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Chapter 7

Monitoring forest cover and deforestation

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7.1. INTRODUCTION AND MAIN OBJECTIVES

Forests provide a range of goods and services that benefit peoples' livelihoods and wellbeing and that play an important role in economies around the world. It is widely acknowledged that reliable and timely information on forest resources are essential to assess the full benefits of forests, as well as facilitate governments and other stakeholders in assessing and monitoring the effectiveness of policies and programs related to forestry and other land uses (MacDicken, 2015).

Moreover, global demand for agricultural products such as food, feed, and fuel is a major driver of cropland and pasture expansion across much of the developing world (DeFries *et al.*, 2010). Whether these new agricultural lands replace forests, degraded forests, or grasslands greatly influences the environmental consequences of expansion. Across the tropics, between 1980 and 2000, over 55 percent of new agricultural land was obtained at the expense of intact forests, and another 28 percent of disturbed forests (Gibbs *et al.*, 2010). Recently, deforestation driven by commercial cropland has significantly increased, with hotspots occurring in South America (de Sy *et al.*, 2015).

Poor information and statistics on forest resources may lead to insufficient or inaccurate knowledge of the country's forest resource utilization, impede successful planning and policy decisions regarding forestry and other land uses, mislead donors in identifying targeted priorities and projects, and hinder proper assessment of the progress being made towards Sustainable Forest Management (MacDicken *et al.*, 2015) and other development goals.

The Reduction of Emissions from Deforestation and forest Degradation (REDD+) activities held under the United Nations Framework Convention on Climate Change (UNFCCC) are expected to offer results-based payments to developing countries for reducing greenhouse gas emissions from forested lands (UNFCCC, 2014). It is necessary

to determine reference data on forest carbon losses against which future rates of change can be evaluated, and to establish reliable methods for monitoring, reporting and verifying such changes. Most developing countries must yet develop forest monitoring systems at national level in the framework of REDD+.

Although some national agencies (in particular, those of Brazil, India and Mexico) are making great progress at country level from, in the past, several tropical countries had limited capacity to implement such monitoring systems. Capacity-building efforts are now being made to strengthen the technical skillsets necessary to implement national forest monitoring at institutional levels (Romijn *et al.*, 2015). It is highly desirable to help developing countries to foster and enhance their own statistical capacity to produce statistics on forest resources.

The last few decades have seen great progress in producing and disseminating information on global forest cover resources among major international agencies such as the Food and Agriculture Organization of the United Nations (FAO; see FAO, 2015a) or the World Resources Institute. Robust examples advancing such approaches, applied on the full tropical belt, and examples of good practices adopted at national scale are also included in this review.

Advances in measuring approaches and techniques based on satellite remote sensing are of tremendous interest (Achar and Hansen, 2012). Data and methods are no longer an obstacle to the implementation of REDD+ within the Paris Agreement (UNFCCC, 2016). Moreover, the global community of Earth Observation and carbon experts have prepared technical guidelines on methodological issues relating to the integration of remote sensing and ground-based observations to estimate emissions and removals of greenhouse gases in forests: the GOF-C-GOLD REDD sourcebook (GOF-C-GOLD, 2016), and the GFOI Methods and Guidance Documentation (GFOI, 2014). These guidelines are intended to be instruments to assist countries in identifying data gaps in their national forest inventory systems and to provide operational guidance on developing national forest monitoring systems. Countries are encouraged to incorporate the international standards into their forest monitoring program to promote international comparability.

Improvements in national monitoring capacities to produce forest area estimates ultimately benefit policy-makers, economic entities and the livelihoods of forest-dependent people, enhancing the availability and quality of data on forest resources, and thus ensuring better policy and investment decisions.

The purpose of this chapter is to provide guidelines on the use of remote sensing for forest cover statistics and to present the existing approaches to the use of remote sensing for assessing forest cover and evolution, from global to national scales. This review seeks to support the development of national REDD+ interventions and forest monitoring systems.

7.2. THE USE OF REMOTE SENSING TO MONITOR FOREST COVER – BACKGROUND INFORMATION

Technically, it became possible to rely upon remote sensing imagery to monitor forest area change from the 1990s. The feasibility and accuracy of such monitoring depends largely upon national circumstances (in particular, with regard to data availability); that is, potential limitations relate more to definitions, resources and data availability than to methodologies (GOF-C-GOLD, 2016).

7.2.1. Definition of forests, deforestation and degradation

Several terms, definitions and other elements relevant to REDD+ activities are not formally established (including terms such as “deforestation” and “forest degradation”). As decisions regarding REDD+ are based on the current modalities prescribed by the UNFCCC and the Kyoto Protocol, the definitions provided in those two documents will be used in this chapter, and are set out below (see GOFC-GOLD, 2016, for further details).

Forest land – Under the UNFCCC, forest land includes all land with woody vegetation consistent with thresholds used to define forest land in the national greenhouse gas inventory. It also includes systems with a vegetation structure that does not, but that *in situ* could potentially reach, the threshold values used by a country to define the forest land category. Moreover, the presence of other uses that may be predominant should be taken into account.

Estimations of deforestation are affected by the definitions of ‘forest’ versus ‘non-forest’ land, as these may vary widely in terms of tree size, area and canopy density. There are myriad definitions of forest. However, most definitions share certain threshold parameters, including for the minimum area, minimum height and minimum level of crown cover. In its 2015 forest resource assessment, FAO (FAO, 2015a) uses a minimum cover of 10 percent, a minimum height of 5 m and a minimum area of 0.5 ha, adding that forest use should be the predominant use. Most remote sensing studies, on the other hand, use a land cover definition (Magdon *et al.*, 2014), because land use cannot be determined by remote sensing alone.

