Chapter 2

Remote sensing and measuring deforestation

2.1. Introduction: forests, deforestation and forest degradation

Forests make up a third of the planet's landmass, covering close to 4 billion hectares. The largest forested areas are located in the Boreal and Equatorial zones. This current distribution isn't fixed, but has continuously changed over time due to the influence of environmental change and anthropogenic impact. A third of current forested areas is made up of forest that is considered primary or intact [FAO 10]. The remaining two thirds are subject to anthropogenic activity and have, as a result, an uncertain future.

Each year, several million hectares of forest disappear and others are subject to degradation. Deforestation is the complete destruction of forest cover. Conversion into agricultural or pastoral land is the principal cause of deforestation. Once certain areas are abandoned, forest cover can once again develop, leading to what are known as secondary forests. Unlike deforestation, degradation is partial destruction of the forest cover. It is defined as a loss of the forest's capacity to provide ecosystemic services (carbon storage, forest products, etc.) following anthropogenic activity [THO 13]. This degradation is characterized by the breaking up of forested areas following illegal land clearing, overexploitation of wood (figure 2.1), fires, etc. Degraded forests include a large diversity of forest types depending on the nature, intensity and frequency of the degradation.

Forests provide a diversity of products and ecosystemic services. The living biomass of forests stores around 300 pg of carbon which means it plays an important role in the potential mitigation of climate change. Forests also represent a reservoir

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of biodiversity, especially tropical forests. Knowing the extent of forested areas, the state of forests and how they change over time is therefore particularly important with regard to current environmental concerns linked to climate change.

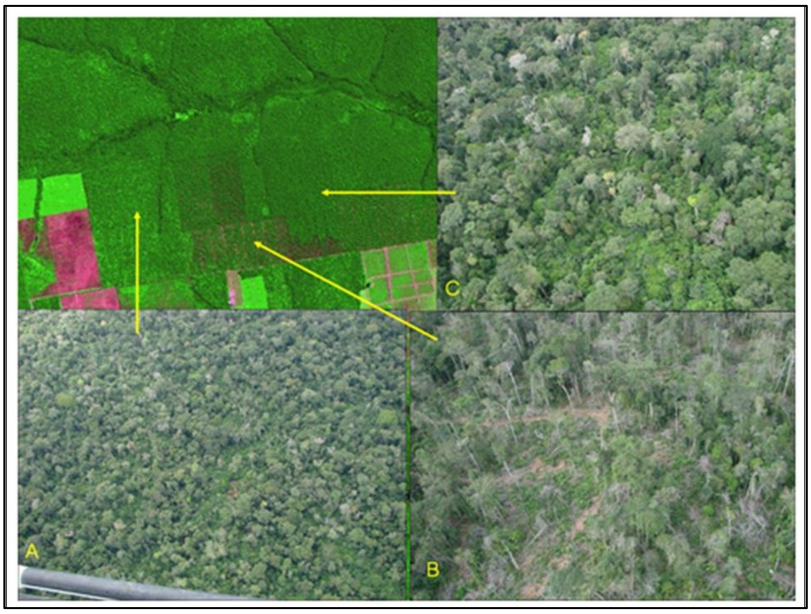

Figure 2.1. *An example of information collected by remote sensing: A) moderate forest degradation with cutting sites in the process of regeneration in a Landsat image in a color composite with mid infrared, near infrared and red (In the red, green and blue channels respectively) ; B) intense degradation with large portions of the ground visible following forest exploitation ; C) average degradation with traces of exploitation and old roads. Used with the permission of Brazil's National Institute for Space Research (INPE, http://www.obt.inpe.br/prodes/index.php).*

Remote sensing has emerged as the only tool capable of continuously providing reliable data on the regional or continental scale. Unlike other types of land use, forests are a type of vegetation that is easily recognizable on satellite images. Despite the advent of remote sensing in the 1970s, estimates of forest area and its evolution over time on a planetary scale have only been available since the beginning of the 2000s.

In this chapter, we present an overview of the different sources of images and techniques for processing and analysis used to document deforestation and measure its extent. Monitoring programs on a planetary scale will be presented, as well as a regional program (Brazilian Amazon). Finally, the problem of forest degradation, a new and significant challenge, will be demonstrated using a tool developed in French Guiana.

2.2. Which images should be used for measuring deforestation? Limits and advantages

The satellite data used to provide estimates of deforestation can be of two types. On one hand, optical data, acquired in visible and infrared wavelengths, is sensitive to operating variables of the vegetation (chlorophyll activity, structure and internal water content of the leaves). On the other hand, radar data, acquired in the field of hyperfrequencies with longer wavelengths, is sensitive to the structure of the vegetation (basal area, stand structure, presence of water).

2.2.1. *The contribution of optical data*

2.2.1.1. *Optical data at low and medium spatial resolution*

The observation deforestation began with data from NOAA's (National Oceanic and Atmospheric Administration) series of satellites with an Advanced Very High Resolution Radiometer (AVHRR). These images were frequently used during the 1980s and 1990s [TUC 84, MAL 89, MAY 98]. The AVHRR scanning radiometer detects radiation in the visible, near IR, mid IR and thermal IR parts of the spectrum, with a spatial resolution of 1.1 km and a daily temporal frequency. This low spatial resolution data has been used to produce regional evaluations of deforestation especially in the Brazilian Amazon [NEL 87, SHI 94] and in Central Africa [MAL 95]. At the end of the 1990s, SPOT-VEGETATION images, with a spatial resolution identical to the NOAA-AVHRR images, were used to produce estimates of deforestation, notably in Southeast Asia [STI 04].

However, the low spatial resolution of these images is a major limitation for monitoring deforestation, since they can't to measure impact on areas smaller than km^2 which are nevertheless very common. Images with a higher resolution have therefore been used more frequently such as those from MODIS (Moderate Resolution Imaging Spectroradiometer) sensors of the TERRA and AQUA platforms. With a resolution of 250 m, 500 m or 1 km in optical wavelengths, these images are available for free and summarized every sixteen days. The processing makes it possible to minimize the influence of clouds. However, these measurements remain subject to problems with the angular configuration of the images [SAL 07, SAM 10].

2.2.1.2. *Optical data with high and very high spatial resolution*

Since the the mid-1980s, Landsat data with two MSS (Multi Spectral Scanners) and a TM (Thematic Mapper) became the principle source of data used to provide estimates of deforestation [SKO 93, DEF 02, ACH 04, HAN 08]. The high spatial resolution (30 to 60 meters), historical depth (data collected since 1972) and the open access two million images since 2009 (http://glovis.usgs.gov/) make it a unique data set. Nevertheless, these images have a number of limitations for monitoring deforestation: limited availability for the first decades (before 1990), clouding over of images common in tropical zones and a low frequency of images (a satellite takes 18 days to return to the same place). To correct this problem, these images can be combined with MODIS images [MOR 05]. For example, thanks to the temporal acquisition of the sensors at low and medium resolutions, it is possible to identify sectors where degradation can be studied in more detail with data at high and very high spatial resolutions [KAT 15]).

