially those of satellite multispectral sensors (Miettinen et al 2014, Buettel et al 2017). Coarse spatial resolution sensors such as MODIS have a pixel size of 250 m or greater and this spatial resolution is generally regarded as too coarse for mapping forest degradation, although its high temporal resolution can help smooth the time series and thus partially compensate for the coarse spatial resolution. Hence MODIS data can be used to indicate near-real time forest changes, and may be useful for early warning of forest degradation (GOFI 2016). Among the RS systems with medium spatial resolution imagery, Landsat with spatial resolution of 30 m is one of the most commonly used sensors for monitoring forest cover change (including degradation). Its historical archive is important for establishing reference levels as required in climate policy. However, despite its widespread application in forest degradation detection, its capacity is limited, especially in small scale, local level degradation detection, for example that caused by low intensity selective logging in specific locations (Ellis et al 2017, Hernandez-Gomez et al 2019). High spatial resolution images (finer than 10 m) are often used at a small scale and allow more accurate detection, but imply higher costs and more images for processing, making them less appropriate for national level analyses. Consequently, high resolution optical data have been used mainly to provide training data for detection algorithms or sample-based verification.

Temporal resolution also needs to be addressed in measuring the dynamics of forest degradation. Accurate characterization of forest degradation requires lengthy observation periods to track gradual forest change (Pinheiro et al 2016). Lambin et al (2003) suggested that satellite images with sufficient frequency are needed to differentiate the natural forest cover change that is due to phenology of vegetation, from forest degradation. Moreover, selective logging tends to leave small openings in the canopy, the detection of which not only requires higher spatial resolution images but also images with higher temporal resolution, as regeneration of the canopy cover may be rapid—particularly in the humid tropics—with neighboring trees rapidly taking advantage of the gaps (Franke et al 2012). Annual RS data can thus underestimate the extent of logging since evidence of logging disappears in 1–3 years, sometimes even within months after the event, depending on the severity of the damage (Matricardi et al 2005). Sub-annual time series analysis offers observations with higher frequency that help to capture the optical signature (such as from logging) before the evidence of logging disappears (De Sy et al 2012).

3.3. Propagation of uncertainty in forest degradation estimates

Regardless of the forest variable to be modeled (biomass, tree/canopy cover, or forest structure), the uncertainty of its relationship with the RS imagery for each date must be properly analyzed and propagated over the multitemporal comparisons (Mowrer et al 2000, Lu 2006, Pelletier et al 2012).

Aboveground biomass for example, is often calculated using allometric equations based on measured diameter at breast height and sometimes also tree height, meaning that plot-level data on aboveground biomass for each date comes with an estimation error that must be propagated further into biomass-RS relationships at each date (a source of uncertainty in its own), and between dates as well (Ryan et al 2012, Lu et al 2016). Equally important are errors introduced during atmospheric and geometric corrections of RS imagery and in the selection of RS-derived variables for the estimation models (Bullock et al 2020b). Paraphrasing McRoberts et al (2011), without a proper and complete evaluation of error sources in RS datasets, these would be of little utility for scientific inference. Ecosystem dynamics, such as dry vs wet seasons, can add varying degrees of uncertainty in aboveground biomass, tree cover, and forest structure estimations when using RS technology (McNico et al 2018). In the end, the best way to validate a given model for aboveground biomass and/or forest degradation, is to use independent datasets, but this is often a challenge as it means the validation dataset was not used during the construction of the model (i.e. for calibration). The challenge is to have enough calibration data for a robust relationship, without compromising the validation process.

It is well beyond this review to do an indepth exploration of uncertainty management in RS of forest degradation, but we stress that the main sources of error in single-date relationships
(e.g. between biomass and RS derived variables) must be accounted for, and further propagated throughout the multi-temporal comparisons that are needed to account for changes in forest density.

4. Detecting forest degradation by type of disturbance

This section provides a review of studies on assessment of forest degradation with RS, grouped by the types of disturbances which are considered to have caused the degradation. These include selective logging, fires, shifting cultivation, fuelwood extraction, pests, hurricanes, tsunamis, over-hunting and drought, all of which may cause reduction in forest carbon storage and hence to emissions.

4.1. Selective logging

Selective logging is one of the most well studied forest disturbances relating to degradation in moist tropical forests (Asner et al 2005, 2006, 2009, Oliveira et al 2007, Asner 2009, Shimabukuro et al 2014, Shimizu et al 2017). It is a pervasive activity in moist tropical forests: in the Brazilian Amazon it is a major source of forest degradation, possibly encompassing an area larger than that reported for deforested (Asner et al 2005, Bullock et al 2020b). In Southeast Asia unsustainable selective logging is also the dominant driver of degradation (Miettinen et al 2014). During the process of selective logging, a limited number of marketable tree species are cut, and logs are transported off site to sawmills. This causes a spatially diffuse thinning of large trees and as noted above, temporary gaps in the canopy cover, which are difficult to monitor by satellite observations (Asner et al 2005). Medium resolution satellite images such as Landsat (30 m) and SPOT (10–20 m) have been applied to measure forest logging since they can detect forest clearing down to 0.1 ha resolution (Asner 2009). For identifying selective logging, the temporal resolution is also important because of the fast regrowth especially in humid tropical forests (Souza and Roberts 2005a). Using a spectral mixture analysis (SMA), Asner et al (2009) showed that medium spatial resolution images such as Landsat, SPOT, ASTER, and ALI imagery data are nearly identical in detecting the forest clearings that are due to selective logging. Asner et al (2005) quantified selective logging between 1999 and 2002 by applying a Monte Carlo unmixing approach and using Landsat images to detect forest canopy openings, surface debris, and bare soil in the top five timber-producing states of the Brazilian Amazon. They found that selective logging added 60%–123% more forest damage than had been reported for deforestation alone in the same study period. In the Peruvian Amazon, forest degradation from selective logging increased regional carbon emissions by 47% over deforestation (Asner et al 2010). Shimizu et al (2017) found that the area selectively logged often correlates with the number of trees logged. Hethcoat et al (2019) mapped low intensity forest degradation in the Brazilian Amazon caused by selective logging using Landsat images and a Random Forest algorithm trained by a detailed selective logging dataset. Their study provided an effective method for detecting selective logging pantropically with freely available data sets and has positive implications for monitoring logging and implementing carbon-based payments for ecosystem service schemes in humid tropical forests affected by selective logging.

Although all these methods that use optical sensors estimate the areas involved in degradation, they do not at the same time produce estimates of the amount of biomass (or carbon) lost, nor do they assess the intensity or rate of biomass loss. LiDAR-based measurements can provide accurate measurements of features of logging activity such as roads, skid trails and gaps (Melendy et al 2018). Multitemporal LiDAR data can provide forest canopy and understory structure change and are therefore capable of characterizing forest degradation caused by logging and monitoring tropical forest biomass dynamics (Pinage et al 2019). Indirect estimation of greenhouse gas emissions was also tested by constructing regressions with timber volumes, considering features of logging including areas of roads, skid trails and gaps (Pearson et al 2018). Fast recovery is another characteristic of logging, and time series SMA is therefore a promising method for its detection (Bullock et al 2020b, Pinheiro et al 2016).

4.2. Fires

In addition to selective logging, fire, both natural and induced by human activities, is a major cause of forest degradation (Nepstad et al 1999, Hosonuma et al 2012). Forest fire susceptibility often increases substantially following unsustainable logging activities that open the canopy, make the microclimate drier and increase the amount of dry fuel (Gerwing 2002, Cochrane 2003, Asner et al 2006). Forest fire is also related to shifting cultivation in tropical forest areas where fire is often used to prepare cultivation fields in denser forests or for clearance of the ground vegetation layer in open forests (Thompson et al 2013, Miettinen et al 2014). Forest fires may also occur in undisturbed forests, especially during extreme droughts and El Niño events (Aragão et al 2018, Nepstad et al 2004, Matricardi et al 2010). The frequency and extent of fire is likely to increase in the future because of larger, longer, and more severe droughts associated with global warming (Thompson et al 2013, Yang et al 2018), as exemplified by the temperate forest fires that occurred in eastern Australia between September 2019 and January 2020 (Boer et al 2020).
RS has been widely used to map and quantify forest fire extent—from local to global scales—as well as to assess pre-fire susceptibility, fire effects and post-fire recovery, among other issues (Chuvieco et al 2020). For the assessment of fire effects—including emissions—RS datasets have focused primarily on detecting active or past burned areas (Chuvieco et al 2020). Shimabukuro et al (2019), for instance, mapping burned areas in the Brazilian Amazon based on multi-temporal Landsat segmentation of shade fraction images (the areas related to degradation processes were those that were burned but remained as forest). They found that degradation by fire has increased in frequency and extent in forested areas and has become one of the main causes of forest degradation and carbon emissions in the Amazon basin. Another recent study in the Brazilian Amazon also based on Landsat found that, compared with forest canopy cover impacted by selective logging activities, forest disturbed by fires recovers more slowly (up to 5 years) (Matricardi et al 2013). Lohberger et al (2017) used high-spatial resolution Sentinel-1A SAR imagery (10 m) to classify burned areas in Indonesia’s 2015 fires and to estimate emissions from them. In addition to the spatial resolution of the SAR dataset, its radar imagery has the significant advantage of not being affected by cloudiness, smoke and haze and it can, therefore, map active fires or burned areas closer to the fire event, which may reduce errors such as those derived from rapid tropical vegetation regrowth (Siegert and Hoffmann 2000).