For the purposes of the Kyoto Protocol, parties select a single value for crown area, tree height and area to define forests within their national boundaries (UNFCCC, 2006). The selection is made from within the following ranges, with the understanding that young stands that have not yet reached the necessary cover or height are included as forest:

- Minimum forest area: 0.05 to 1 ha
- Potential to reach a minimum height at maturity *in situ* of 2 to 5 m
- Minimum tree crown cover (or equivalent stocking level): 10 to 30 percent

The definition of forest allows some flexibility to countries when designing a monitoring plan, because the analysis of remote sensing data can adapt to different minimum tree crown cover and minimum forest area thresholds. However, consistency in forest classifications for all REDD+ activities is critical for integrating different types of information, including remote sensing analysis. The use of different definitions affects the technical requirements for Earth Observation and may influence cost, availability of data, and the ability to integrate and compare data through time.

Deforestation – Most definitions characterize deforestation as the long-term or permanent conversion of land from forest use to other non-forest uses. Under Decision 16/CMP.1, the UNFCCC defined deforestation as: “the direct, human-induced conversion of forested land to non-forested land.” (UNFCCC, 2006).

In practical terms, this definition entails a reduction in crown cover from above to below the threshold for the forest definition. Deforestation causes a change in land use, usually in land cover. Common changes include conversion of forests to annual cropland, to pasturelands, to perennial plants (such as oil palm or shrubs), and to urban lands or other human infrastructure.

Forest degradation – Forest degradation occurs due to various processes, including unsustainable logging, shifting cultivation, firewood collection or burning. It leads to a reduction of biomass, opening of forest canopies and changes in the structure of forests. It also modifies species composition, thus affecting ecosystem services, including future potential for carbon capture and storage.

A report authored by the Intergovernmental Panel on Climate Change (IPCC, 2003) presents five different potential definitions for degradation, along with their respective pros and cons. The report suggested the following characterization for degradation:

“A direct, human-induced, long-term loss (persisting for X years or more) or at least Y percent of forest carbon stocks [and forest values] since time T and not qualifying as deforestation”.

In practice, it is likely to be difficult to agree upon the values for X, Y and T. Therefore, it is also possible that no specific definition is necessary, and that any “degradation of forest” will be reported simply as a net decrease of carbon stock in the category of “Forest land remaining forest land” at national or subnational level. The GFOI Methods and Guidance Document (GFOI, 2014) does not attempt to formally to define degradation, although it does set out steps for estimating degradation using IPCC methods.

7.2.2. Specifications for monitoring deforestation from remote sensing

Tropical forest mapping and monitoring is a key application domain for Earth Observation (EO) because of the need for recurrent and frequent data to produce annual information on forest cover in humid and seasonal domains, and regular information on forest disturbance processes. It benefits from long-term consistent archives of Landsat imagery for forest area change, for instance supporting various mature and operational applications such as the Global Forest Watch (GFW) platform¹ of the World Resources Institute and the PRODES project² of the Brazilian National Space Agency. Previous attempts to integrate moderate to fine-resolution EO imagery into operational forest degradation mapping and monitoring have largely failed because of inadequate technical parameters, high costs and uncertain long-term prospects. Currently, the EO community mostly uses Landsat sensors (30 m), with products having global coverage and an annual frequency. Today, the use of such imagery (approximately 30 m) leads mainly to the creation of tree cover percentages or forest/non-forest binary maps, which are released at yearly intervals (Hansen *et al.*, 2013).

The remote sensing techniques to monitor changes in forest areas (e.g. deforestation) provide high-accuracy area estimates and may also allow for the spatial mapping of the main forest ecosystems (GOFCC-GOLD, 2016). As a minimum requirement, it is recommended to use Landsat-type remote sensing data (30-m resolution) or finer-resolution imagery (e.g. Sentinel-2 data at 10 m resolution) to monitor forest cover changes, with the Minimum Mapping Unit (MMU) measuring between 1 to 5 ha. These data will allow to assess changes in forest areas (in particular, to derive the area deforested and forest regrowth for the period considered). A hybrid approach combining automated digital segmentation and classification techniques with visual interpretation and/or validation of the resulting classes/polygons should be preferred, as this constitutes a simple, robust and cost-effective method.

Different spatial units may be used to detect forest and forest change. Current national and regional remote sensing monitoring systems provide several examples of MMU: Brazil’s PRODES system³ for monitoring deforestation in the Brazilian Legal Amazon region (initially 6.25 ha, today 1 ha for digital processing); India’s national forest monitoring system (1 ha); the EU-wide CORINE land cover/land use change monitoring system (5 ha); the Peruvian Ministry of Environment’s deforestation monitoring programme (0.1 ha); and the Global Forest Watch deforestation monitoring system (0.1 ha).

Currently, there are two main sources of free global mid-resolution (30 m × 30 m to 10 m × 10 m) remote sensing imagery: NASA (Landsat satellites), for data acquired since the early 1980s; and the European Space Agency, or ESA (Sentinel satellites, through Copernicus programme) for data acquired since the mid-2010s, although some quality issues arise with respect to certain parts of the tropics (resulting from clouds, seasonality, etc.). All Landsat

1 <http://www.globalforestwatch.org/>.

2 <http://www.obt.inpe.br/prodes/index.php>.

3 The PRODES project of the Brazilian Space Agency (INPE) has been producing annual rates of gross deforestation since 1988. PRODES has quantified approximately 750 000 km² of deforestation in the Brazilian Amazon through 2010, a total that accounts for approximately 17 percent of the original extent of the forest.

data from archives of the United States of America (in particular, the United States Geological Service, or USGS) are available for free. Brazilian/Chinese remote sensing imagery from the CBERS satellites is also freely available. CBERS-4 is part of the second phase of this Sino-Brazilian cooperation. The imagery is now used in important projects involving deforestation control and environmental monitoring in the Amazon Region. Other areas, such as water resources monitoring, urban growth, soil occupation and education, are also benefitting from CBERS-4 imagery. In fact, it is currently fundamental for large-scale national and strategic projects. Two important examples are the aforementioned PRODES⁴ project and CANASAT⁵ (monitoring of sugar-cane areas). Data fusion between CBERS-4 and Sentinel-2 are already being considered.

TABLE 1. CHARACTERISTICS OF LANDSAT-8 OLI AND SENTINEL-2 SENSORS.