On the local scale, images with very high spatial resolution are occasionally used for estimating the deforestation and degradation of forests. This is the case with SPOT-6/7 (1.5 m), RapideEye (5 m), Ikonos (0.81 m), Pleiades (0.5 m), and GeoEye (0.34 m) (http://www.satimagingcorp.com/satellite-sensors/) images. Surfaces with a small area, including relatively limited impact, are then analyzed in detail.

This type of image can for example be used to estimate the impacts on vegetation of a rapid increase in population as a result of migration (one recent example is the events in the Central Africa Republic in 2014).

All of this data is not free, and in general the finer the resolution the higher the price. However, all of the medium-resolution images from Landsat satellites are free and open access. Each source of information therefore has a cost that needs to be calculated according to goals, needs and resources.

2.2.2. *Contribution of radar data*

Measuring deforestation with optical satellite data is often very difficult due to the persistence of clouds in wet tropical zones. Thanks to its characteristic "all-weather sensor," SAR (Synthetic Aperture Radar) radar data has a strong potential for observation in tropical zones.

For mapping and monitoring deforestation with radar images, two approaches are often used:

– an approach based on the intensity of the radar backscatter;

– an approach taking into account the coherence of the radar signatures and the in phase component [TOU 99].

In the latter approach, the basic principle consists of comparing coherence before and after the impacts on the forest, coherence being sensitive to the stability of the forest [ZEB 92]. The main limit of this approach is the reduced availability of the images. As a result, the majority of studies are based on backscatter of the strength of microwaves.

As a general rule, the performance of radar sensors in characterizing a forest increases with the wavelength [LET 11]. This is linked to the capacity for signatures with strong wavelengths to penetrate the canopy cover and as a result a better identification of the state of the forest (dense/open, intact/degraded). C-band waves (~ 5.6 cm – RADARSAT-2, Sentinel) and X (~ 3.1 cm – TerraSAR-X, COSMO-SkyMed, etc.) cannot penetrate very far into the vegetation cover, since they interact with a large number of forest components such as leaves, twigs and small branches. L-band waves (~ 23.6 cm – ALOS/PALSA) are not affected by the fine structure of the surface and can easily make it possible to distinguish forests from deforested areas [SHI 14]. The P-band (λ ~ 69 cm) is also adapted to forestry applications. The future BIOMASS space mission, with a band-P radar sensor, will not only make it possible to distinguish and estimate forest cover, but also to estimate the biomass of tropical forests [HOT 14].

2.3. Methods for monitoring deforestation

2.3.1. *With the help of optical data*

The use of optical data to identify deforestation or forest degradation takes into account spatial and temporal variations in reflectance. The combination of channels for obtaining indicators of photosynthetic activity such as the NDVI (*Normalized Difference Vegetation Index*[1]) or the EVI (*Enhanced Vegetation Index*[2]) makes it possible to locate the pixels corresponding to forest and the pixels corresponding to bare soil. The sharp decline in the values clearly show that the forest has been degraded or deforested. This can be made from one pixel to the other in the same image or the same pixel with images acquired on different dates. This section

1. NDVI = (PIR-R)/(PIR+R) where PIR is the near infrared reflectance and R is red reflectance.

2. EVI = G [(PIR – R) / ((PIR) + (C1.RED) - (C2.B) + L)] where G=2.5 ; C1 and C2 are the coefficients for mitigating the contamination of aerosols (from a value of 6 and 7.5 respectively), B is the reflectance of the blue band and L is an adaptation coefficient (equal to 1).

presents a technique for monitoring deforestation, developed by the Carnegie Institution for Science. A semi-automatic system for analyzing the environment is offered by the team led by Gregory Asner (The Carnegie Landsat Analysis System Lite – CLASlite [ASN 09]). Using this analysis system, the user can process nine different satellites to produce maps of deforestation and degradation in tropical forests. CLASlite performs several functions:

– Radiometric and atmospheric calibrations to obtain surface reflectance (top of canopy – TOC);

– umixing spectral data (Spectral Mixture Analysis – SMA). This approach considers pixels made up of more than one type of soil cover to be “mixed.” For example, a pixel located on the edge of a forest contains a portion of bare soil and a portion of vegetation. In contrast, the pixels referred to as “pure” are made up of a single type of ground cover. The SMA method aims to determine[3] the internal composition of mixed pixels on the basis of the spectral characteristics of pure pixels known as endmembers. These pure pixel endmembers must show all of the classes of soil cover in one image. CLASLite distinguishes between three pure classes of soil cover: photosynthetic vegetation (PV), non-photosynthetic vegetation (NPV), which especially represents senescent vegetation and wood, and bare soil (S). The spectral signatures of these three pure elements are stored in a vast library owned by CLASLite, constructed from field measurements (spectrometer) and hyperspectral satellite observations (Hyperion sensor). By using an unmixing model (Automated Monte Carlo Unmixing Model), CLASlite determines the proportion of PV, NPV and S for each pixel in the processed image, with the sum of the three equaling 100%;

– calculating the level of forest cover. Measuring tropical deforestation is crucial for understanding the global functioning of the biosphere and its interactions with the atmosphere. Establishing baseline measurements in order to calculate changes in tropical forests over time is therefore a challenge of the utmost importance. To establish these references, the FAO (Food and Agriculture Organization of the United Nations) provides a forest resources assessment (FRA). It was found that for the reference year (1990), the surface area of tropical forests in 90 countries was 1.756 billion hectares [FAO 95], which was then corrected to 1.926 billion [FAO 01] and finally to 1.949 billion [FAO 06]. All of these estimates, made by the same international organization (which specializes in the subject), for the same reference year, varied by 10%, which suggests imprecision and errors [GRA 08]. Using a model (Automated Monte Carlo Unmixing model) supplied by a database of spectral signatures is the best solution to the problem;

3. For each spectral band of the pixel, reflectance is seen as a linear combination of the reflectance of each endmember.

– classifying the images into two classes (forest and non-forest), depending on the proportion of photosynthetic vegetation, non-photosynthetic vegetation and bare soil contained within each pixel;

– detecting changes in forest cover between the dates of the satellite images to determine the evolution of deforestation and degradation over time.

CLASlite's spectral analysis algorithm is capable of detecting changes in the forest cover in the order of 1%, which corresponds to a Landsat pixel with an area of 10 m². CLASlite offers a potential for very detailed detection of tropical forest degradation, in particular allowing detection of the damage done to the crowns of trees during forest exploitation (figure 2.2). CLASlite software has been free and usable everywhere since December 2013. All that's necessary is to download it and complete a short online training course.