To date, however, much less attention has been paid to the appraisal of forest fire intensity (i.e. energy released) and fire/burn severity (i.e. organic matter loss) (sensu Keeley 2009), which is key to attaining more accurate estimates of emissions. An outstanding effort toward this is the Monitoring Trends in Burn Severity program, which was established in 2006 in the US (http://www.mtbs.gov), aiming at assessing location, extent, burned area boundaries and burn severity based on Landsat multitemporal analysis of large fires (≥202 or 405 ha depending on location) (Picotte et al 2020). The MTBS program defined burn severity as visible alteration of vegetation, dead biomass and soil that occurs within a fire perimeter (Eidenshink et al 2007). MTBS analysts map burn severity within four classes (unburned vs low, moderate, or high burn severity) and correlate RS-derived indices such as the difference Normalized Burn Ratio—dNBR, that estimates changes in reflectance from vegetation and non-vegetation surfaces after a fire—with ground assessments from plots (e.g. through the Composite Burn Index, CBI, which assesses damage to live and dead biomass). Although the MTBS dataset is extremely valuable, there are still significant omission and commission errors in the burned area product (Picotte et al 2020). In addition, the classified severity product is of limited use to research due to lack of consistency in developing severity class thresholds and of empirical relationships with ecological metrics (Kolden et al 2015). The latter issue is of particular concern in the context of this review because the lack of spatially and temporally comprehensive field data impedes direct measures of the ecological effects of burn severity (Picotte et al 2020). All these significant limitations severely hamper the estimation of emissions. Therefore, assessing the differential impact of fires on forest degradation—depending on their severity—and the resulting differences in emissions needs substantial improvement in ground data coverage as well as in the consistency and accuracy of RS burned area and burn severity maps.

An effort worth mentioning that focuses specifically on emissions is the Global Fire Emissions Database (GFED), which is now available in its fourth version and which has a spatial resolution of 0.25 degrees (www.globalfiredata.org). Van Der Werf et al (2017) used the GFED with an upgraded modeling system and higher quality input datasets to quantify global fire emission patterns during 1997–2016. Improvements in estimates were achieved by the inclusion of a small fires layer that led to more accurate burned area maps, more comprehensive ground data that enabled enhanced representations of fuel consumption (including that in frequently burning landscapes), and differences in natural patterns of fire severity across biomes (e.g. combustion completeness and fire-induced tree mortal-ity in the boreal forests of North America are significantly higher than in their counterparts of Eurasia and such differences were accounted for). However, uncertainties in all data layers are still substantial, particularly at higher resolutions and regarding the small fire burned area approach. Therefore, this dataset is of limited usefulness to analyze fire emissions from forest degradation at local and landscape scales.

### 4.3. Fuelwood collection and shifting cultivation

Fuelwood collection and shifting cultivation both cause low intensity yet noticeable changes in forest structure. Since fuelwood collection for traditional energy does not usually cause extended forest canopy change but mostly affects forest density, it is often difficult to detect using RS methods (Peres et al 2006). Few RS methods have been reported so far for this use, and such studies have had to rely heavily on ground data for calibration and for disentangling the underlying causes of the observed changes (Ryan et al 2014). However, harvesting of firewood and production of charcoal are very common practices in rural areas of developing countries, although their intensity varies from place to place (Heltbert et al 2000, Davidar et al 2010, Miettinen et al 2014, Bologna et al 2015). Fuelwood harvesting is known to be more...
likely to occur nearer to areas of human habitation and its impacts vary greatly, depending on the local conditions (Helbert et al. 2000, Davidar et al. 2010). For example, the presence of alternative fuel in rural communities can have an important impact on the biomass and regeneration in the surrounding forests (Agarwala et al. 2017). In some places, fuelwood consumption represents a source of chronic degradation and has the potential to threaten biodiversity and cause net carbon emissions (Mahiri and Howorth 2001, Specht et al. 2015). Estimations of forest degradation resulting from domestic consumption can be difficult to document and estimate at larger scales (Garcia-Barrios et al. 2009). It is significant that in much of the literature estimating fuelwood impact on forests, RS methods were not applied, and few spatially explicit mappings of fuel-related forest degradation have been carried out. Bologna et al. (2015) quantified the impact of charcoal production on forest cover loss using very high spatial resolution satellite imagery (0.5 m). By using literature, and local knowledge based assumptions on ranges of kiln and tree parameters, they estimated an average production of 24 000 tons of charcoal and 2.7% tree loss for the 2 year interval (2011–2013). Ryan et al. (2014) quantified drivers of forest degradation in Mozambique by relating the biomass change to field-identified drivers. They found that charcoal production was responsible for about 13% of the biomass loss in the study area. Low intensity forest degradation from fuelwood gathering could not be successfully monitored with Landsat images and requires higher spatial resolution images.

Shifting cultivation causes temporal vegetation dynamics: trees are cut down and burned, the land is used for a few years for agriculture, and thereafter left fallow, such that secondary forest grows. It is often cited as being responsible for deforestation as well as forest degradation in tropical regions, although this would only occur if the land did not regenerate forest during the fallow. We note however that in some countries shifting cultivation is considered to be an agricultural land use and therefore not a temporary use of forest. In this case, the initial change from forest to shifting cultivation is considered to represent deforestation and subsequently the area remains non forest and is not monitored for forest emissions. This is a pragmatic approach for countries and avoids having to try to capture ongoing degradation in shifting cultivation systems, but in most cases it does not reflect reality, since typically shifting cultivation involves cyclical use of forest land with periods of fallow which are characterised by natural regeneration of (secondary) forest. Shifting cultivation leaves cleared patches that are sometimes considerably larger than those caused by selective logging (sometimes up to 1–3 ha, although most parcels are significantly less than 1 ha). A challenge in the quantification of small scale shifting cultivation is that it produces a mosaic landscape that is often misclassified in a system of discrete land cover classes (Mertz 2009). These patches may be visible for a few years but they become covered with secondary vegetation and disappear in the longer term (10–20 years). Not surprisingly, there is often confusion about whether clearances observed are temporary, for shifting cultivation, or permanent, indicating long term land use change, when the change analysis is done using RS. Hett et al. (2012) applied a landscape mosaic approach for forest degradation assessment to capture shifting-cultivation practices in Laos using Landsat images. Instead of looking at the spatial-temporal changes at the pixel level, they characterized the deforestation and forest degradation at landscape mosaic level and showed that the area subject to shifting-cultivation has increased in extent and that practices of shifting cultivation have caused forest degradation. However, although they were able to quantify the areas involved, they were not able to assess the intensity of loss of biomass per hectare. Hurni et al. (2013) carried out a spatially explicit analysis to delineate the dynamics of shifting cultivation landscape in northern Laos based on analysis of time series of MODIS and Landsat data and landscape metrics. They found an overall reduction in the area dominated by shifting cultivation, although some regions showed an expansion. Again, though they could assess the area change, they could not show how much biomass was lost. Shifting cultivation exemplifies the problem of estimating changes in carbon stocks in forests and woodlands (Mertz 2009), although high frequency time series radar data have shown promising results in detecting carbon change in shifting cultivation (Ryan et al. 2012).

It is worth mentioning that although in some parts of the world free cattle grazing in forests is an additional cause of forest degradation, as a result of browsing on young tree shoots and trampling of soil, we were not able to find any scientific articles which attempt to assess this through RS. Human collection of cattle fodder from forests is also a potential degradation factor which has not been addressed in this sense.

4.4. Hurricanes, tsunamis, pests, invasive species, over-hunting and drought

Natural phenomena such as hurricanes and tsunamis affect forest ecosystems and human livelihoods and may result in intense degradation over quite large swathes of forest (much more intense than degradation caused by fuelwood harvesting, selective logging or shifting cultivation). For instance, a single major event can significantly reduce the carbon storage and sequestration capacity in coastal forests (Mcnulty 2002). Areas hit by these natural disturbances are easy to identify in remotely sensed images because of the widespread destruction in canopy
cover and structure, clearly established spatial patterns of landfall and penetration, and a known date of occurrence (Sirilukchayanon et al 2008, Klemas 2009, Rogan et al 2011). As with any forest disturbance, the accurate estimation of the ecological effects of tsunamis and hurricanes (e.g. carbon uptake and release) requires robust ground data at the plot level, though RS approaches have been developed to assess forest damage at larger scales without ground inventories (e.g. Wang et al 2010, Gang et al 2020).

Hurricanes are a dominant disturbance agent in areas that are particularly prone to them, such as the Yucatán Peninsula of Mexico, where Rogan et al (2011) used MODIS enhanced vegetation index data and found that most wind-damaged plots were in medium-statured forest and mangrove dominated vegetation. Ellis et al (2017) showed that hurricane damage is exacerbated by fires that later consume the fallen vegetation, and that hurricanes are therefore directly or indirectly one of the important sources of degradation in this area. Chambers et al (2007) mapped hurricane Katrina’s impacts on U.S. Gulf coast forests using SMA on Landsat and MODIS imagery. They calibrated a gradient of changes in non-photosynthetic vegetation with ground plot data where they quantified tree mortality and damage, species composition, and biomass loss. Finally, they developed an empirically-based Monte Carlo model to estimate carbon footprint of the hurricane, which they estimated as equivalent to 50%–140% of the net annual U.S. carbon sink in forest trees. Zeng et al (2009) synthesized field measurements, satellite image analyses, and empirical models to assess forest and carbon cycle impact for the continental U.S. from 1851 to 2000. Their results showed averages of 97 million trees affected each year, 53 tons annual biomass loss and 25 tons of carbon release per year.