Country	Satellite and sensor	Resolution and coverage	Cost for data (archive)	Feature
United States of America	Landsat-8 OLI	15 m – 30 m 180 x 180 km ²	All data archived at USGS may be accessed free of charge	Data are systematically acquired since June 2013
EU	Sentinel-2	10 m- 20 m Swath 290 km	All data archived at ESA may be accessed free of charge	Data are systematically acquired since July 2016

Optical mid-resolution data (such as Landsat data) have been the primary tool for deforestation monitoring. Other, newer, types of sensors, such as radar (ERS1/2 SAR, JERS-1, ENVISAT-ASAR and ALOS PALSAR 1/2) and LiDAR, are potentially useful and appropriate (De Sy *et al.*, 2012). Radar, in particular, alleviates the substantial limitations of optical data in persistently cloudy parts of the tropics. Data from LiDAR and radar have proven to be useful in project studies; however, to date, they are not widely used operationally for forest monitoring over large areas. In the future, the utility of radar may increase depending on data acquisition, access and scientific developments.

7.2.3. Specifications for monitoring forest degradation from remote sensing

Most forest degradation can be detected by means of remote sensing methods; however, optimal approaches and methodologies for monitoring forest degradation are likely to vary depending on the type and location of the degradation, as well as on the forest types concerned. Robust methods to monitor forest degradation (and forest regrowth) remain under development. As stated in the GOF-C-GOLD REDD+ Sourcebook (2016), measuring forest degradation or forest regrowth and related changes in forest carbon stock is more challenging than measuring deforestation, because such forest changes are not easily detectable through remote sensing, but require more frequent and better imagery and processing.

⁴ <http://www.obt.inpe.br/prodes/>.

⁵ <http://www.dsr.inpe.br/mapdsr/>.

Monitoring forest degradation is limited by the technical capacity to sense and record the change in canopy cover: small changes are unlikely to be apparent unless they produce a systematic pattern in the satellite imagery. Many activities cause the degradation of carbon stocks in forests; however, not all of them can be monitored well with a high degree of certainty, and not all of them must be monitored using remote sensing data (Miettinen *et al.*, 2014). To develop a monitoring system for degradation, it is first necessary to identify the causes of degradation and assess their likely impact on carbon stocks:

- The areas of forests undergoing selective logging – with the presence of gaps, roads, and log decks – are likely to be observable in remote sensing imagery, especially the network of roads and log decks. Gaps in canopy caused by harvesting of trees have been detected in imagery such as that captured by Landsat, using more sophisticated analytical techniques to process frequently collected imagery (Grecchi *et al.*, 2017).
- The degradation of carbon stocks caused by forest fires may be more difficult to monitor with existing satellite imagery (Miettinen *et al.*, 2016). Almost all fires in tropical forests have anthropogenic causes.
- Degradation resulting from over-exploitation for fuelwood or other local uses of wood is often followed by animal grazing, that prevents regeneration – a situation more common in drier forest areas. This situation is unlikely to be detectable from satellite image interpretation unless the rate of degradation was intense, thus causing larger changes in the canopy.

7.2.4. Availability of Landsat data

In 1972, NASA launched the first Landsat satellite with a mid-resolution sensor that was capable of collecting land information at a landscape scale. This satellite was the first in a series of (seven, to date) Earth-observing satellites that have enabled continuous coverage since 1972. Subsequent satellites were launched every two to three years. Still in operation, Landsat 7 covers the same ground track repeatedly every 16 days. To continue the series, the Landsat Data Continuity Mission (Landsat 8) was launched in 2013.

Almost complete global coverage captured by these Landsat satellites since the early 1990s may be downloaded free of charge from the USGS web portals⁶: in particular, such imagery consists in the Global Land Survey (GLS) data sets. These data serve a key role in establishing historical deforestation rates, although in some parts of the humid tropics (such as Central Africa), persistent cloudiness is a major limitation to using them. The full Landsat 8 OLI (since June 2013) and Landsat 7 ETM+ (since 1999) USGS archives, and all USGS archived Landsat 5 TM data (since 1984), Landsat 4 TM (1982-1985) and Landsat 1-5 MSS (1972-1994) may be ordered at no charge from the USGS.

To date, given its low cost and unrestricted license use, Landsat has been the workhorse source for mid-resolution (10–50 m) data analysis. Key limitations in the use of Landsat sensors consist in the mixed nature of the measured signal, and the difficulties in identifying forest cover disturbances. The latter aspect is especially important in areas where small-scale processes are significant. Alternative sources of data include ASTER, SPOT, IRS, CBERS, DMC, AVNIR-2 or Sentinel-2.

7.2.5. Availability of Sentinel-2 data

Sentinel-2A (S2A) was launched in 2015 and provides wide-area optical imagery with resolutions of 10 m (visible and near-infrared, or NIR), 20 m (red-edge, NIR and short-wave infrared, or SWIR) and 60 m (visual to short-wave infrared for atmospheric correction) from October 2015 onwards.

⁶ <http://glovis.usgs.gov/>.

The S2A has a wide swath width (290 km) and a 10-day revisit frequency. S2A coverage is global (capturing land masses). The launching of the S2's identical B unit is scheduled for 2017, and will increase the S2's revisit capacity to five days. The Copernicus programme already envisages C and D versions of these Sentinels to guarantee data availability until at least 2027.

The Sentinel 2 sensors – together with Landsat 8 – will provide core capacity upon which a viable set of globally consistent services in the forestry domain can be based, thus setting the stage for a number of innovative and challenging applications, and for the redesign of monitoring systems for a more accurate monitoring of forest degradation.

Sentinel-2 Product Level 2A is the standard level for which a processing tool will be made available through the Copernicus program (on the ESA Sentinel-2 Toolbox)⁷. Level-1C products contain applied radiometric and geometric corrections (including orthorectification and spatial registration in a fixed cartographic geometry). Level-2A products are at the bottom of atmosphere reflectance in cartographic geometry. Currently, Level-2A products must be processed by the user. A higher level of processing of satellite imagery data (Level 3) would be required for REDD+ countries. Level 3 should consist in adequate image mosaics (that minimize cloud coverage) from the Sentinel-2 satellite time series, composed every 30 days or every three months over the tropical belt. The specifications for a standard Sentinel-2 Level 3 core product, to be made systematically and freely available through a free and open distribution platform, were prepared by the Copernicus programme in 2017.