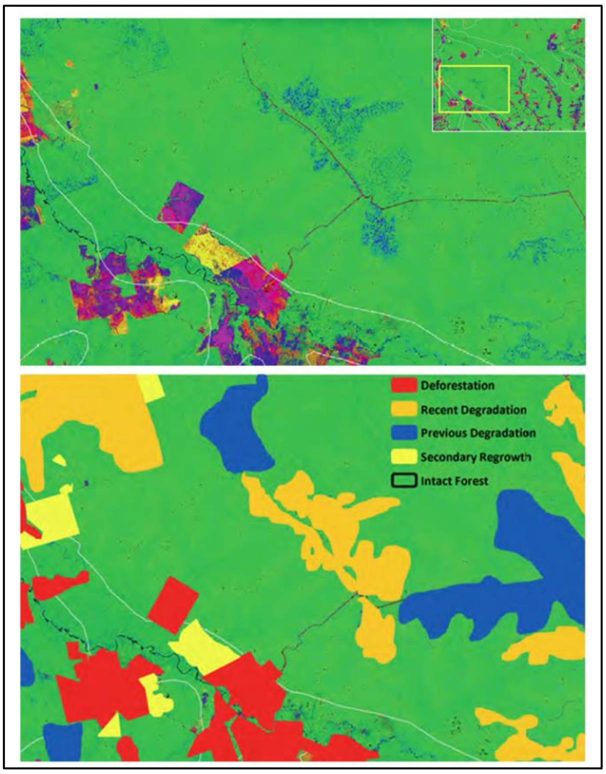

Figure 2.2. *Illustration of a local map of deforestation and forest degradation using CLASlite software. Above, the raw output of processing from a Landsat image. Below, sketch map with CLASlite showing the different states of the forest (deforestation in red, recent degradation in orange, previous degradation in blue and*

secondary regrowth in yellow). With the kind permission of Gregory P. Asner, Carnegie Institution for Science.

2.3.2. *Using radar data*

When using radar data, a pretreatment process is necessary. The sensitivity of the backscatter of radar microwaves to the parameters of the forest can be disrupted by several sources, including the speckle effect, effects of the forest structure (density, biomass, leaf surface, coverage level, crown cover) and environmental conditions (topography, soil moisture content). In the presence of these various sources of noise, mapping the parameters of the forest is a difficult task that cannot be done without comprehensive methodology. Image preprocessing consists of reducing geometric and radiometric distortion while taking topography into account. First there is the preprocessing of images that consists of reducing the geometric and radiometric distortion caused by the geometry of radar viewing angles and topography. Detecting deforestation is based on methods for detecting changes in microwave backscatter radar, that require radiometric normalization, topographic correction and the reduction of *speckle* [QUE 00].

2.3.2.1. *Radiometric normalization*

Radiometric normalization of SAR images is considered necessary for forestry applications since the images used are generally acquired at different times and with different methods (incidence of entry angles of microwaves in particular). Radiometric normalization makes it possible to work on images where the thresholds used for separating forest/non-forest are relevant and robust.

2.3.2.2. *Topographic correction*

In order to minimize the effect of topography on radar backscatter, it is necessary to use a digital terrain model (DTM) to minimize dependence on microwave backscatter at local incidence angles [VIL 15].

2.3.2.3. *Reducing* speckle

It is often necessary to apply a filter to reduce the effect of speckle in radar images. These are adaptive filters that are applied to reduce speckle while retaining the fine structures present in the images as much as possible. Among the filtering methods used, there is multi-image filtering (use of a time series of images) developed by Quegan *et al.* [QUE 00] which makes it possible to get corrected images with a better smoothing out of speckle. This filter is based on the following relation:

$$P_n(x,y) = \frac{\langle P_n(x,y)\rangle}{N} \sum_{i=1}^{N} \frac{P_i(x,y)}{\langle P_i(x,y)\rangle} \quad avec \quad n = 1,2,\dots N \qquad [2.1]$$

– $P_n(x,y)$ is the radar microwave backscatter of the output image n for the pixel (x,y);

– $P_i(x,y)$ is the radar microwave backscatter of the input image for the pixel (x,y);

– $<P_i(x,y)>$ is the average local intensity of the radar microwave backscatter (within a given window) of the input image i for pixel (x,y);

– N is the number of images.

With this filter, the radiometric resolution of the images is improved without damaging the spatial resolution. A cartographic is desirable to make it possible to visualize the deforestation/degradation evident in a radar image.

2.4. Programs for estimating deforestation on a global scale

Until very recently, the only figures available on the evolution of forest cover on a global scale were those from the FAO. Since 1946, the FAO has compiled and analyzed statistics and national inventories provided by each country. A report is published every 5 years [FAO 12]. The evolution of forested areas is a report on the loss of forested areas through deforestation and the gains in surface area by tree plantations or by expansion of the forest. This data is nevertheless very heterogeneous between countries because of the diversity of methods, terms and definitions employed. It is generally accepted that estimates of the evolution of forested areas made from these national inventories are marred by numerous errors and imprecision. In 2007, to compensate for these problems, the FAO and the European Commission's Joint Research Centre (JRC) launched a work program based on remote sensing to evaluate the evolution of forested areas. The worldwide results were published in 2012 [FAO 12] then the results specific to tropical areas [ACH 14]. Another source of statistical information on the evolution of forest resources on a global scale using remote sensing has been provided by Hansen *et al.* [HAN 13]. Finally, the Japan Aerospace Exploration Agency (JAXA) also offers estimates of forested areas worldwide at a 25 meter resolution (http://www.eorc.jaxa.jp/ALOS/en/palsar_fnf/data/index.htm). The data is available for 2007, 2008, 2009 and 2010 with ALOS-1. These estimates should resume following the launch into orbit of ALOS-2 in May 2014. These three programs, presented below, provide estimates of deforestation on a global scale using remote sensing.

2.4.1. *The FAO/JRC program*

Assessing forest cover on the global scale is based on a systematic sampling based on each intersection of a degree of longitude and latitude. This sampling includes around 13,000 measuring points each one covering a surface of 10 km x 10 km, for a total 1% of the earth's land area. For each sample, Landsat images from the years 1990, 2000 and 2005 (optical bands 1 to 5 and 7) have been interpreted and classified. They come from the *Landsat Global Land Survey* (GLS) of the *United States Geological Survey*. The processed images (correction of radiometric differences) have been segmented and classified with the help of eCognition® software. The segmentation consists of identifying a polygon, or set of pixels similar from a spectral perspective. Around 7 million polygons were analyzed for each period and classified according to the land cover (by automated supervised classification). These classifications have been interpreted, corrected and validated by forest experts who have a solid understanding of the terrain and by experts in remote sensing, who **used** images with very high resolution (http://www.fao.org/forestry/fra/fra2010/fr/). A map unit is considered to be classified as “forest” when the tree cover is more than 30%.