Pests and insects may cause defoliation, affect tree health and even cause tree mortality, all of which can be detected with optical RS (Hall et al 2016, Senf et al 2017). For example, several vegetation indices can be used to detect the changes in the vigor of affected forests (Eklundh et al 2009). The effect on carbon stocks is not necessarily immediate, since pests may affect long-term natural forest growth rather than standing stocks. Nonetheless, factors such as climate change and forest mismanagement facilitate more severe outbreaks of pests and insects that can lead to significant tree mortality across large tracts of forests and, subsequently, to substantial increases in carbon emissions (Kurz et al 2008a, 2008b, Seidl et al 2018). In certain areas, however, carbon emissions may be overcome by forest enhanced carbon uptake owing to the rise in atmospheric CO₂ concentration (Arora et al 2016). RS data on forest degradation related to pests and insect outbreaks have been key in most studies that use models aimed at calculating emissions due to such disturbances. Because of the differential severity of outbreaks on forest at the stand and landscape levels, extensive ground plot data is necessary to decrease model uncertainty.

Among the studies on forest degradation due to pests and insect invasion, Eklundh et al (2009) applied a multi-temporal MODIS 16-day composite vegetation index to map the defoliation caused by pine sawfly. Their method uses differences in summer mean values and angles of the seasonal profiles to indicate decreasing foliage density and to identify pixels with forest damage, which could locate insect damage, although not the damage intensity. Cohen et al (2010) applied Landtrendr (a trajectory-based time series analysis; see section 5.3) and annual Landsat based time series data to detect insect-related degradation and regrowth with reasonable robustness. Very high spatial resolution satellite imagery such as GeoEye-1 has also been demonstrated as a promising tool for mapping canopy mortality caused by insect outbreaks (Dennison et al 2010). Strand et al (2007) reported the use of RS for monitoring forests affected by invasive tree species and insects from several regions of the world. They note that over-hunting and invasive species can also cause degradation in forests, and if changes are severe enough to cause a change in state of a forest, the extent to which the forest has been degraded could be determined through RS. Drought driven degradation was studied by Verbesselt et al (2012) who applied a time series MODIS normalized difference vegetation index (NDVI) product spanning 2000 to 2011 over Somalia using a generic real-time disturbance detection approach. Their results illustrate the severity of the drought affecting the photosynthetic capacity of the vegetation. Huang and Andre-Regg (2012) demonstrated the feasibility of Landsat imagery in assessing drought induced forest degradation, suggesting promising opportunities for large scale systematic carbon dynamic monitoring in degraded forest.

It is evident from the above discussion that different types of degradation leave very different signatures on forests, with correspondingly different possibilities for detection and measurement using RS. Perhaps the most comprehensive analysis of detectability of degradation comes from Peres et al (2006), who classified detectability of different threats to tropical forests using conventional RS techniques. According to this study, the highly detectable threats include deforestation, forest fragmentation, recent slash-and-burn agriculture, major canopy fires, major highways, conversion to tree monocultures, hydroelectric dams and other forms of flood disturbance, and large-scale mining. The marginally detectable threats include recent mechanized selective logging, surface fires, a range of edge-effects, ‘old’ slash-and-burn agriculture, small-scale gold mining,
unpaved secondary roads (6–20 m wide), and selective thinning of canopy trees. Here the marginally detectable threats include threats that could be detected, at least partially, using high-resolution methods or specialized detection algorithms that are expensive, technically challenging to implement and available only for limited or specific areas. The almost undetectable threats include hunting and exploitation of animal products, harvest of most non-timber plant products, ‘old’ mechanized selective logging, small-scale non-mechanized logging, narrow sub-canopy roads (<6 m wide), under-story thinning and clear cutting, invasions of exotic species, spread of pathogens, changes in net primary productivity, community-wide shifts in plant species composition and other cryptic effects of climate change, mostly higher-order effects (dispersal and pollinator factors related to extinction of mutualists). This study refers to detection of areas that have become degraded over time; it does not attempt to estimate the actual loss of biomass/carbon stocks involved in each type.

5. Suitable RS data and methods for mapping, monitoring and quantifying forest degradation

This section presents suitable RS data and methods that have been applied not only to improve the detection and monitoring of forest degradation but also in some cases to quantify it, sometimes with the ultimate goal of estimating greenhouse gas emissions. As explained and illustrated in the previous section, methods for monitoring forest degradation by RS vary depending on the type of disturbances, the type of forest, the intensity of the impact and data and methods available (Miettinen et al 2014). The methods presented here include SMA, time series image analysis, and visual interpretation; the promising data to quantify forest degradation include LiDAR and radar because of their sensitivity to forest structure and biomass, as well as their capacity to link forest structure change to degradation and to estimate aboveground biomass (Mitchell et al 2017).

5.1. Spectral mixture analysis (SMA)

SMA is based on a linear mixture model which assumes that the image spectra in the pixel is a linear combination of n pure spectra (Defries et al 2000). The SMA model decomposes proportional cover based on reflectance of ‘end-members’ or pixels containing 100% of the land cover types of interest (Defries et al 2000). Image end-member candidates can be identified through a pixel purity index as recommended by Souza et al (2005b). They can also be extracted from a reference image.

SMA has been applied to forest degradation detection mainly for cases of illegal logging and fires (Asner et al 2005, 2009, Souza et al 2005b). Souza et al (2003) applied SMA on SPOT images to map degraded forest and found that the SMA is more applicable in areas heavily degraded by recurrent logging and burning. Wang et al (2005) applied a linear model to a modified soil adjusted vegetation index derived from Landsat ETM + imagery and found that in the canopy fraction cover map, the fraction distribution ranged from 0 to 0.4 in clear-cut areas, was higher than 0.8 in undisturbed forests, and had a wider range (0.3–1.0) in degraded forests. Shimabukuro et al (2014) showed that forest degradation due to selective logging can be detected and mapped using high-resolution soil fraction images derived from Landsat images using SMA. However, forest degradation due to fires (burned forest) can only be mapped using a time series of images because burned areas can also be related to a deforestation process when burning is used to clear the remaining vegetation. Especially for logging, textural and contextual analysis is often combined with the SMA fraction images since logging is spatially related to either logging decks or skid trails (Deutscher et al 2013). SMA measures the amount of vegetation lost either by the decrease of the component green vegetation (in percentage terms) or by the increase of non-photosynthetic vegetation. This can be related to carbon stock loss if there is information on carbon density (tons C ha$^{-1}$). Asner et al (2009, 2010) demonstrated this by integrating satellite imaging, airborne LiDAR and field plots to estimate the above ground carbon density. Carbon emissions resulting from forest degradation can then be calculated by combining the carbon density map with the percentage loss of forest cover.

Most of the applications of SMA are for logging and forest fire detection. As noted above, selective logging often happens at small scales and is therefore difficult to be detected accurately through conventional medium and coarse spatial resolution RS images. However, as SMA enables the decomposition of the pixels into sub-pixel components of green vegetation, non-photosynthetic vegetation, soils and shadow, such images are also potentially useful to detect and quantify forest degradation (Souza et al 2013). Indeed, the use of very high spatial resolution imagery allows the capture of even smaller scaled forest disturbances (Franke et al 2012). SMA has yet to be tested for detecting degradation caused by other types of disturbance such as shifting cultivation, cattle grazing, and fuelwood collection. Shifting cultivation can better be characterized by time series analysis (Dutrieux et al 2016) and landscape mosaic method (Hett et al 2012) since they present as a periodic shift between cultivation and fallow. An approach that combines SMA and time series analysis takes advantages of both methods and has proved successful in detecting tropical forest degradation (Bullock...
et al. (2020b). However, these methods, while allowing the calculation of area affected, do not provide an indicator of the intensity of the carbon loss in any given time period, which is necessary for calculating emissions due to shifting cultivation. For this, ground data are irreplaceable to correlate with RS observations.

### 5.2. Time series analysis

A time series is a sequence of observations taken sequentially in time (Box et al. 2015). In a time series, an important feature is that adjacent observations are dependent; therefore, a time series analysis is concerned with techniques for the analysis of this dependence, most often with stochastic and dynamic models (Box et al. 2015). In monitoring vegetation dynamics with RS, time series analysis can be defined as an approach to analyzing temporally dense (i.e. very frequent) satellite images over a defined time period. Time series analysis applied in disturbance detection uses repeat data in the locations (pixels) where at a certain time the forest might has suffered disturbance. The quantification of the amount of vegetation loss due to the disturbance can usually not be directly measured with this technique; it would need to be obtained from field measurements of biomass density; thus while time series may assist in more accurate mapping of areas affected by degradation over time, they do not necessarily provide all the data that is needed to estimate emissions. Vegetation indices are commonly used variables in time series analysis for vegetation disturbance or regeneration. MODIS has provided a synthesized vegetation index (MOS13Q1) including NDVI and EVI at 250 m resolution and at 16-day intervals since 2000 (Kuenzer et al. 2015). Time series approaches have been developed for vegetation dynamics monitoring especially since the Landsat imagery archive became freely available in 2008 (Huang et al. 2010, Kennedy et al. 2010). Freely available time series Landsat and Sentinel-1 & 2 images offer good opportunities for monitoring the areas subject to forest degradation, although there are still issues related to data pre-processing, analysis and accuracy assessment that need to be resolved (Banskota et al. 2014).

A RS time series usually consists of three components: trend, seasonal and residual (Verbesselt et al. 2010). For example, in a time series obtained over a tropical forest area, the trend component shows the long term condition of the vegetation, e.g. it indicates whether the vegetation is stable, increasing or decreasing; the seasonal component shows the repetitive seasonal change that relates to wet and dry seasons; while the residual component is what remains after the trend and seasonal components are removed from the time series, and can represent short term fluctuations from e.g. disturbances such as fire, logging, grazing, although it may also reflect noise in the data (Kuenzer et al. 2015).