The technical quality of the Sentinel sensors significantly enhances the separation of land cover classes in forest land use, both for forest land (that is, forest types) and the complex domain of mosaics of agriculture and forest (including shifting cultivation). The 10 to 20 m spatial resolution of S2A (and S2B), combined with a ten-day (or five days with both S2A and S2B) revisit frequency will resolve the forest cover status and small-scale disturbances delineation at plot and log level detail. Slower forest conversion changes – in particular, the progressive removal of fuel wood or agricultural land abandonment leading to forest regrowth – will benefit from the high level of spatial details and the possibility to select the most relevant seasonal acquisitions. The complementarity of visible, NIR and SWIR channels (from S2) is unique in this respect too. Furthermore, the spectral compatibility of S2 with Landsat-8 and much improved atmospheric correction will greatly expand intersensor consistency and the potential for data fusion.

The finer spatial resolution (10 m) and the higher temporal frequency (a revisit time of five to ten days) of Sentinel-2 acquisition will enable more accurate and regular detection and quantification of forest degradation in tropical countries than is possible from current medium-resolution satellite imagery. Consequently, in the near future, satellite imagery from the Sentinel-2 satellite sensor will provide potential for incremental change in the assessment of forest conditions.

The introduction of Sentinel-2 will potentially lead to a diffusion of forest monitoring capacities to national and regional government levels in the next five to ten years, for instance, as an extension or a component of National Forest Inventory (NFI) systems. This will require significant capacity building efforts, which should be, insofar as possible, directed towards anchoring a robust methodological framework. To the greatest extent possible, this should lead to standardized forest area estimates and map products at national level with an agreed level of accuracy and quality that can be integrated into regional and global applications.

In summary, Landsat-type data are most suitable for assessing historical rates and patterns of deforestation. The availability of free and open Landsat-8 and Sentinel-2 data has increased for recent years; therefore, more detailed assessments of coverage periods lesser than five years may be possible in several parts of the world.

⁷ http://www.esa.int/Our_Activities/Observing_the_Earth/Copernicus/Sentinel-2/Data_products.

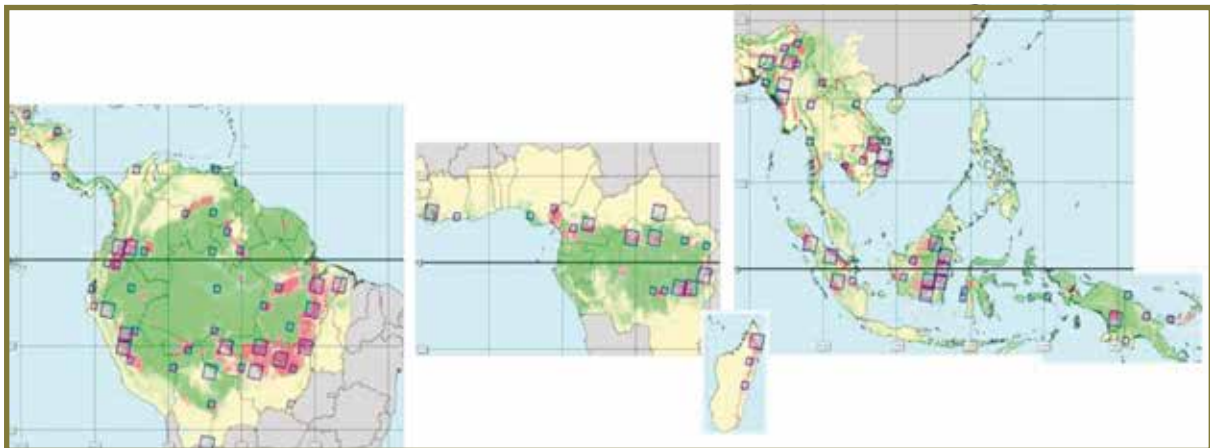
7.3. THE FAO GLOBAL FOREST RESOURCES ASSESSMENT'S REMOTE SENSING SURVEY

7.3.1. Background on statistical sampling designed to estimate deforestation from optical sensors having moderate spatial resolution

It would be ideal to conduct an analysis that covers the full spatial extent of the forested areas with imagery having moderate spatial resolution (Landsat-type), termed “wall-to-wall” coverage; however, this may not be practical over large and heterogeneous areas. In addition, it would place commensurate constraints on the resources available for analysis. For digital analysis with moderate-resolution satellite images at pan-tropical or continental levels, several approaches have been successfully applied by sampling within the total forest area, to reduce the costs and time required to conduct the analysis.

A sampling procedure that adequately represents deforestation events can capture deforestation trends (Achard *et al.*, 2002; Richards *et al.*, 2000). Since deforestation events are not randomly distributed in space, particular attention is required to ensure that the statistical design is adequately sampled within areas of potential deforestation (figure 1), for example through a high-density systematic sampling when resources are available (Mayaux *et al.*, 2005).

FIGURE 1. LOCATION OF SAMPLE UNITS OF THE TREES-II SURVEY



Achard *et al.*, 2002; Richards *et al.*, 2000

For its global Forest Resources Assessment 2010 programme (FRA 2010), FAO continued to develop its monitoring of forest cover changes at global to continental scales to complement national reporting. Technological improvements and better access to remote sensing data made it possible to expand the scope of the survey, compared to FRA 2000. The findings of the FRA 2000 tropical Remote Sensing Survey (RSS) (figure 2) were included as a chapter in the FRA 2000 Main Report (FAO, 2001) and reported upon in Drigo *et al.* (2009).

FIGURE 2. LOCATION OF SAMPLE UNITS OF THE FOREST RESOURCES ASSESSMENT 2000 PROGRAMME



FAO, 2001; Drigo *et al.*, 2009

7.3.2. General sample approach selected for the Global Remote Sensing Survey

The remote sensing surveys of FRA 2010 and FRA 2015 have been extended to all lands (not only the pan-tropical zone). These surveys aimed to estimate forest change based on a sample of moderate-resolution satellite imagery, and were designed to provide consistent and comparable estimates of tree cover and forest land-use changes over two decades at global and regional scales, to complement the increasing number of national statistics in FRA main reports that are based on national remote sensing surveys.