2.4.2. *The* Global Forest Change program

Unlike the previous program which relies on a sampling of points, analysis by Hansen *et al.* [HAN 13] is exhaustive and worldwide. The database is an open access (http://earthenginepartners.appspot.com/science-2013-global-forest). This analysis constitutes the main source of information of the *Global Forest Watch* (http://www.globalforestwatch.org/) site. The observation period is more limited than that of the JRC since it extends over twelve years (2000 to 2012). Since February 2014, this program provides high-resolution data (30 meters) detailing the annual expansion, and loss and gains of forests worldwide. This database is the result of analyzing 654,178 Landsat 7 ETM+ scenes. The processing has been done on the Google-Earth-Engine environmental analysis platform. Each Landsat footprint has been temporally made into a mosaic to provide data (forest, loss of forest, increase in forests) with 30 m spatial resolution. Various spectral metrics have been calculated from the optical reflectance values. Four classes of forest are distinguished according to the percentage of tree cover (0-25%, 25-50%, 50-75% and 75%). The loss of forest area is the sum of these four classes. On the other hand, the increase in surface area is the sum of the two classes with tree cover of more than 50% (figure 2.3).

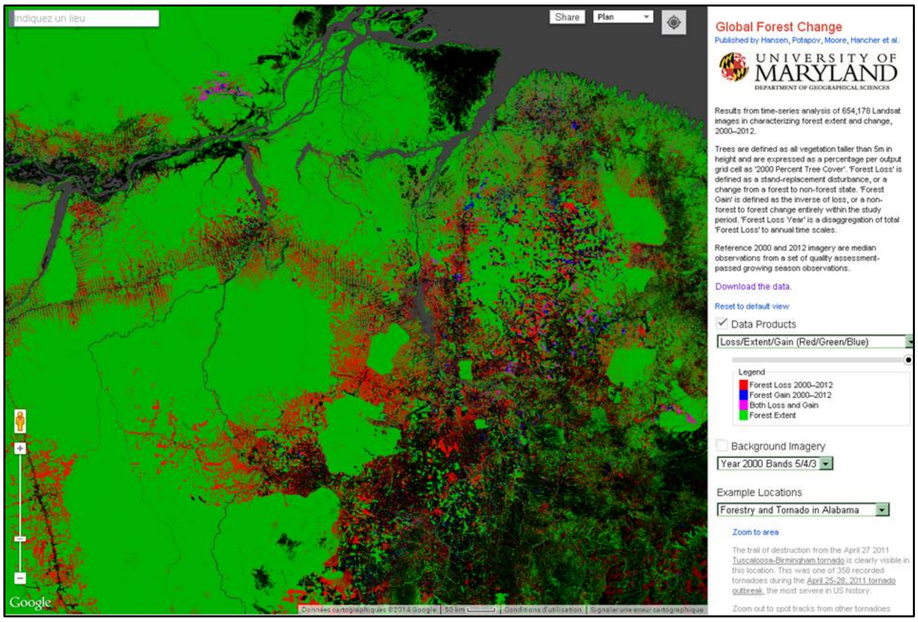

Figure 2.3. *Illustration homepage (Amazon region) for downloading data produced by the* Global Forest Change *(GFC, http://earthenginepartners.appspot.com/science-2013-global-forest). The extent of mature forest is represented by the green, forest loss is in red and forest gain is in blue. The unclassified pixels are shown in black. The information is available per year between 2000 and 2012 at 30 m de spatial resolution. With the kind permission of Hansen/UMD/Google/USGS/NASA.*

The estimates of forest areas for the two periods in consideration (before and after 2000) vary by a factor of 1 to 3 depending on the data (national inventories versus images) and methods (FAO/JRC and Hansen *et al.*, see table 2.1). A comparison of the estimates of net loss of forest area produced by the two remote sensing programs (table 2.1) shows a sizeable difference between the two programs: 6.2 million hectares for FAO/JRC [FAO 12] and 12.4 million hectares for Hansen *et al.* [HAN 13] for the years after 2000. These results can be explained principally by the differences in defining "forest." Indeed, considering only Hansen's work where forest is considered to have a canopy cover more than 50%, we get a net loss of 5.4 million hectares (data not presented here), closer to the 6.2 of FAO/JRC [FAO 12]. The main problem is measuring tree cover of partially wooded land such as of tree savannah or dry open woodland (such as in the Sudano-Sahelian zone or in Southern Africa for example) and whether they can be categorized (or not) as forests. The different definitions of between these two approaches makes comparing the methods difficult. If the availability of images and the means employed to analyze them have long been an obstacle to measuring deforestation, it now seems that the priority is to find a common and shared definition of what can be classified as a forest.

In addition to the problem of definition, differences in estimation can also be explained by methods of analysis and validation that are still not consolidated (table 2.1). Using the same methodological framework as that of the FAO and JRC [FAO 12], Achard *et al.* [ACH 14] provide higher estimates of deforestation in tropical zones (5.9 million hectares**)** those estimated on a global scale (5.2 M.ha-1) for the period 2000-2010.

	Zone studied	Period studied	Loss	Gain	Net loss (in millions of hectares)
FAO [FAO 10]	Globe	1990-2000			**8.3**
		2000-2010			**5.2**
FAO/JRC [FAO 12]	Globe	1990-2000	9.5	6.8	**2.7**
		2000-2005	13.5	7.3	**6.2**
Hansen *et al.* [HAN 13]	Globe	2000-2012	19.1	6.7	**12.4**
	Regions (climatic zones)				
Hansen *et al.* [HAN 13]	Tropical	2000-2012	9.2	2.1	**7.2**
	Boreal		5.1	1.7	**3.3**
	Subtropical		2.5	1.6	**0.9**
	Temperate		2.3	1.3	**1.0**
Achard *et al.* [ACH 14]	Tropical	1990-2000	8.0	1.9	**6.1**
	Tropical	2000-2010	7.6	1.5	**5.9**

Table 2.1. *Annual estimates of gains and losses and gains in forest area in millions of hectares*

2.4.3. *The Japanese Space Agency's program for mapping forest cover*

Mapping deforestation on the global scale has always been a priority of Japan's space agency (JAXA) since the launch of the first JERS-1 L-band radar in 1992, followed by the ALOS-1/PALSAR radar in 2006, and recently, in 2014, the launch of ALOS-2/PALSAR [SHI 14]. JAXA has provided global coverage forested areas for the years 2007 to 2010 with a spatial resolution of 25 meters (http://www.eorc.jaxa.
jp/ALOS/en/palsar_fnf/data/index.htm, figure 2.4). These maps have been validated with a precision of 90% in comparison with ground data.

In the near future, maps of forest cover will be derived from PALSAR-2 sensor in Full Band Dual mode, with 10 meters of spatial resolution.