In Hirschmugl et al. (2017) four approaches to time series analysis for forest degradation were introduced: (1) threshold-based change detection, which separates intact from degraded forest using a thresholding procedure. This has the drawback that the thresholds are empirically determined and difficult to transfer to other study areas; (2) curve fitting, which is based on regression models between the spectral variables and time. The slope of the regression curve can be used to separate change processes such as increase or decrease of the crown cover. This approach relies on statistical assumptions of data normality and equal variance, which are sometimes difficult to meet; (3) trajectory fitting which is a supervised method with trajectories representing specific training signatures related to degradation types. It only works if the observed trajectory matches a predefined typical degradation curve; and (4) trajectory segmentation (LandTrendr), which decomposes the trajectory into straight-line segments to capture broad trends (Kennedy et al. 2010). It is, however, limited in application since phenology is not considered. As higher spatial resolution time series data such as Sentinel-2 become available, the challenge is to adapt these methods to high spatial resolution time series data (Hirschmugl et al. 2017). Also, more disturbance type-oriented methods need to be developed. However, at whatever scale, these methods are based on observation of canopy cover change, which is only a very rough indicator of total biomass change; using the results to estimate emissions from degradation would give high levels of uncertainty.

Time series analysis that considers seasonality, such as the Breaks For Additive Seasonal and Trend (BFAST) has been tested with both low and medium spatial resolution images and is capable of detecting forest disturbances in historical time series or can be applied to near-real time disturbance detection (Verbesselt et al. 2010, 2012). Like most other change detection methods, BFAST does not provide interpretive information about the source of disturbance (Verbesselt et al. 2012). Also, it is still a challenge to define a threshold for the magnitude of change in order to separate forest degradation from deforestation (Gao et al. 2019).

Time series analysis has been applied to map degradation in different forest biomes. Some examples include highland vegetation degradation and regeneration monitoring in Mongolia with MODIS NDVI (Eckert et al. 2015); logging induced forest disturbance in Myanmar using Landsat imagery (Shimizu et al. 2017), forest degradation and deforestation detection in Brazilian Amazon with time series of landsat and SMA (Bullock et al. 2020a, b), disturbance regrowth dynamics in tropical forest, in Peru using Landsat series (Devries et al. 2020b). However, these methods, while allowing the calculation of area affected, do not provide an indicator of the intensity of the carbon loss in any given time period, which is necessary for calculating emissions due to shifting cultivation. For this, ground data are irreplaceable to correlate with RS observations.

In Hirschmugl et al. (2017) four approaches to time series analysis for forest degradation were introduced: (1) threshold-based change detection, which separates intact from degraded forest using a thresholding procedure. This has the drawback that the thresholds are empirically determined and difficult to transfer to other study areas; (2) curve fitting, which is based on regression models between the spectral variables and time. The slope of the regression curve can be used to separate change processes such as increase or decrease of the crown cover. This approach relies on statistical assumptions of data normality and equal variance, which are sometimes difficult to meet; (3) trajectory fitting which is a supervised method with trajectories representing specific training signatures related to degradation types. It only works if the observed trajectory matches a predefined typical degradation curve; and (4) trajectory segmentation (LandTrendr), which decomposes the trajectory into straight-line segments to capture broad trends (Kennedy et al. 2010). It is, however, limited in application since phenology is not considered. As higher spatial resolution time series data such as Sentinel-2 become available, the challenge is to adapt these methods to high spatial resolution time series data (Hirschmugl et al. 2017). Also, more disturbance type-oriented methods need to be developed. However, at whatever scale, these methods are based on observation of canopy cover change, which is only a very rough indicator of total biomass change; using the results to estimate emissions from degradation would give high levels of uncertainty.

Time series analysis that considers seasonality, such as the Breaks For Additive Seasonal and Trend (BFAST) has been tested with both low and medium spatial resolution images and is capable of detecting forest disturbances in historical time series or can be applied to near-real time disturbance detection (Verbesselt et al. 2010, 2012). Like most other change detection methods, BFAST does not provide interpretive information about the source of disturbance (Verbesselt et al. 2012). Also, it is still a challenge to define a threshold for the magnitude of change in order to separate forest degradation from deforestation (Gao et al. 2019).
et al 2015), forest cover loss monitoring in tropical dry forest in lowland Bolivia (Dutriex et al 2015), forest degradation detection in semi-deciduous tropical forest, Mexico, using Landsat imagery (Romero-Sanchez and Ponce-Hernandez 2017), and the detection of miombo dry forest degradation by annual Landsat time series in Angola (Schniebel et al 2017). Grogan et al (2016) address the question of whether time series change detection is affected by diverse forest types (e.g. dry deciduous vs evergreen) in tropical dry regions. They found that clearances were underestimated in evergreen forest and overestimated in dry-deciduous forest, which suggests that forest type needs to be considered in time series change mapping, especially in heterogeneous forest regions. Time series biophysical data such as precipitation and temperature are often incorporated as ancillary data to explain the detected vegetation dynamics (Neeti et al 2012, Verbesselt et al 2012, Romero-Sanchez and Ponce-Hernandez 2017).

Time series analysis has been shown as a promising approach for vegetation dynamics monitoring, forest degradation detection and biomass change monitoring. Web-based big data processing platforms such as Google Engine and Sepal have all incorporated time series analysis in their platforms. Seasonality is still a problem that not all the time series approaches can address. An even bigger problem resides in the fact that it is still not quite clear how to separate explicitly forest degradation from forest clearance. Accuracy assessment is another problem for time series analysis since both spatial and temporal accuracy needs to be assessed. Moreover it is time consuming to derive the accuracy assessment data, which is often based on visual interpretation of time series images of higher spatial resolution; and in general, if the time series catches canopy cover changes, the actual carbon losses (emissions) cannot be directly estimated. However, there is hope in view on this, since time series radar images present great potential in obtaining estimates of biomass or carbon storage change. The BIOMASS sensor from the European Satellite Agency (ESA) (launch in 2022) which collects radar data in P-band is expected to see through leafy treetop, build up maps of tree height and volume, and therefore provide information on global forest biomass and carbon content and thus fill the current gap in forest biomass density monitoring.

5.3. Visual interpretation of high spatial resolution images for mapping forest degradation

Visual interpretation has been used to identify areas which have been subjected to forest degradation at large scales by mapping indicators such as canopy openness, logging roads, fire scars, power lines, and settlements (Nandy et al 2011, Shearman et al 2009). Most of the forest degradation mapping research carried out in Southeast Asia has included a strong visual interpretation component, especially for extended areas (Miettinen et al 2014). Visual interpretation as a method for forest degradation identification has concentrated on disturbances such as selective logging. For example, Miettinen and Liew (2010) identified visible signs of degradation in peat swamp forest including canopy openness, fire scars, small-holder encroachment and logging canals by visually interpreting SPOT4 and 5 images. Satellite images with spatial resolution ranging from 5–30 m are often used. Even with very high spatial resolution images, it is challenging when the logging intensity is low, as in the case of non-mechanized or selective logging. Logging roads are often the best indicators of logging intensity (Bryan et al 2013, Gaveau et al 2014). The results of this method depend on the spatial resolution of images. With very high spatial resolution images, visual interpretation can obtain very precise results; however, it can suffer from the limitations of time and labor and potential user bias, and produces areal estimates but not quantities of biomass lost, which would be needed for estimation of emissions.

5.4. Mapping forest degradation using LiDAR, Radar and UAV

LiDAR, on the other hand, offers the possibility of assessing changes in biomass stock in forest as well as detection of area, as it uses lasers to estimate the three-dimensional canopy distribution of the vegetation, as well as the topography underneath the canopies, resulting in precise estimates of both the height of the vegetation and the structure of the canopy and ground elevation (Boudreau et al 2008), i.e. providing data which could potentially be used for degradation emissions estimates. Ellis et al (2016) found that LiDAR maps of an area impacted by logging (220 ha) agreed well with ground-based maps (217 ha, RMS error 3%). However, skid trail positions agreed only 59% due to the rapid forest regeneration. De Carvalho et al (2017) evaluated the impacts of selective logging on tree regeneration at one, four, and eight years after harvests in Antimary State Forest, Brazil. They found that the agreement was higher using LiDAR within a year of the harvest and suggested it is important to acquire LiDAR data that is close to the time of disturbance as otherwise vegetation regrowth can obscure the signals of disturbance. However, from the point of view of estimating carbon emissions, what is important is the amount of biomass present, and the fact that there has been considerable regrowth since the initial measurement means that degradation in climate change terms may have been minimal. LiDAR has been shown to be able to predict biomass well, based on the correlation between LiDAR measurements and ground measurements (Zolkos et al 2013). LiDAR has been shown to detect changes in biomass and
carbon in temperate (Boudreau et al 2008) and tropical forests (Meyer et al 2013). Optical data are very important for capturing changes in the forest cover but combination with LiDAR allows the association of this with carbon stock change in affected areas (Potapov et al 2012). An advantage of use of LiDAR is that the data do not get saturated in areas of high biomass. The major limitation is the high cost of acquisition (GOFC-GOLD 2016). It is important to mention the Global Ecosystem Dimension Investigation (GEDI) LiDAR Ecosystem mission led by the University of Maryland in collaboration with NASA Goddard Space Flight Center (https://gedi.umd.edu/mission/mission-overview/). GEDI measurements are taken continuously day and night between 51.6 degrees north and south, covering both tropical and temperate forests (Dubayah et al 2020). This 2-year mission, launched in December 2018, makes accurate measurements of canopy height, vertical canopy structure, and surface elevation and shows promise in improving measurements of biomass and forest carbon. All GEDI data products are available for free download at different resolution and time intervals. The details can be found at (https://gedi.umd.edu/data/download/).