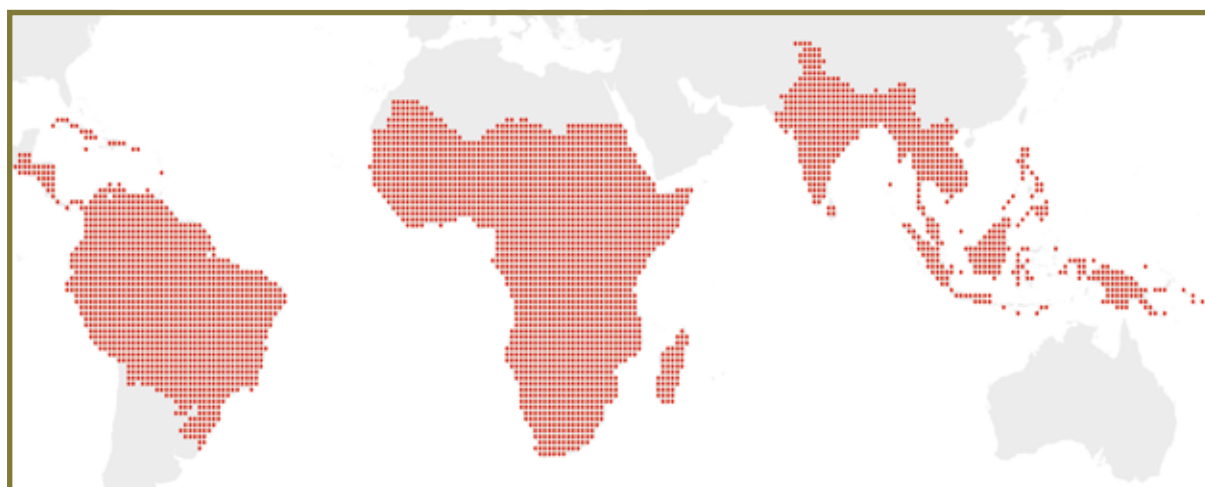
In a coordinated effort, FAO and the Joint Research Centre (JRC) of the European Commission produced estimates of forest land use change from 1990 to 2005 for RSS 2010 (FAO and JRC, 2012). This global survey was then extended to the year 2010 (to cover the period from 1990 to 2010) for the FRA-2015 (Achard *et al.*, 2014; Keenan *et al.*, 2015).

The FRA 2010 RSS is based on a much higher number of smaller sample units than the previous FRA exercises, with a systematic grid – sample units are located at each intersection of the $1^\circ \times 1^\circ$ lines of latitude and longitude that falls over land. This global systematic sampling scheme was developed jointly by FAO and the JRC to estimate the rates of deforestation at global or continental levels at intervals of five to ten years (Mayaux *et al.*, 2005).

Each sample unit has a core size of $10 \text{ km} \times 10 \text{ km}$ with an external 5-km buffer for forest cover contextual information (that is, the full size of sample units is $20 \text{ km} \times 20 \text{ km}$ for land cover information). These dimensions were chosen to allow for spatially explicit monitoring at a scale relevant to land management.

This sampling scheme leads to approximately 13 500 sample units for the terrestrial part of the globe, or approximately 9 000 sample units when excluding desert areas, and represents approximately 1 percent of the land surface (0.8 percent along the Equator) with the geographical grid (figure 3).

FIGURE 3. LOCATION OF SAMPLE UNITS OF THE REMOTE SENSING SURVEY (RSS) OF THE FRA-2010 OVER THE TROPICS.



7.3.3. Selection and preprocessing of satellite imagery

The FAO FRA RSS 2010 is a global study with consistent methods and time series that can be extended to include more recent periods. Time series of moderate-resolution remote sensing data are attached to each sampling location through a quality-controlled, standardized and decentralized process. The following paragraphs briefly describe the satellite data set and preprocessing steps used for the FAO FRA RSS 2010 over the tropical regions.

For each sample unit, orthorectified Landsat (E)TM Landsat images were acquired at no cost from the GLS archives, which are created and made available by the USGS (Gutman *et al.*, 2013). For each sample unit, four images were selected with the lowest possible cloud cover and as close as possible to the target dates of 30 June for the years 1990, 2000, 2005 and 2010. Where GLS data was unavailable, of bad quality (such as Landsat 7 SLC-off data) or cloudy for the area of the sample units (Potapov *et al.*, 2010), alternative satellite scenes were acquired from the Landsat archives of the USGS or of other space agencies, such as Brazil's INPE (Beuchle *et al.*, 2011). The range of image acquisition dates was 1986–1993, 1999–2003, 2004–2007, and 2009–2011 for the years 1990, 2000, 2005 and 2010 respectively.

The selected images underwent an extensive preprocessing, including an image geolocation check, conversion to top-of-atmosphere reflectance, cloud-masking, de-hazing and image normalization on the basis of pseudo-invariant features (Bodart *et al.*, 2011). For multitemporal image analysis, a good geometric match of the images is fundamental. In this context, the geolocation of some images required enhancement. For this purpose, the Landsat ETM image (from the year 2000) was determined to be the “master image”. Consequently, the “slave image”, consisting mostly in Landsat 5 imagery, was shifted until a correct overlay with the master image was achieved.

7.3.4. Processing and analysis of satellite imagery

This section describes the analysis carried out over the tropical regions.

After preprocessing, the satellite imagery was used in an automated multistep image segmentation to subdivide the sample unit (10 000 ha) into delineated areas (polygons) with similar spectral and structural attributes. The target MMU was 5 ha. On the segmented imagery, a supervised automated land cover classification was carried out, which was later converted to a land use classification with the help of expert human interpretation.