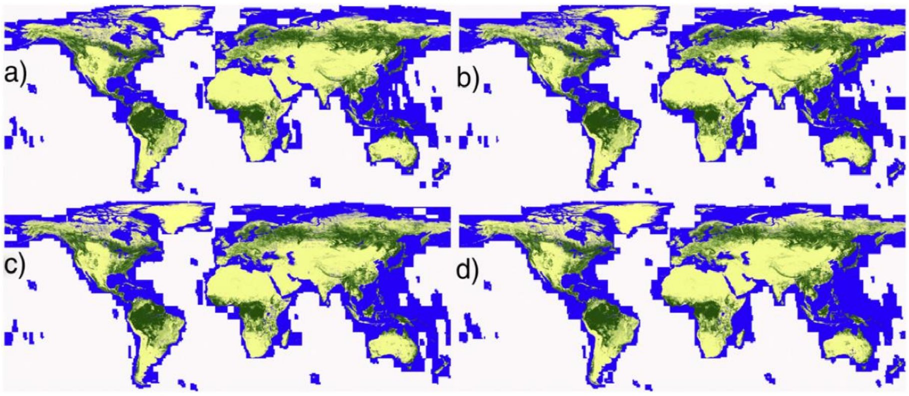

Figure 2.4. *Worldwide mosaics of forest cover (in dark green) at 25 m resolution from ALOS-1/PALSAR images. (a) 2007, (b) 2008, (c) 2009, (d) 2010 (http://www.eorc.jaxa.jp/ALOS/en/palsar_fnf/data/index.htm)*

2.5. Programs evaluating deforestation and degradation on a regional scale: some case studies

2.5.1. *Estimating deforestation on a regional scale: the case of Brazil*

2.5.1.1. *Application based on optical data in the Brazilian Amazon*

Brazil is a unique case among countries in tropical zones, having developed satellite checking tool for monitoring deforestation and made the data available to the public.

A program monitoring deforestation in Amazônia Legal[4], PRODES, was launched in 1988. This program was integrated, starting in 2005, into an arsenal of measures forming the action plan for preventing and controlling deforestation in Amazônia Legal (PPCDAM). The plan is a set of restrictions, control measures and application of new public policies. It was implemented by the federal government and mobilized 14 ministries as well as all of the Amazonian states.

4. Amazônia Legal extends over 9 Brazilian states. The administrative area includes the seven states in the northern region of the country (Acre, Amazonas, Amapá, Pará, Rondônia, Roraima and Tocantins) as well as the two states of Mato Grosso and a part of Maranhão. All of the monitoring indicators for vegetation provided by the National Institute for Space Research (INPE) always refers to this territory.

The National Institute for Space Research (INPE, http://www.obt.inpe.br) has developed different programs for monitoring deforestation (table 2.2). They have two main objectives:

– providing spatial and temporal estimates of deforestation and forest degradation (the PRODES and DEGRAD programs respectively, figure 2.5); these estimates are widely disseminated and made available to every level of the country's government (federal, federated and district) as key components of environmental policies. Since 2005, Brazil has recorded an 82% reduction of its annual rate of deforestation rate (figure 2.6);

– establishing a monitoring tool for the area with information about deforestation in real time that allows rapid control and intervention on the ground. The DETER program provides bimonthly alerts on a minimum area of 25 hectares using analysis of MODIS images.

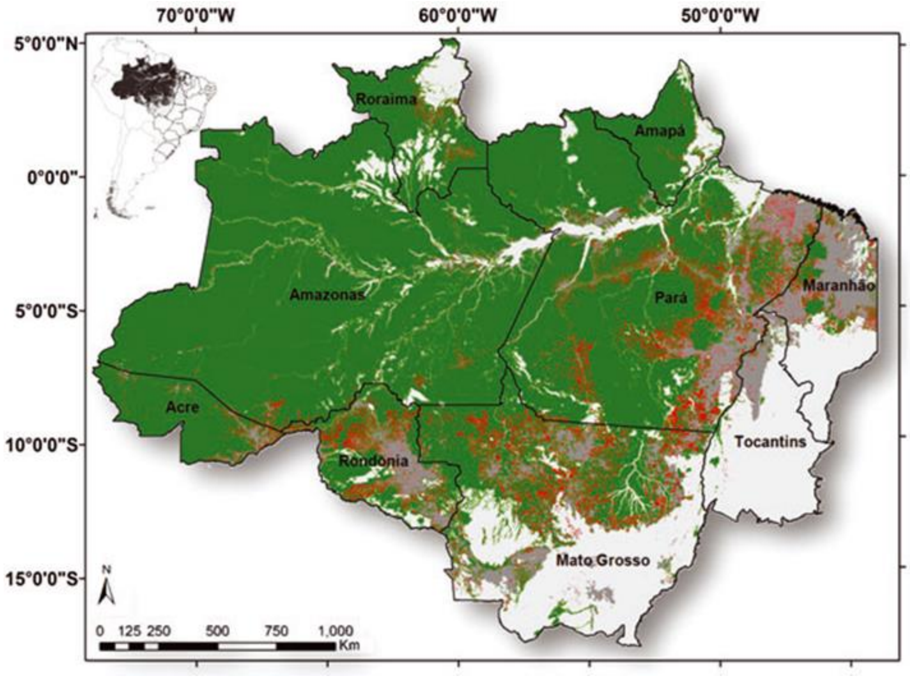

Figure 2.5. *This map shows the forest cover in the Brazilian Amazon in green, deforestation between 2000 and 2010 in red and the previously deforested forests (before 2000) in grey. The non-forest zones are in white. With the kind permission of Brazil's National Institute for Space Research (INPE, http://www.obt.inpe.br/prodes/index.php).*

Program	Year of implem entation	Product	Images	Minimum Surface detected
PRODES: monitoring deforestation in Amazônia Legal	1988	Map and yearly deforestation rate	Landsat/CBRES (resolution 30 m)	> 6.25 ha
DETER: monitoring deforestation in real time	2004	Deforestation & degradation alert (bimonthly)	MODIS	25 ha
DEGRAD: mapping forest degradation	2008	Map and yearly degradation rate	Landsat/CBRES (resolution 30 m)	> 6.25 ha

Table 2.2. *Technical specifications of programs monitoring deforestation in the Brazilian Amazon*