SAR (synthetic aperture radar) for forest monitoring complements optical sensors in two main respects: (1) it allows observations at cloudy sites since cloud and atmospheric effects do not affect radar backscatter; and (2) L-band (23 cm wavelength) SAR backscatter has a direct relationship with woody biomass (Mitchard et al 2009). L-band SAR facilitates deforestation detection (Almeida-Filho et al 2009) and identification of regeneration (Chen et al 2018). Also, the multiple polarization of SAR facilitates the characterization of forest structure (GOFC-GOLD ). TerraSAR-X operates at a fine spatial resolution of 5 m, which presents good potential in forest degradation mapping. Among the sensors that are in operation, ALOS PALSAR-2 with the L-band shows great potential in measuring forest changes. However, its high cost presents a limitation in its application, especially over large areas. The P-band (70 cm wavelength) BIOMASS sensor which is scheduled to be in operation from 2020 also has potential in monitoring forest degradation. L-band SAR has been applied to estimate biomass in forest areas with low biomass (Ryan et al 2012, 2014). The texture information derived from SAR describes the structure and geometric properties of the forest canopy and shows good correlation with variation in biomass stocks. Previously, Deutscher et al (2013) and Ryan et al (2012) have demonstrated the application of SAR data in quantifying forest degradation by illegal logging and by small-scale agriculture. However, SAR becomes saturated in forest with medium to high biomass (between 30 and 100 tons C ha⁻¹) and is thus not suitable to map forest biomass in all conditions (Mitchard et al 2009, Lucas et al 2010). A better result can be obtained with the combination of optical, LiDAR and SAR data (Montesano et al 2013).

Unmanned aerial vehicles (UAV), also called drones, can carry remote sensors such as optical or hyperspectral cameras and LiDAR sensors, among others, and thus provide new ways to measure forests and supplement expensive or labor-intensive inventory methods (GOFC-GOLD ). Drones could capture images with very high spatial resolution as well as fine temporal resolution and provide detailed texture information on forest structure. Hence drones can be sensitive to small scale disturbance and the information they capture can be used to characterize forest degradation caused by different disturbance types (Bourgoin et al 2020). Therefore, drones could potentially provide cost-effective and frequent monitoring of aboveground carbon density at intermediate scales (100–100 000) ha in combination with ground data or LiDAR collection (Messinger et al 2016). Drone images obtained with optical sensors have been used to assist in the classification of the severity of burned forest (Rossi et al 2018). LiDAR mounted drones have been shown to be suitable for individual tree mapping (Jaakkola et al 2010). The main advantages, in addition to their very high spatial and temporal resolutions, are their low cost compared to airborne LiDAR or very high spatial resolution satellite images. Also, they are simple to operate and therefore can potentially be used by local communities in the context of REDD + and similar schemes (Paneque-Gálvez et al 2014, Vargas-Ramirez and Paneque-Gálvez 2019). The disadvantages include limited capabilities for covering larger areas and vulnerability to weather conditions, for example, strong winds and uneven sunshine condition (GOFC-GOLD).

6. Discussion and conclusion

Most of the methods reviewed in this study can be used to identify areas affected by degradation, especially where logging and forest fires are the causes. Reliable methods have not yet been established for estimating areas of degradation caused by shifting cultivation, cattle grazing and fuelwood collection which are some of the principal causes of forest degradation in tropical developing countries. The capacity of the methods is related to the intensity of the degradation (greater intensity is easier to detect), and to the characteristics of the data such as the spatial and temporal resolution of the satellite images. Higher spatial and temporal resolution images generally allow the detection of smaller scale disturbance; however, this usually implies limited study area and higher cost.
Many RS-based studies on forest degradation do not relate the detected changes to particular disturbances (Verbesselt et al. 2010). They detect changes in reflectance as measured by e.g. NDVI, and if any study of the drivers is included, this is based on separate ground level investigation. It would be helpful to know which RS method is suitable or has been successfully applied to degradation caused by particular types of disturbance. SMA appears to be particularly promising for detecting logging and forest fires. However, the effectiveness of this method in detecting other forms of degradation such as that caused by shifting cultivation, cattle grazing, and fuelwood collection has yet to be tested. Time series analysis is optimal because it can detect forest disturbance at the most appropriate time and separate degraded forest from naturally open forest. Especially for shifting cultivation, the fallow period and the cultivation period can be made visible in time series data, and the condition of the vegetation before the practice of shifting cultivation and a certain time after can be captured as well.

Very few of the methods can measure the intensity of the degradation, i.e. the proportion of biomass lost in any one area over time, which is an essential element for calculating emissions due to forest degradation. For this, only LiDAR and radar are applicable because of their capacity to measure the 3-D structure of the forests and their good correlation with the field biomass measurement data (Ryan et al. 2012, 2014). In Table 1, we have listed the RS approaches for detecting different types of forest degradation and at different scales; in the fourth column we indicate what would be needed to translate this into emissions, although without more experience, we can only generalise these suggestions. The alternative to using RS as the cornerstone for such emissions estimations would be to quantify the processes driving forest degradation, from ground level or secondary data sources, but intensive field work for verifying and associating the identified biomass loss with particularly land use activities would be needed for this. For logistical reasons, it is likely that this could only be carried out for limited study areas (Ryan et al. 2014). However, within given regions, a number of small studies of this kind could possibly be used to calibrate the RS signatures of typical activities and construct typical biomass gradients. By combining field measurements in sample areas and satellite images it might then be possible to arrive at

| Types of disturbance and scale | Sensor type suitable for estimating area of degradation | Sensors (mode, spatial resolution/launch year) | Approaches to estimating emissions from degradation |
|-------------------------------|--------------------------------------------------------|----------------------------------------------|-----------------------------------------------|
| Logging, fires, shifting cultivation **Fine scale (<1 ha)** | Very high (<5 m) or high resolution (5–10 m) optical data; & X-band SAR (Lei et al. 2018) | GeoEye (Pan 0.41 m, Ms 1.65 m/2008) WorldView-3 (Pan 0.31, Ms 1.24 m/2014) SPOT-6/7 (Pan 2 m, Ms 8 m/2012/2014) RapidEye (5 m/2009) TanDEM-X (3D DEM: 12 m/2011) TerraSAR-X (SL 1.7–3.5 m, SM 3 m/2007) | (1) Sample based ground observation data from: (a) Permanent plot (b) Field sampling of disturbed forests vs undisturbed forests (c) Terrestrial LiDAR (2) Combination of RS and ground data: |
estimates of biomass loss or gain over much larger areas (Morales-Barquero et al. 2014).

Acknowledgments

This research was supported by the Mexican Programa de Apoyo a Proyectos de Investigación e Innovación Tecnológica (PAPIIT), Grant Number IA104117, and by the Consejo Nacional de Ciencia y Tecnología (CONACYT) grant number ‘Génesis Básica’ SEP-285349, also by a CONACYT Catedra program [1539].

Data availability statement

All data that support the findings of this study are included within the article (and any supplementary information files).

ORCID iDs

Yan Gao  https://orcid.org/0000-0003-1345-1583
Margaret Skutsch  https://orcid.org/0000-0001-6120-4945
Jaime Paneque-Gámez  https://orcid.org/0000-0002-9926-2742
Adrian Ghilardi  https://orcid.org/0000-0002-7286-0670