For each sample unit, the preprocessed images from the four “epochs” (that is, the years 1990, 2000, 2005 and 2010) were subjected to a multistep segmentation using eCognition software (Trimble©), followed by an object-based classification process based on membership functions defined by a collection of spectral signatures taken from across the tropical belt (Raši *et al.*, 2011 and 2013). An MMU of 5 ha (or 50 pixels at 30 m × 30 m resolution) is considered for the interpretation of the satellite imagery to identify the forest cover changes. A finer “detection unit level” at approximately 1 ha was used in a first automated segmentation and labelling step before aggregation to 5-ha objects for the interpretation phase.

Objects were classified into five land cover classes: Tree Cover, Tree Cover Mosaics, Other Wooded Land, Other Land Cover and Water (see table 2 for a description of each class). The Tree Cover class was defined in compatibility with the FAO definition of forest (FAO, 2010).

TABLE 2. LAND COVER CLASSES USED BY THE JRC.

Class name	Class description
Tree cover (TC)	Objects covered by 70–100 percent of trees, where trees are defined as plants higher than 5 m and with a wooden stem, and tree canopy density is greater than 30 percent
Tree cover mosaic (TCM)	Objects covered by 30–70 percent of trees
Other wooded land (OWL)	Objects covered with more than 50 percent of plants lower than 5 m with one or more wooden stem(s)
Other land cover (OLC)	Land not covered by the TC, TCM or OWL classes, comprising natural grassland, agricultural land, built-up areas, bare soil and rock
Water (W)	Rivers and lakes

The resulting classified objects, with an MMU of 5 ha, underwent an intensive process of correction of the land cover information assigned for each target year (Eva *et al.*, 2012).

The JRC and FAO scientists collaborated with more than 100 remote sensing and forestry experts from tropical countries, including largely forested countries such as Brazil, India, Indonesia and the Democratic Republic of Congo.

It must be noted that for the FRA 2010 RSS reporting (FAO and JRC, 2012), FAO employs a land use classification (FAO, 2010b), including a “Forest” land use class⁸; this is better suited to assessing drivers than a land cover classification, such as that used by the JRC (de Sy *et al.*, 2015). A young forest plantation is considered as “Forest” in the FAO survey (trees able to reach more than 5 m), but is classified as “Other land cover” according to the JRC legend if the trees are not visible or lower than 5 m.

⁸ The “Forest” class of the FAO FRA 2010 report is defined as: “Land spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover of more than 10 percent, or trees able to reach these thresholds in situ. It does not include land that is predominantly under agricultural or urban land use.”

7.3.5. Statistical analysis

The land cover and land cover change information available for all sample units is used to produce statistical estimates for the entire area of interest. Considering that very few satellite images were acquired at the exact same date of their respective epochs, the land cover (change) information of each sample unit is first linearly “normalized” (as a best approximation) to the target dates of 30 June for the years 1990, 2000, 2005 and 2010 to produce land cover statistics. For this purpose, we assume that the land cover changes detected occurred linearly over time.

Areas lacking data due to clouds, poor satellite coverage or low-quality imagery in any of the reference years were considered as an unbiased loss of data, and assumed to have the same proportions of land cover as non-cloudy areas within the same site. This is achieved by converting the 1990–2000 and 2000–2010 land-cover change matrices to area proportions relative to the total cloud-free land area of the sample units. For the missing sample units (4, 39 and 3 for 1990–2000 and 3, 39 and 3 for 2000–2010, from totals of 1 230, 2 045, and 741 sample units, for South America, Africa and Southeast Asia, respectively) a local average was used from surrounding sample sites as surrogate results. The following weights ($\delta_{jj'}$) were applied to obtain the local average of missing sites:

$$\delta_{jj'} = 1/d(j, j') = 1 / \left((dif(lat))^4 + (dif(long))^4 \right) \quad [1]$$

where $d(j, j')$ is the distance between two sites.

For the statistical estimation phase, the sample units are weighted in relation to their statistical probability of selection. Indeed, although the sampling frame is systematic, it does not give equal probability to all sample units because the distance between sample units along a parallel is not the same as the distance along a meridian. All sample units are given a weight, which is equal to the cosine of the latitude to account for this unequal probability. The impact of these weights is moderate in tropical areas. The selected sample units that contain a proportion of sea compensate for those non-selected sample units that contain a proportion of land (when the centre of the sample unit is located in the sea), because they were considered as full sites.

The proportions of land cover changes were then extrapolated to the study area using the Horvitz-Thompson Direct Expansion Estimator (Särndal *et al.*, 1992). The estimator for each land cover class transition is the mean proportion of that change per sample unit, given by Equation 2:

$$\bar{y}_c = \frac{1}{m} \sum_{i=1}^n w_i \cdot y_{ic} \quad [2]$$

where y_{ic} is the proportion of land cover change for a particular class transition in the i th sample unit. The weight of the sample unit is w_i and m is the sum of the sample weights.

In case of systematic sampling, the usual “random case” estimator is positively biased (Stehman *et al.*, 2011). Alternative estimators based on a local estimation of the variance enable a partial solution of the problem, that is, to reduce the bias. Here, an estimator of the standard error based on local variance estimation is used:

$$s^2 = (1 - f) \frac{\sum_{j \neq j'} w_{jj'} \delta_{jj'} (y_j - y_{j'})^2}{2 \sum_{j \neq j'} w_{jj'} \delta_{jj'}} \quad [3]$$

where f is the sampling rate, the weight $w_{jj'}$ is an average of the weights w_j and $w_{j'}$ and $\delta_{jj'}$ is a decreasing function [1] of the distance between j and j' (note that if it is determined to set $\delta_{jj'} = 0$, the usual variance estimator is obtained). The standard error (se) is then calculated as:

$$se = \frac{s}{\sqrt{n}} \quad [4]$$

where n is the total number of available sample sites (that is, not accounting for the missing sites even if these are replaced by a local average).

Land cover changes were estimated by assessing the matrices of change (see table 3), for the decades 1990–2000 and 2000–2010. An object labelled as Tree Cover Mosaic (TCM) was considered as 50 percent forest cover, defined by the average of the upper and lower percent limit. Consequently, forest cover loss was calculated as being 100 percent of the tree cover converted to Other Wooded Land (OWL), Other Land Cover (OLC) or Water (W) plus 50 percent of the tree cover converted to TCM and 50 percent of the TCM converted to OL, OWL or W.