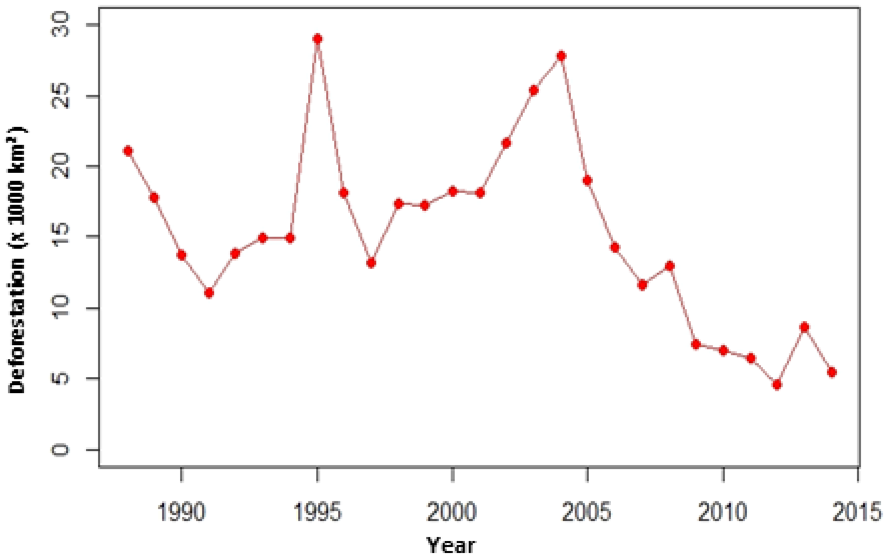

Figure 2.6. *Yearly rate of deforestation in the Brazilian Amazon (source: http://www.obt.inpe.br)*

Using data provided by the PRODES program, the Brazilian Agricultural Research Corporation (Embrapa) and the INPE have analyzed changes in land use (http://www.inpe.br/cra/projetos_pesquisas/terraclass2010.

php). The assessment made in 2010 show that 18.2%, an area of 739 672 km^2", the Amazon had been deforested. Close to two thirds of this surface (61.9 %) has been turned into grazing land in various states of degradation. 22.2% of the deforested surface is once again colonized by the forest (secondary forests). Aguiar [AGU 12] estimates that deforestation in the Amazon emits 0.15 to 0.28 pg of carbon annually, which is almost a third of the planet's carbon emissions, due to changes in land use. The phases of this typology are not fixed in time, but pass from one state to the other depending on management practices. For example, degradation of grazing lands causes forest regrowth, which can once again be burned to create new grazing land. This mosaic of landscapes is not fixed but is constantly evolving over time and space.

The non-governmental organization Imazon has developed a program for monitoring deforestation and forest degradation which produces monthly bulletins and annual maps of deforestation and forest degradation in Brazil (http://imazon.org.br/). Its system is based on the spectral analysis of mixed pixels Landsat. The goal is to find the proportion of active vegetation, inactive vegetation, bare soil and drop shadow in each pixel to determine its class. The analysis benefits from a large database of spectral signatures precisely indicating the different qualities of the desired elements. The principle is therefore similar to the one developed in CLASlite, but the tool is used continuously and operationally to provide information about the state of the forests of the Brazilian Amazon.

2.5.1.2. *Application based on radar data (State of Pará)*

Figure 2.7 shows an example in Brazil (State of Pará) using the L-band to distinguish the forest from non-forest zones. For forested areas, a large amount of microwave backscatter is recorded by the sensor (light color). On the other hand, deforested surfaces act like mirrors that reflect the radar signal in the opposite direction of the sensor, which produces low values (in black). By comparing the image acquired by JERS-1 in 1993 with the one acquired by ALOS-1 PALSAR in 2010, we can identify deforestation over a period of 19 years. The images show that deforestation wasn't significant in the 1990s and that the phenomenon has increased since the 2000s.

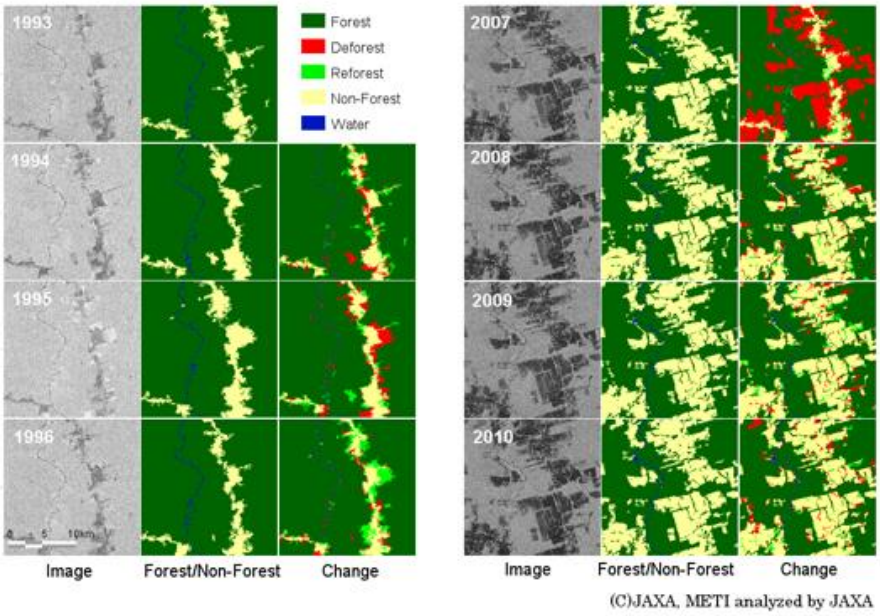

Figure 2.7. *Deforestation in the Amazon between 1993 and 2010 (State of Pará, Brazil). From left to right, L-band backscatter, forest (in dark green)/non-forest (yellow) and map of changes in reference to 1993. The red indicates deforestation while the green shows reforesting (source: http://www.eorc.jaxa.jp/ALOS/en/new/amazonFNF_1993-2010.jpg).*

2.5.2 Estimating forest degradation in French Guiana

Anthropogenic impact on forests are not limited to deforestation. Forest degradation also represents a serious threat. In the Amazon, deforestation has decreased significantly since 2005, but we can see a concomitant increase in forest degradation. According to Asner *et al.* [ASN 05], the surface area of forests degraded by forest exploitation represents between 12,000 and 20,000 km² per year between 1999 and 2002. Forest degradation is therefore a significant source of carbon emissions. Identifying this degradation remains problematic, complicated and costly [ASN 09, ASN 05, SOU 13]. It represents a new serious challenge for remote sensing, both for estimating the surface area of degraded forests and for quantifying its impact on ecosystem services.

New methods are being developed to meet this challenge. In French Guiana, the ONF (National Forestry Commission) and CIRAD (French Agricultural Research Centre for International Development) have developed a tool for monitoring the impacts of forest exploitation. The impact of timber cutting on tropical rainforests appears on optical images as small isolated objects in an ocean of verdure. These objects can be linear (roads), in the form of points (clearings), or both (mining operations are linear alternating with areas of bare soil and sedimentation basins full of water that is more or less clean). Detecting clearings is possible with satellite acquisition from 6 to 12 months after exploitation [GON 09]. The simplest technique is based on the local contrast between photosynthetically active surfaces identified using the NDVI (the canopy) and impacted surfaces that no longer have this capacity. By using wavelengths dedicated to observing vegetation (red [0.61-0.68 µm], near infrared [0.79-0.89 µm] and mid infrared [1.58-1.75 µm]), the contrast is enough to identify the impacted pixels by using reflectance thresholds. The use of indexes also provides access to this information. Applying thresholds to the Normalized Difference Vegetation Index (NDVI) or Normalized Difference Water Index (NDWI[5]) values and mid infrared [1.58-1.75 µm] makes it possible to identify pixels impacted by forest exploitation. The advantage of these robust methods is they are able to use data from SPOT and Landsat satellites [PIT 13], as well as future data from Sentinel-2, in a semi-automatic way.