References

Agarwala A, Ghoshal S, Verchot L, Martius C, Abuja R and Defries R 2017 Impact of biogas interventions on forest biomass and regeneration in southern India Global Ecol. Conserv. 37 213–23
Almeida-Filho R, Shimabukuro Y E, Rosenqvist A and Sanchez G A 2009 Using dual-polarized ALOS PALSAR data for detecting new fronts of deforestation in the Brazilian Amazonia Int. J. Remote Sens. 30 3733–43
Aragão L E O C et al 2018 Nat. Comm. 9 536
Arora V K, Peng Y, Kurz W A, Frye J C, Hawkins B H and Werner A T 2016 Potential near-future carbon uptake overcomes losses from a large insect outbreak in British Columbia, Canada Geophys. Res. Lett. 43 2950–8
Asner G P, Broadbent E N, Oliveira P L C, Keller M, Knapp D E and Silva J N M 2006 Condition and fate of logged forests in the Brazilian Amazon PNAS 103 12947–50
Asner G P, Knapp D E, Balají A and Pérez-Acosta G 2009 Automated mapping of tropical deforestation and forest degradation: cLASlite J. Appl. Remote Sens. 3 033543
Asner G P, Knapp D E, Broadbent E N, Oliveira P J, Keller M and Silva J N 2005 Selective logging in the Brazilian Amazon Science 310 480–2
Asner G P, Powell G V, Mascaro J, Knapp D E, Clark J K, Jacobson J, Kennedy-Bowdoin T, Balají A, Pérez-Acosta G and Victoria E 2010 High-resolution forest carbon stocks and emissions in the Amazon PNAS 107 16738–42
Asner G P 2009 Tropical forest carbon assessment: integrating satellite and airborne mapping approaches Environ. Res. Lett. 4 034009
Baccini A, Walker W, Carvalho L, Farina M, Sulla-Menashe D and Houghton R 2017 Tropical forests are a net carbon source based on new measurements of gain and loss Science 358 230–4
Banskota A, Kayastha N, Falkowski M J, Walder M A, Froese R E and White J C 2014 Forest monitoring using Landsat time series data: a review Can. J. Remote Sens. 40 362–84
Boer M M, de Dios V R and Bradstock R A 2020 Unprecedented burn area of Australian mega forest fires Nat. Clim. Change 10 170–2
Bolognesi M, Vrieling A, Rembold F and Gazdán H 2015 Rapid mapping and impact estimation of illegal charcoal production in southern somalia on worldview-1 imagery Energy Sustainable Dev. 25 40–49
Bourgoin C et al 2020 UAV-based canopy textures assess changes in forest structure from long-term degradation Ecol. Indic. 113 106386
Boudreau J, Nelson RF, Margolis HA, Beaudoin A, Guimond L and Kimes DS 2008 Regional aboveground forest biomass using airborne and spaceborne LiDAR in Québec Remote Sens. Envir. 112 3876–3890
Box G E, Jenkins G M, Reinsel G C and Ljung G M 2015 Time Series Analysis Forecasting and Control 5th edn (John Wiley & Sons) Hoboken, NJ
Buettel J, Ondel S and Brook B 2017 Missing the wood for the trees? New ideas on defining forests and forest degradation Rethinking Ecol. 11 15–24
Bullock E L, Woodcock C E and Olofsson P 2020b Monitoring tropical forest degradation using spectral unmixing and Landsat time series analysis Remote Sens. Envir. 238 110968
Bullock E L, Woodcock C E, Souza C J and Olofsson P 2020a Satellite-based estimates reveal widespread forest degradation in the Amazon Global Change Biol. 26 2956–69
Bryan J E, Sheerman P L, Asner G P, Knapp D E, Aoro G and Lokes B 2013 Extreme differences in forest degradation in Borneo: Comparing practices in Sarawak, Sabah, and Brunei PLOS ONE 8 e69679
Chambers J Q, Fisher J J, Zeng H, Chapman E L, Baker D B and Hurt G C 2007 Hurricane Katrina's carbon footprint on U.S. Gulf coast forests Science 318 1107
Chen W, Jiang H, Moriya K, Sakai T and Cao C 2018 Monitoring of post-fire forest regeneration under different restoration treatments based on ALOS/PALSAR data New For. 49 105–21
Chowdhury R R 2006 Driving forces of tropical deforestation: the role of remote sensing and spatial models Singapore J. Trop. Geogr. 27 82–101
Chuvieco E, Aguado I, Salas J, Garcia M, Yebra M and Oliva P 2020 Satellite remote sensing contributions to wildland fire science and management Curr. For. Rep. 6 81–96
Cochrane M A 2003 Fire science for rainforests and tropical forests New For. 238 110968
Coben W B, Yang Z and Kennedy R 2010 Detecting trends in forest disturbance and recovery using yearly time series: 2. TimeSync-tools for calibration and validation Remote Sens. Environ. 114 2911–24
Davidar P, Sahoo S, Mammen P C, Acharya P, Puyravaud J-P, Arjunan M, Garrigues J P and Roessingh K 2010 Assessing the extent and causes of forest degradation in India: where do we stand? Biol. Consers. 143 2937–44
De Carvalho A L, Neves d’Oliveira M V, Putz F E and de Oliveira L C 2017 Natural regeneration of trees in selectively logged forest in western Amazonia For. Ecol. Manage. 392 36–44
De Sy V, Herold M, Achard F, Asner G P, Held A, Kellndorfer J and Verbeeck J 2012 Synergies of multiple remote sensing data sources for REDD++ monitoring Curr. Opin. Environ. Sustain. 4 696–706
Defries R S, Hansen M C and Townsend J R G 2000 Global continuous fields of vegetation characteristics: A linear mixture model applied to multi-year 8 km AVHRR data Int. J. Remote Sens. 21 1389–414
Dennison P E, Brunelle A R and Carter V A 2010 Assessing canopy mortality during a mountain pine beetle outbreak
using GeoEye-1 high spatial resolution satellite data Remote Sens. Environ. 114 2431–5
Deutscher J, Perko R, Gutjahr K, Hirschmugl M and Schardt M 2013 Mapping tropical rainforest canopy disturbance in 3D by COSMO-SkyMed spotlight InSAR-Stereo data to detect areas of forest degradation Remote Sens. 5 648–63
Devries B, Decuyper M, Verbesselt J, Zielies A, Herold M and Joseph S 2015 Tracking disturbance-regrowth dynamics in tropical forests using structural change detection and Landsat time series Remote Sens. Environ. 169 320–34
Dubayah R et al 2020 The global ecosystem dynamics investigation: high resolution laser ranging of the Earth’s forests and topography Sci. Remote Sens. 1 100002
Dupuis C, Lejeune P, Michez A and Fayolle A 2020 How can remote sensing help monitor tropical moist forest degradation? — a systematic review Remote Sens. 12 1087
Dutrieux I P, Jakovac C C, Latifah S H and Kooistra L 2016 Reconstructing land use history from Landsat time-series case study of a swidden agriculture system in Brazil Int. J. Appl. Earth Obs. Geoinf. 47 112–24
Dutrieux I P, Verbesselt J, Kooistra L and Herold M 2015 Monitoring forest cover loss using multiple data streams, a case study of a tropical dry forest in Bolivia IFSRS J. Photogramm. Remote Sens. 107 112–25
Eckert S, Husler F, Liniger H and Hodel E 2015 Trend analysis of MODIS NDVI time series for detecting land degradation and regeneration in Mongolia Agric. 113 16–28
Eidenshink J, Schwind B, Zhu Z, Quayle B and Howard S 2007 A project for monitoring trends in brn severity Fire Ecol. Spectral Issue 3 3–21
Eklundh L, Johansson T and Solberg S 2009 Mapping insect defoliation in Scots pine with MODIS time-series data Remote Sens. Environ. 113 1566–73
Ellis E, Romero-Montero J and Hernandez-Gomez I 2017 Deforestation processes in the state of Quintana Roo, Mexico Trop. Conserv. Sci. 10 1–12
Ellis P, Griscom B, Walker W, Goncalves F and Cormier T 2016 Mapping selective logging impacts in Borneo with GPS and airborne LiDAR For. Ecol. Manage. 365 184–96
FAO 2006 Choosing a forest definition for the clean development mechanism
FAO 2010 Global forest resources assessment 2010 main report FAO working paper 144/E (Rome: Food and Agriculture Organization (FAO) of the United Nations (UN))
FAO 2011 Assessing forest degradation, towards the development of globally applicable guidelines Working paper 177 http://www.fao.org/3/a-i24797e.pdf/
Franke J, Navratil P, Keck V, Peterson K and Siegenthier F 2012 Monitoring fire and selective logging activities in tropical peat swamp forests IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 5 1811–20
Frolking S, Palache M W, Clark D B, Chambers J Q, Shugart H H and Hurnt G C 2009 Forest disturbance and recovery: a general review in the context of spaceborne remote sensing of impacts on aboveground biomass and canopy structure J. Geophys. Res. 114 1–21
Gang Ch Pan S, Tian H, Wang Zh Xu R, Bian Z, Pan N, Yao Y and Shi H 2020 Satellite observations of forest resilience to hurricanes along the northern Gulf of Mexico For. Ecol. Manage. 472 118243
Ganguly S, Schull M A, Samanta A, Shabanov N V, Milesi C, Nemani R R, Knayzukhin Y and Myneni R B 2008 Generating vegetation leaf area index earth system data record from multiple sensors, part 1: theory Remote Sens. Environ. 112 4333–45
Gao Y, Quevedo A, Sztanoi Z and Skutsch M 2019 Monitoring forest disturbance using time series MODIS NDVI in Michoacán, México Geocarto Int. (https://doi.org/10.1080/10106049.2019.1661032)
Garcia-Barrios L, Galvan-Miyoshi Y M, Valdivieso-Perez I, Masera O R, Bocco G and Vandermeer J 2009 Neotropical forest conservation, agricultural intensification, and rural out-migration: the Mexican experience BioScience 59 863–73
Gaveau D L A et al 2014 Four decades of forest persistence clearance and logging on Borneo PLOS ONE 9 e101654
Gerwing J J 2002 Degradation of forests through logging and fire in the eastern Brazilian Amazon For. Ecol. Manage. 157 131–41
Ghazoul J, Burivalova Z, Garcia-Ulloa J and King L A 2015 Conceptualising forest degradation Trends Ecol. Evol. 30 622–31
Ghazoul J and Chazdon R 2015 Degradation and recovery in changing forest landscapes: a multiscale conceptual framework Annu. Rev. Environ. Resour. 42 161–88
Goetz S J, Hansen M, Houghton R A, Walker W, Lapore N and Busch J 2015 Measurement and monitoring needs, capabilities and potential for addressing reduced emissions from deforestation and forest degradation under REDD+ Environ. Res. Lett. 10 123001
GOFC-GOLD 2016 A sourcebook of methods and procedures for monitoring and reporting anthropogenic greenhouse gas emissions and removals associated with deforestation, gains and losses of carbon stocks in forests remaining forests, and forestation. GOFC-GOLD Report version COP22-1 (The Netherlands: GOFC-GOLD Landscape Cover Project Office, Wageningen University)