7.3.6. Accuracy/consistency assessment of estimates of forest cover changes

The observations (source data sets) used to produce the results given in this chapter are derived from satellite interpretations. These surrogates to ground observations may be subject to error or uncertainty (bias) (Foody, 2010); however, these issues were not addressed in this assessment. The use of such surrogate data for assessing area change is inevitable in many areas of the tropics where no ground observations exist and where large areas of inaccessible forests can only be monitored at affordable costs by exploiting satellite data. However, an independent assessment was performed over 1 185, 1 552 and 830 points (for a total of 3 567 points) distributed systematically within a random subsample of 240, 338 and 166 sample units in South America, Africa and Southeast Asia, respectively (a central point plus four points in the corners taken in each sample unit). In addition, from a 9 x 9 systematic grid (81 points taken at a distance of 1 km in each sample unit), all points identified as change in land cover during the decade from 1990 to 2000 were selected, resulting in 1 663, 1 194 and 1 425 points (for a total of 4 282) respectively for the three subregions. The corresponding polygons were carefully visually reinterpreted by independent experts using any available ancillary information (such as imagery from Google Earth, with due attention to the date of image capture). This enables an assessment of the “consistency” of the results of the interpretation.

To complement this consistency assessment, the results were also compared to the INPE interpretations for the decade from 1990 to 2000 (INPE, 2013) for a random selection of 34 sample units among the 411 sample units falling in the Brazilian Legal Amazon (Eva *et al.*, 2012).

7.3.7. Results for the tropics

Results of the FRA 2010 RSS have been published at global level for 1990–2000 and 2000–2005 (FAO and JRC 2012) and at tropical or regional scales for 1990–2000 and 2000–2010 (Achard *et al.*, 2014; Beuchle *et al.*, 2015; Bodart *et al.*, 2013; Eva *et al.*, 2012; Mayaux *et al.*, 2013; Stibig *et al.*, 2014). This section briefly reports the main results for the tropical region, to illustrate the outcomes of this RSS.

In 1990, there were 1 635 million ha of tropical forest and 964 million ha of other wooded land. By 2010, the forest area had fallen to 1 514 million ha, with an overall net loss over the two decades of 56.9, 30.9 and 32.9 million ha in South and Central America and the Caribbean, sub-Saharan Africa and South and Southeast Asia, respectively. Other

wooded land increased in that period to 975 million ha, mainly due to the increase of 18.6 million ha in Southeast Asia. In 2010, humid tropical forests accounted for approximately 64 per cent of the tropical forest cover, that is, 972 million ha from a total of 1 514 million ha, with the following regional distribution: 599 million ha in South America, 210 million ha in Africa and 163 million ha in Southeast Asia.

At global level, the gross loss of tropical forests was of 8.0 million ha y-1 during the 1990s (0.497 per cent annually), with a slight decrease of 7.6 million ha y-1 during the 2000s (0.494 per cent annually), mainly due to reduced deforestation rates in the humid forests of Africa and Southeast Asia (from 0.70 to 0.36 million ha y-1 and from 1.70 to 1.22 million ha y-1, respectively) (Achard *et al.*, 2014). Large non-forest areas were also reoccupied by forests, reaching 1.9 million ha y-1 in the 1990s and 1.6 million ha y-1 in the 2000s.

7.3.8. Precision of the estimates for the tropics

The estimates of forest area changes (gross loss, gross gain and net loss) have small statistical standard errors due to the large sample size: from 4 percent to 10 percent at global level, and from 11 percent to 19 percent on average at regional level. A dedicated accuracy assessment was carried out for the land cover maps of the tropical sample units for the 1990–2000 period. The overall agreements between the RSS results and the reinterpretations considered as reference information are of 92.9 percent for the forest labels and 85.5 percent for the forest change labels. The potential bias in these results (due to errors of interpretations) were assessed by comparing estimates derived from our sample to estimates derived from the reference data set. The relative difference is of -8.9 percent for the global forest area estimate – that is, a lower forest area estimate is derived from the RSS study compared to the reference data set – and of 11.2 percent for the global gross deforestation estimate; in other words, larger deforestation estimates were obtained from the RSS study. Comparison to the INPE interpretations for the 1990–2000 period for a random selection of 34 sample sites displays a good correspondence between the INPE interpretations and the RSS results, both for the forest area of the year 1990 and for deforestation in the 1990–2000 period, with slopes close to 1 (1.017 and 1.008 respectively) and an R2 close to 1 (0.986 and 0.978 respectively) (Eva *et al.*, 2012).

7.3.9. Intensification of the sampling scheme for forest cover change estimation at national scale

The global systematic sampling scheme described above can be intensified to produce results at the national level. Deforestation estimates derived from two levels of sampling intensity have been compared with estimates derived from the official inventories for the Brazilian Amazon and for French Guyana (Eva *et al.*, 2010).

By extracting nine sample data sets from the official wall-to-wall deforestation map derived from satellite interpretations produced for the Brazilian Amazon for the year-long period from 2002 to 2003 (INPE, 2016), the global systematic sampling scheme estimate gives 2.8 million ha of deforestation with a standard error of 0.1 million ha. This compares with the full population estimate from the wall-to-wall interpretations of 2.7 million ha deforested. The relative difference between the mean estimate from the sampling approach and the full population estimate is of 3.1 percent and the standard error represents 4 percent of the full population estimate. The testing of the systematic sampling design within the Brazilian Amazon resulted in a low standard error of less than 5 percent of forest cover change rate.

To intensify the sampling intensity of this global survey over French Guyana, Landsat-5 TM data were used for the historical reference period (1990) and a coverage of SPOT high-resolution visible sensor imagery at a resolution of 20 m × 20 m was used for 2006. The estimates of deforestation between 1990 and 2006 from the intensified global sampling scheme over French Guyana are compared with those produced by the national authority to report

on deforestation rates for its overseas department under the rules established by the Kyoto Protocol rules (Stach *et al.*, 2009). The latter estimates derive from a sampling scheme of almost 17 000 plots derived from the traditional forest inventory methods carried out by the country's *Inventaire Forestier National* (IFN) and analysed from same spatial imagery acquired between 1990 and 2006. The intensified global sampling scheme leads to an estimate with a relative difference from the IFN of 5.4 percent. These results, as well as other studies (Steininger *et al.*, 2009), demonstrate that the intensification of the global sampling scheme can provide forest area change estimates that are close to those achieved by official forest inventories with precisions of less than 10 percent, although only the estimated errors from sampling are considered and not errors from the use of surrogate data.