In French Guiana, selective logging of the forest causes gaps in the canopy that are detected operationally by SPOT images at 10 m resolution (figure 2.8). The figure shows a plot of land of 400 ha with a main logging track running through it. Following a mini-tornado after logging, part of the stand has been significantly damaged by large openings (colored pink surrounded by a blue border). In the logged parts that were not disturbed by the tornado (below), the gaps have been identified on a color composite thanks to value thresholds applied to the NDVI, the NDWI and mid infrared (NDVI in red, NDWI in green and mid infrared in blue). These thresholds make it possible to isolate the impacts (gaps/roads, outlined in red).

5. NDWI = (PIR-MIR)/(PIR+MIR) where NIR is the near infrared reflectance and MIR is the mid infrared reflectance. According to the work of Gao [GAO 96].

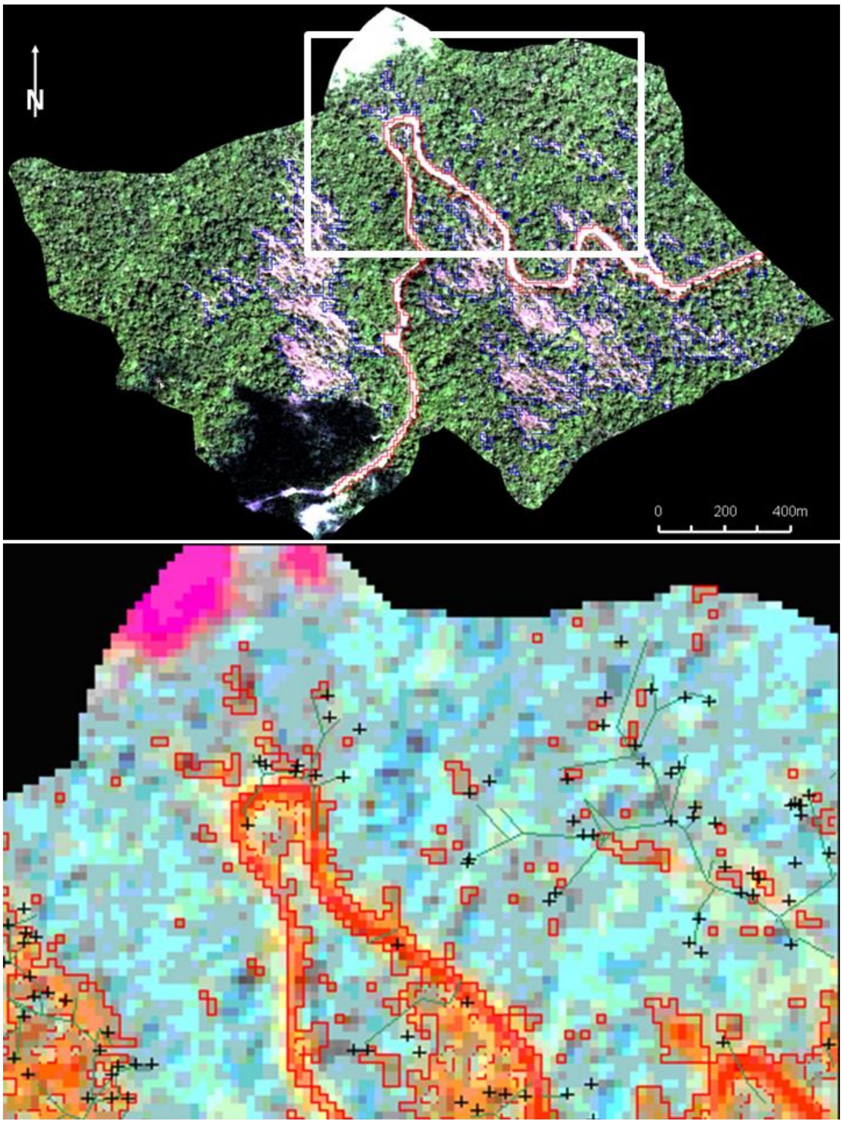

Figure 2.8. *Example of logging operation observed by satellite in French Guiana (latitude 5.33N Longitude -53.22W). Above, general view of the operation from a color composite at 10 m resolution (SPOT-5). Below, part of a color composite (NDVI in red, NDWI in green and mid infrared in blue) after processing identifying the clearings (pixels with a red margin). Validation data from the ground has been added: the black crosses show the stumps and the skidding tracks are in green [GON 09].*

Similarly, detecting roads and tracks is also necessary for forest management. The opening, use and abandonment of road networks are geographic indicators of the opening and degradation of the forest. Documenting this dynamic is possible using SPOT archives and Landsat. Laporte *et al.* [LAP 07] have used photointerpretation to map the networks of roads in Central Africa in order to show scale of logging activities within the forest. When you show the red, near infrared and mid infrared spectral bands in color composites as red, green and blue respectively, the active roads in brown and the intact forest in dark green (figure 2.9) are clearly visible. In order to automatically process the archive over large areas, Bourbier *et al.* [BOU 13] have proposed a method using Landsat data to allow managers to visualize the local (in a concession) or national dynamic of logging road networks (figure 2.9). This example shows the assessment of the opening of the canopy using of Landsat data where the networks of roads are visible through photointerpretation (1). Using a method based on thresholding (2), the “non-forest” pixels are identified. After cleaning using a morphological filter that removes isolated pixels with a small range (3), a synthesis of several dates completes the detection of networks of roads and tracks (4). Finally, an aggregation of pixels in a cell of a chosen size (250, 500 or 1,000 m) allows for the evaluation of the percentage of “non-forest” pixels on a given surface or cell (5). This indicator can then be compared over time thanks to the archive (6) and it is possible to analyze the impact of opening the road network in 2001 (going from 100% to 70% of forest for the red curve that represents a cell) and its gradual closure (up to 90% for the red curve and 100 % for the green curve).