GOFI 2017 Integration of Remote-sensing and Ground-based Observations for Estimation of Emissions and Removals of Greenhouse Gases in Forests: Methods and Guidance from the Global Forest Observation Initiative 2.0 edn (Rome: Food and Agriculture Organization)
Griffiths P, Kuenmerle T, Baumann M, Radeloff V C, Abrudan I V, Lieveskovsky J, Munteanu C, Oostpawicz K and Hostert P 2014 Forest disturbances, forest recovery, and changes in forest types across the Carpathian ecoregion from 1985 to 2010 based on Landsat image composites Remote Sens. Environ. 151 72–88
Grogan K, Pflugmacher D, Hostert P and Fensholt R 2016 Mapping clearances in tropical dry forests using breakpoints, trend, and seasonal components from modis time series: does forest type matter? Remote Sens. 8 657
Guariguata M R, Nasi R and Kanninen M 2009 Forest degradation: it is not a matter of new definitions Conserv. Lett. 2 286–7
Hall R J, Castilla G, White J C, Cooke B J and Skakun R S 2016 Remote sensing of forest pest damage: a review and lessons learned from a Canadian perspective Can. Entomol. 148 S296–S356
Harris N L et al 2016 Attribution of net carbon change by disturbance type across forest lands of the conterminous United States Carbon Balance Manage. 11 1–21
Hellbert R, Arndt T C and Sekhar N U 2000 Fuel-wood consumption and forest degradation: a household model for domestic energy substitution in rural India Land Econ. 76 213–32
Hernandez-Gomez I V, Cerdan-Cabreria C R, Navarro-Martinez A, Vazquez-Luna D, Armenta-Montero S and Ellis E A 2019 Assessment of the CLASite forest monitoring system in detecting disturbance from selective logging in the Selva Maya, Mexico Silva Fennica 53 1–10
Hethcoat M G, Edwards D P, Carreiras J M B, Bryant R G, Franca F M and Quegan S 2019 A machine learning approach to map tropical selective logging Remote Sens. Environ. 221 569–82
Hett C, Castella J C, Heinimann A, Messerli P and Pfund J L 2012 A landscape mosaics approach for characterizing swidden systems from a REDD+- perspective Appl. Geogr. 32 608–12 4333–45
Hirschmugl M, Gallau H, Dees M, Datta P, Deutscher J, Koutsias N and Schardt M 2017 Methods for mapping forest disturbance and degradation from optical earth observation data: a reviewCurr. For. Rep. 3 32–45
Hosonuma N, Herold M, De Sy V, De Fries R, Brockhaus M, Verchot L, Angelsen A and Rummin E 2012 An assessment of
degradation of forests and forest degradation drivers in developing countries Environ. Res. Lett. 7 12
Huang C, Goward S N, Masek J G, Thomas N, Zhu Z and Vogelmann J E 2010 An automated approach for reconstructing recent forest disturbance history using dense Landsat time series stacks Remote Sens. Environ. 114 183–98
Hurini K, Heit C, Heinimann A, Messeri P and Wissmann U 2013 Dynamics of shifting cultivation landscapes in Northern Lao PRD between 2000 and 2009 based on an analysis of MODIS time series and Landsat images Hum. Ecol. 41 21–36
IPCC 2003 IPCC report on definitions and methodological approaches to inventory emissions from direct human-induced degradation of forests and devegetation of other vegetation types pp 16
Jaakkola A, Hyyppa J, Kakko A, Xu X, Kaatinen H, Lehtomaki M and Lin Y 2010 A low-cost multi-sensoral mobile mapping system and its feasibility for tree measurements ISPRS J. Photogramm. Remote Sens. 65 514–22
Keeley J E 2009 Fire intensity, fire severity and burn severity: a brief review and suggested usage Int. J. Wildland Fire 18 116–26
Kennedy R E, Yang Z and Cohen W B 2010 Detecting trends in forest disturbance and recovery using yearly Landsat time series: 1. LandTrendr — temporal segmentation algorithms Remote Sens. Environ. 114 2897–910
Klemas V V 2009 The role of remote sensing in predicting and determining coastal storm impacts J. Coast. Res. 25 1264–75
Kolden C A, Smith A M S and Abatzoglou J T 2015 Limitations and utilisation of monitoring trends in burn severity products for assessing wildfire severity in the USA Int. J. Wildland Fire 24 1023–8
Kuenzer C, Dech S and Wagner W 2015 Remote Sensing Time Series: Revealing Land Surface Dynamics, Chapter 1: ‘Remote Sensing Time Series Revealing Land Surface Dynamics: Status Quo and the Pathway Ahead’ (Springer International Publishing) pp 1–24 Switzerland
Kurz W A, Dymond C C, Stinson G, Rampley G J, Neilson E T, Carroll A L, Ebata T and Safranyik L 2008b Mountain pine beetle and forest carbon feedback to climate change Nature 452 987–90
Kurz W A, Stinson G, Rampley G J, Dymond C C and Neilson E T 2008a Risk of natural disturbances makes future contribution of Canada’s forests to the global carbon cycle highly uncertain PNAS 105 1551–5
Lambin E F, Geist H J and Lepers E 2003 Dynamics of land-use and land-cover change in tropical regions Annu. Rev. Environ. Resour. 28 205–41
Lei Y, Treuhaft R, Dos-santos M, Goncalves F and Neumann M 2013 Estimating carbon emissions using Sentinel-1 Synthetic Aperture Radar data and mapping using multi-frequency (X-, C- and L-band) modes at L-band for forest classification purposes in Eastern Amazon, Brazil Int. J. Appl. Earth Obs. Geoinf. 21 122–35
Lohberger S, Stangel M, Atwood E C and Siegert F 2017 Spatial evaluation of Indonesia’s 2015 fire-affected area and estimated carbon emissions using Sentinel-1 Global Change Biol. 24 644–54
Lu D, Chen Q, Wang G, Liu L, Li G and Moran E 2016 A survey of remote sensing-based aboveground biomass estimation methods in forest ecosystems Int. J. Remote Sens. 37 63–105
Lu D 2006 The potential and challenge of remote sensing-based biomass estimation Int. J. Remote Sens. 27 1297–328
Lucas R, Armstrong J and Fairfais R 2010 An evaluation of the ALOS PALSAR L-band backscatter-above ground biomass relationship Queensland, Australia: impacts of surface moisture condition and vegetation structure IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 3 576–93
Mahiri I and Howorth C 2001 Twenty years of resolving the irresolvable: approaches to the fuelwood problem in Kenya Land Degrad. Dev. 12 205–15
Matricardi E A T, Skole D L, Cochrane M A, Qi J and Chomentowski W 2005 Monitoring selective logging in tropical evergreen forests using Landsat: multitemporal regional analyses in Mato Grosso, Brazil Earth Interact. 9 1–24
Matricardi E A T, Skole D L, Pedlowa M A and Chomentowski W 2013 Assessment of forest disturbances by selective logging and forest fires in the Brazilian Amazon using Landsat data Int. J. Remote Sens. 34 1057–86
Matricardi E A T, Skole D L, Pedlowa M A, Chomentowski W and Fernandes I C 2010 Assessment of tropical forest degradation by selective logging and fire using Landsat imagery Remote Sens. Environ. 114 1117–29
Mcnico I M, Ryan C M and Mitchard E T A 2018 Carbon losses from deforestation and widespread degradation offset by extensive growth in African woodlands Nat. Commun. 9 3043
Mcnulty S G 2002 Hurricane impacts on US forest carbon sequestration Environ. Pollut. 116 517–524
McRoberts R E 2011 Satellite image-based maps: scientific inference or pretty pictures? Remote Sens. Environ. 115 715–24
Melendy I et al 2018 Automated method for measuring the extent of selective logging damage with airborne LiDAR data ISPRS J. Photogramm. Remote Sens. 139 228–40
Mertz O 2009 Trends in shifting cultivation and the REDD mechanism Current opinion in Environmental Sustainability 1 156–60
Messerling M, Asner G P and Silman M 2016 Rapid assessment of Amazon forest structure and biomass using small unmanned aerial systems Remote Sens. 8 615
Meyer V, Saatchi S, Chave J, Dalling J W, Bohlinan S, Fricker G A, Robinson C, Neumann M and Hubbell S 2013 Detecting tropical forest biomass dynamics from repeated airborne lidar measurements Biogeosciences 10 5421–38
Miettinen J and Liew S C 2010 Status of peatland degradation and development in Sumatra and Kalimantan Ambio 39 394–401
Miettinen J, Stibig H J and Achard F 2014 Remote sensing of forest degradation in Southeast Asia-aiming for a regional view through 3-30m satellite data Global Ecol. Conserv. 2 24–36
Mitchard E T A, Saatchi S S, Woodhouse I H, Nangendo G, Miettinen J, Debruyne J M, Stibig H J and Achard F 2014 Remote sensing of forest degradation for REDD+ Carbon Balance Manage. 12 1–9
Mollicone D et al 2007 An incentive mechanism for reducing emissions from conversion of intact and non-intact forests Clim. Change 83 477–93
Montesano P M, Cook B D, Simon J M, Nelson R F, Ranson K J, Zhang Z and Luthcke S 2013 Achieving accuracy requirements for forest biomass mapping: a spaceborne data fusion method for estimating forest biomass and LiDAR sampling error Remote Sens. Environ. 130 153–70
Morales-Barquero L, Skutsch M, Jardel-Pel A, Melendy L, Debruyne J M, Stibig H J and Achard F 2014 Current remote sensing approaches to monitoring forest degradation in support of countries measure, reporting and verification (MRV) systems for REDD+ Carbon Balance Manage. 12 1–9
Mowrer H T and Congalton R G 2000 Quantifying Spatial Uncertainty in Natural Resources Theory and Applications for GIS and Remote Sensing 1st edn (Boca Raton, FL: CRC Press) pp 244
Naidoo L, Mathieu R, Main R, Kleyhans W, Wessels K, Asner G and Lebon B 2015 Savannah woody structure modelling and mapping using multi-frequency (X-, C- and L-band) Synthetic Aperture Radar data ISPRS J. Photogramm. Remote Sens. 105 234–50
Nandy S, Kushwaha S P S and Dadhwal V K 2011 Forest degradation assessment in the upper catchment of the river Tons using remote sensing and GIS Environ. Ind. 11 509–13
Neeti N, Ragan J, Christman Z, Eastman J R, Millones M, Schneider L, Niclè E, Schmook B, Turner II B L and Ghimire B 2012 Mapping seasonal trends in vegetation using AVHRR-NDVI time series in the Yucatán Peninsula, Mexico Remote Sens. Lett. 3 433–42

Nepstad D O et al 1999 Large-scale impoverishment of Amazonian forests by logging and fire Nature 398 505–8
Nepstad D, Lefebvre P, Lopes da Silva U, Tomassella J, Schlesinger P, Solorzano L, Moutinho P, Ray D and Nenito J G 2004 Amazon drought and its implications for forest flammability and tree growth: a basin-wide analysis Global Change Biol. 10 704–17
Oliveira P J C, Asner G P, Knapp D E, Almeyda A, Galván-Gómez R, Keene S, Raybin R F and Smith R C 2007 Land-use allocation protects the Peruvian Amazon Science 317 1233–6
Paneque-Gálvez J, Mccall M K, Napoletano B M, Wich S A and Koh L P 2014 Small drones for community-based monitoring: an assessment of their feasibility and potential in tropical areas Forests 5 1482–1507
Pearson T R H, Bernal B, Hagen S C, Walker S M, Melendy L K and Delgado G 2018 Remote assessment of extracted volumes and greenhouse gases from tropical timber harvest Environ. Res. Lett. 13 055010
Pearson T R H, Brown S, Murray L and Sidman G 2017 Greenhouse gas emissions from tropical forest degradation: an underestimated source Carbon Balance Manage. 12 3
Pelletier J, Kirby K R and Potvin C 2012 Significance of carbon stock uncertainties on emission reductions from deforestation and forest degradation in developing countries Policy. Econot. 24 3–11
Peres C A, Barlow J and Laurance W F 2006 Detecting anthropogenic disturbance in tropical forests Trends Ecol. Evol. 21 227–9
Picotte J J, Bhattachar J, Howard D, Lecker J, Epting J, Quayle B, Benson N and Nelson K 2020 Changes to the monitoring trends in burn severity program mapping production procedures and data products Fire. Ecol. 16 1–12
Pinheiro T F, Escada M I S, Hostert P, Gollnow F and Muller H 2011 Hurricane disturbance mapping using airborne LiDAR on Amazon Forest Dynamics from Multi-Temporal data Earth Obs. Geoinf. 11 709
Pinheiro T F, Escada M I S, Hostert P, Gollnow F and Muller H 2016 Forest degradation associated with logging frontier expansion in the Amazon: The BR-163 region in Southwestern Pará, Brazil Earth Interact. 20 1–26
Potapov P V, Turubanova S A, Hansen M C, Adusei B, Broich M, Altstatt A, Mane L and Justice C O 2012 Quantifying forest cover loss in Democratic Republic of the Congo, 2000–2010, with Landsat ETM+ data Remote Sens. Environ. 122 106–116
Putz F E and Redford K H 2010 the importance of defining ‘forest’: tropical forest degradation, deforestation, long term phase shifts, and further transitions Biotropica 42 10–20
Rogan J and Chen D 2004 Remote sensing technology for mapping and monitoring land-cover and land-use change Prog. Plann. 61 301–25
Rogan J, Schneider L, Christman Z, Millones M, Lawrence D and Schmook B 2011 Hurricane disturbance mapping using MODIS EVI data in the southeastern Yucatán, Mexico Remote Sens. Lett. 2 539–67
Romero-Sánchez M E and Ponce-Hernández R 2017 Assessing and monitoring forest degradation in a deciduous tropical forest in Mexico via remote sensing indicators Forests 8 1–19
Rossi F C, Fritz A and Becker G 2018 Combining satellite and UAV imagery to delineate forest cover and basal area after mixed-severity fires Sustainability 10 2227
Ryan C M, Berry N J and Joshi N 2014 Quantifying the causes of deforestation and degradation and creating transparent REDD+ baselines: A method and case study from central Mozambique Appl. Geogr. 53 45–54
Ryan C M, Hill T, Woollen E, Ghee C, Mitchard E, Cassells G, Grace J, Woodhouse I H and Williams M 2012 Quantifying small-scale deforestation and forest degradation in African woodlands using radar imagery Global Change Biol. 18 243–57
Sanchez-Azofeifa G A, Harris R C and Skole D L 2001 Deforestation in Costa Rica: a quantitative analysis using remote sensing imagery Biotropica 33 378–84
Sasaki N and Putz F E 2009 Critical need for new definitions of ‘forest’ and ‘forest degradation’ in global climate change agreements Cons. Lett. 2 226–32
Schmoebl A, Frantz D, Roder A, Stellmes M, Fischer K and Hill J 2017 Using annual landsat time series for the detection of dry forest degradation processes in South-Central Angola Remote Sens. 9 1–14
Seid R, Klönen G, Rammer W, Esil F, Moreno F, Neumann M and Dullinger S 2018 Invasive alien pests threaten the carbon stored in Europe’s forests Nat. Commun. 9 16–26
Senf C, Seidl R and Hostert P 2017 Remote sensing of forest insect disturbances: current state and future directions Int. J. Appl. Earth Obs. Geoinf. 60 49–60
Shearnman P L, Ash J, Mackey B, Bryan J E and Lokes B 2009 Forest conversion and deforestation in Papua New Guinea 1972–2002 Biotropica 41 379–90
Shimabukuro Y E, Arai E, Duarte V, Jorge A, Dos Santos E G, Cruz Gasparini K A and Dutra A C 2019 Monitoring deforestation and forest degradation using multi-temporal fraction images derived from Landsat sensor data in the Brazilian Amazon Int. J. Remote Sens. 40 5475–96
Shimabukuro Y E, Beuchle R, Grecchi R C and Aichard F 2014 Assessment of forest degradation in Brazilian Amazon due to selective logging and fires using time series of fraction images derived from landsat ETM+ images Remote Sens. Lett. 5 773–82
Shimizu K, Ponce-Hernandez R, Ahmed O S, Ota T, Win Z C, Mizoue N and Yoshi S 2017 Using Landsat time series imagery to detect forest disturbance in selectively logged tropical forests in Myanmar Can. J. For. Res. 47 289–96
Siepert F and Hoffmann A A 2000 The 1998 fires in East Kalimantan (Indonesia): a quantitative evaluation using high resolution, multitemporal ERS-2 SAR images and NOAA-AVHRR hotspot data Remote Sens. Environ. 72 64–77
Siriulkhayanon P, Sun W and Oyana T J 2008 Assessing the impact of the 2004 tsunami on mangroves using remote sensing and GIS techniques Int. J. Remote Sens. 29 3553–76
Souza C Jr, Firestone L, Silva I M and Roberts D 2003 Mapping forest degradation in the Eastern Amazon from SPOT 4 through spectral mixture models Remote Sens. Environ. 87 494–506
Souza C Jr and Roberts D 2005a Mapping forest degradation in the Amazon region with IKONOS images Int. J. Remote Sens. 26 425–9
Souza C Jr M, Roberts D A and Cochrane M A 2005b Combining spectral and spatial information to map canopy damage from selective logging and forest fires Remote Sens. Environ. 98 329–43
Souza C Jr M, Siqueira J V, Sales M H, Fonseca A V, Ribeiro J G, Numata I, Cochrane M A, Barber C P, Roberts D A and Barlow J 2013 Ten-year Landsat classification of deforestation and forest degradation in the Brazilian Amazon Remote Sens. 5 5493–513
Specht M J, Ribeiro S, Albuquerque U, Tabarelli M and Melo F 2015 Burning biodiversity: fuelwood harvesting causes forest degradation in human-dominated tropical landscapes Global Ecol. Conserv. 3 200–9
Strahler H, Hoff R, Stritholt J, Miles L, Horning N, Fosnight E and Turner W 2007 Sourcebook on Remote Sensing and Biodiversity Indicators CBD Technical Series No. 32 (Montreal: Secretariat of the Convention on Biological Diversity)
Tanase M A, Santoro M, de la Riva J, Pérez-Cabello F and Le Toan T 2010 Sensitivity of X-, C-, and L-Band SAR Backscatter to Burn Severity in Mediterranean Pine Forests IEEE Trans. Geosci. Remote Sens. 48 3663–75
Tanase M A et al 2019 Synthetic aperture radar sensitivity to forest changes: A simulations-based study for the Romanian forests Sci. Total Environ. 689 1104–14
Thompson I D, Guariguata M R, Okabe K, Bahamondez C, Nasi R, Heymell V and Sabogal C 2013 An operational framework for defining and monitoring forest degradation Ecol. Soc. 18 1–20
UNFCCC 2002 Report of the Conference of the parties on its seventh session, held at Marrakesh from 29 October to 10 November 2001 (FCCC/CP/2001/13/Add.1, UNFCCC, Marrakesh, Morocco, 2001). [www document] http://unfccc.int/resource/docs/cop7/13a01.pdf Accessed March 3 2020
Van Der Werf G R et al 2017 Global fire emissions estimates during 1997–2016 Earth Syst. Sci. Data 9 697–720
Vargas-Ramírez N and Paneque-Gálvez J 2019 The global emergence of community drones (2012-2017) Drones 3 1–24
Verbesselt J, Hyndman R, Zeileis A and Culvenor D 2010 Phenological change detection while accounting for abrupt and gradual trends in satellite image time series Remote Sens. Environ. 114 2970–80
Verbesselt J, Zeileis A and Herold M 2012 Near real-time disturbance detection using satellite image time series Remote Sens. Environ. 123 98–108
Wang C, Qi J and Cochrane M 2005 Assessment of tropical forest degradation with canopy fractional cover from Landsat ETM+ and IKONOS imagery Earth Interact. 9 1–18
Wang W, Ji Q, Hao X, Liu Y and Stanturf J A 2010 Post-hurricane forest damage assessment using satellite remote sensing Agric. For. Meteorol. 150 122–32
Yang Y, Saatchi S S, Xu L, Yu Y, Choi S, Philips N, Kennedy R, Keller M, Knyazikhin Y and Myneni R B 2018 Post-drought decline of the Amazon carbon sink Nat. Commun. 9 3172
Zeng H, Chambers J Q, Negron-Juarez R I, Hurdtt G C, Baker D B and Powell M 2009 Impacts of tropical cyclones on U.S. forest tree mortality and carbon flux from 1851 to 2000 PNAS 106 7888–92
Zolkos S G, Goetz S J and Dubayah R 2013 A meta-analysis of terrestrial aboveground biomass estimation using lidar remote sensing 2013 Remote Sens. Environ. 128 289–98