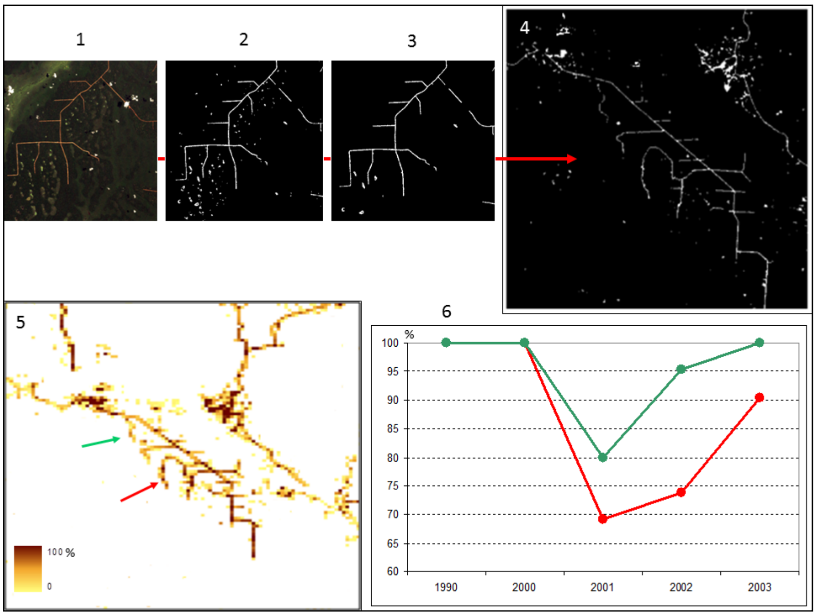

Figure 2.9. *Extraction of information concerning networks of logging roads in Central Africa: 1) color composite from a Landsat image with 30 x 30 m resolution (TM3 in red, TM2 in green and TM1 in blue) ; 2) following the application of thresholds on the channels, the non-forest pixels are identified (in white) ; 3) use of a spatial morphological filter to eliminate isolated pixels and connect the segments of the road network (in white) ; 4) general view of the study area; 5) application of a 500 x 500 m cell in order to estimate the percentage of pixels considered non-forest; 6) temporal evolution between 1990 and 2003 (x-axis) of the percentage of forest pixels (y-axis) of two 500 x 500 m cells (the curves corresponding to the cells are indicated by the arrows in 5).*

2.6. Outlook

Techniques for detecting deforestation by optical remote sensing and/or radar already offer usable and operational products (such as Brazil's PRODES). There are still a certain number of limits such as the need to consolidate the definition of the concept “forest” and analysis techniques for producing reliable validated data and especially on the planetary scale. Nevertheless, the production of statistical data on deforestation, in both spatial and temporal dimensions, should experience significant development in the next two decades thanks to several factors:

– the availability of images at high and very high spatial resolution continues to diversify following the launch of new satellites (especially the Sentinel-1 and

Sentinel-2 satellite constellations), but also the continuation of the AVHRR, MODIS and Landsat programs in the United States. The platforms of the Sentinel-1 and Sentinel-2 constellations are equipped with sensors that allow observation of tropical forested areas every five days under stable angular conditions, notwithstanding the presence of clouds (http://www.esa.int/Our_Activities/Observing_the_Earth/Copernicus/Overview4). Under these conditions, it will be possible to observe logging areas in almost real time (figure 2.10). The SPOT-4 (Take-5) experiment made it possible to simulate the viewing angles of the orbital conditions of the future Sentinel-2 satellite constellation with SPOT-4 data (http://www.cesbio.ups-tlse.fr/multitemp/?page_id=1685). The images were acquired every 5 days. Between February and June 2013 images were selected from sites around the world (http://www.cesbio.ups-tlse.fr/multitemp/?page_id=1685). The Northern Congo site was observed 4 times under good conditions (without clouds). This frequency is enough to observe the progress of a logging area with the opening of the road (March 4), the extension towards the south (March 19), the first side track (April 3), the second and the beginning of the exploitation (June 2), all using a simple color composite;

– the availability of images also involves radar since the existing programs such as the ALOS/PALSAR radar satellite series of Japan will remain. These observations will be completed in 2020 by the ESA Biomass P-band satellite which will be dedicated to measuring vegetation biomass;

– the combination of ALOS/PALSAR radar data and Sentinel-1 with each other or with optical data of the Landsat and Sentinel-2 sensors is also an opportunity to improve the monitoring of deforestation. This combination will guarantee regular monitoring, reliable and continuous over time and space;

– access to these images by scientists is facilitated by the dissemination policies of different space agencies: The European Space Agency (ESA: http://www.esa.int/Our_Activities/Observing_the_Earth/Copernicus) ; the Japanese Space Agency (JAXA: http://www.eorc.jaxa.jp/ALOS/en/palsar_fnf/data/index.htm), or even the National Aeronautics and Space Administration (NASA: https://earthdata.
nasa.gov/) in the United States;

– the large-scale development of airborne lidar measuring programs should allow more precise in characterization of the canopy structure and in the estimation of biomass. The repetition of such measurement programs will make very detailed estimates of degradation possible. However, the cost of these measurement programs would necessarily limit their repetition;

– today the challenges linked to deforestation, and the necessity of developing reliable monitoring tools are recognized worldwide.

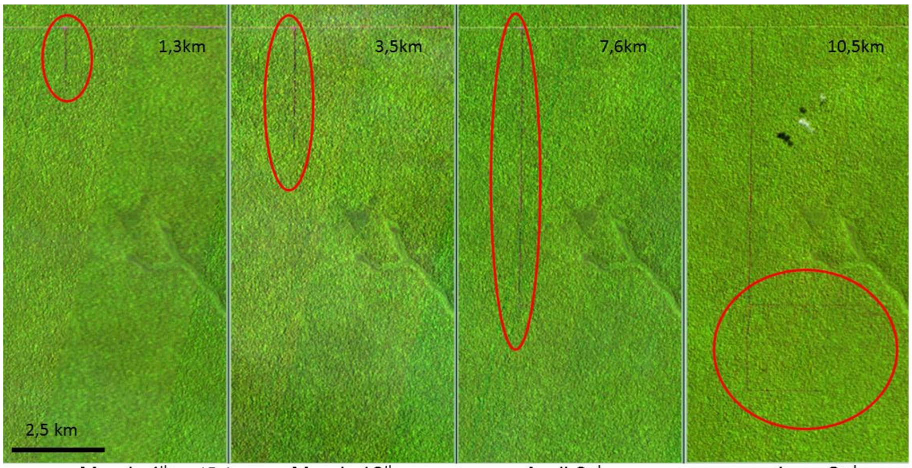

Figure 2.10. *Monitoring forest practices north of Congo-Brazzaville (2.95°North – 17.1° East)*

KEY POINTS. On the planetary scale, forests cover a third of the earth's land area and forests play a crucial role in climate regulation and the production of goods. Knowing the extent of forested areas, the state of forests and how they change over time is therefore particularly important with regard to current environmental concerns linked to climate change. Remote sensing has emerged as the only tool capable of providing reliable data at multiple spatial and temporal scales. The optical data (in visible and infrared wavelengths) and more recently radar data (hyperfrequencies with longer wavelengths) are the two main sources of data. Estimates of net deforestation resulting from the processing and analysis of satellite images on a planetary scale have been available for several years but remain very dependent on the definitions used and the analysis techniques employed. In the future, a greater diversity of optical images and radar should greatly contribute to the development of reliable tools for monitoring deforestation and forest degradation, something essential for responding to one of the greatest environmental challenges of the 21st century.

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