7.3.10. The future of the Global Forest Resources Assessment: towards FRA 2020

The FAO FRA is a continuously improving process: each assessment is an upgrade of the former one as information needs change, new and better data become available and new methods and technologies can be applied. Due to recent developments in the international forestry and policy arena, such as the Paris Agreement and the Sustainable Development Goals (SDGs), FRA must adapt to respond to evolving information needs, in terms of both scope and reporting periodicity.

The FRA has received technical guidance and support from international specialists through expert consultations organized at regular intervals by FAO and the United Nations Economic Commission for Europe (UNECE) over the last 30 years. The first consultation on the FRA was held in 1987; subsequent consultations took place in 1993, 1996, 2002 and 2006 (Kotka I-V) in Kotka, Finland and 2012 in Ispra, Italy. The latest expert consultation was held in June 2017 in Joensuu, Finland.

The objectives of the expert consultation include the provision of recommendations on the scope of the next global assessment, including the country reporting process and the remote sensing component, and discussion of the frequency of reporting on core variables and annual reporting on SDG indicators.

7.4. OTHER EXAMPLES OF RSS USED FOR FORESTRY STATISTICS

7.4.1 Deforestation statistics from the Global Tree Cover product, University of Maryland

More recently, a new approach that employs recommended IPCC good practices and a combination of remote sensing data (De Sy *et al.*, 2012) to quantify tropical forest above-ground carbon (AGC) losses from 2000 to 2012 was presented by the University of Maryland (Tyukavina *et al.*, 2015). This study is an important extension of earlier studies applied to the Democratic Republic of Congo and Peru (Tyukavina *et al.*, 2013; Pelletier and Goetz, 2015).

More specifically, Tyukavina *et al.* (2015) use a sample-based approach combined with a wall-to-wall tree cover loss data set (Hansen *et al.*, 2013) to estimate tropical forest area losses.

The Global Tree Cover data set from the University of Maryland (Hansen *et al.*, 2013) provides wall-to-wall data starting from the year 2000. Hansen *et al.* (2013) divide world land area into four “tree cover” classes – 0–25 percent, 26–50 percent, 51–75 percent and 76–100 percent – when undertaking wall-to-wall mapping using Landsat images. The authors found that in the tropics, the 76–100 percent tree cover class, which broadly corresponds with tropical moist forest, covered 1 324 million ha in the year 2000, while the area having above 25 percent tree cover, of 2 094 million ha, was of the same order of magnitude as the FRA 2015 figure for all tropical forest, a figure that was based on a threshold tree cover of 10 percent (Keenan *et al.*, 2015).

Tyukavina *et al.* (2015) produced an unbiased estimate of forest area loss using a stratified random sample of 3 000 pixels (each approximately 0.1 ha in size) distributed in tropical forested regions. Furthermore, Tyukavina *et al.* distinguished “natural forests” (primary and mature secondary forests, and natural woodlands) from “managed forests” (plantations, agroforestry systems and areas of subsistence agriculture with tree cover rotation). Tyukavina *et al.* confirmed that a sample-based approach can provide more accurate and significantly higher estimates of forest cover losses than a wall-to-wall approach: the higher estimate is explained by small-scale forest dynamics that were not depicted in the wall-to-wall tree cover loss map. Ensuring that these small-scale dynamics are captured correctly can be very important for individual countries’ efforts to set accurate reference levels.

The use of different definitions and methods can lead to very different estimates of forest area losses: for example, Tyukavina *et al.* define forests as areas where the tree canopy cover is greater than 25 percent, while FAO reporting is based on a tree cover threshold of 10 percent and a definition of land use. Moreover, Tyukavina *et al.* account only for gross forest losses, while FAO reports net forest loss (including afforestation and forest regrowth) (Keenan *et al.*, 2015).

Tyukavina *et al.* (2015) illustrate the current capabilities of satellite data with a sample-based approach for estimating forest cover losses in the tropics and related carbon losses.

7.4.2. Example at national level: the Landscape Units of the Brazilian National Forest Inventory

Brazil occupies approximately 8.5 million km², of which 4.9 million are covered by forests (FAO, 2015b). These forests are of enormous importance for the country, in environmental and socio-economic terms, and because of the contribution they make globally by delivering forest services, such as biodiversity conservation and carbon retention. The National Forest Inventory (NFI) of Brazil is compiled by the Brazilian Forest Service (BFS)⁹ of the Ministry of the Environment, in partnership with other institutions such as Embrapa, state environmental agencies, universities, research institutions and specialized herbaria. The NFI is one of the most important components of the National Forest Information System (Freitas *et al.*, 2010), and therefore a key step in producing reliable and regular information on forest resources (Brazilian Forest Service, 2016).

The main purpose of the Brazilian NFI is to generate information on forest resources, both natural and plantation, based on a five-year measurement cycle, to support the formulation of public policies aiming at the use and conservation of forest resources. For some Brazilian states, information on the second cycle is being collected; however, for the majority of the 27 states, data collection is still in the first cycle.

The Brazilian NFI is based on a systematic sampling design, with the distribution of clusters (Field Sample Units, or FSUs) on a national network of sample points that are 648 seconds equidistant from each other, corresponding to approximately 20 km × 20 km between sample points at the Equator line. The cluster is composed by four subunits of 20 m × 50 m each. Field data collection comprises biophysical variables for forest and environment condition assessment, as well as socio-economic variables (interviews) to characterize how people living in nearby forests use and perceive the forest resources (Freitas *et al.*, 2010). In addition, for some states, the NFI preliminary results present information on forest stocks, composition, and health and vitality. The assessment of patterns of change in time is possible by comparing estimates from successive inventory cycles.

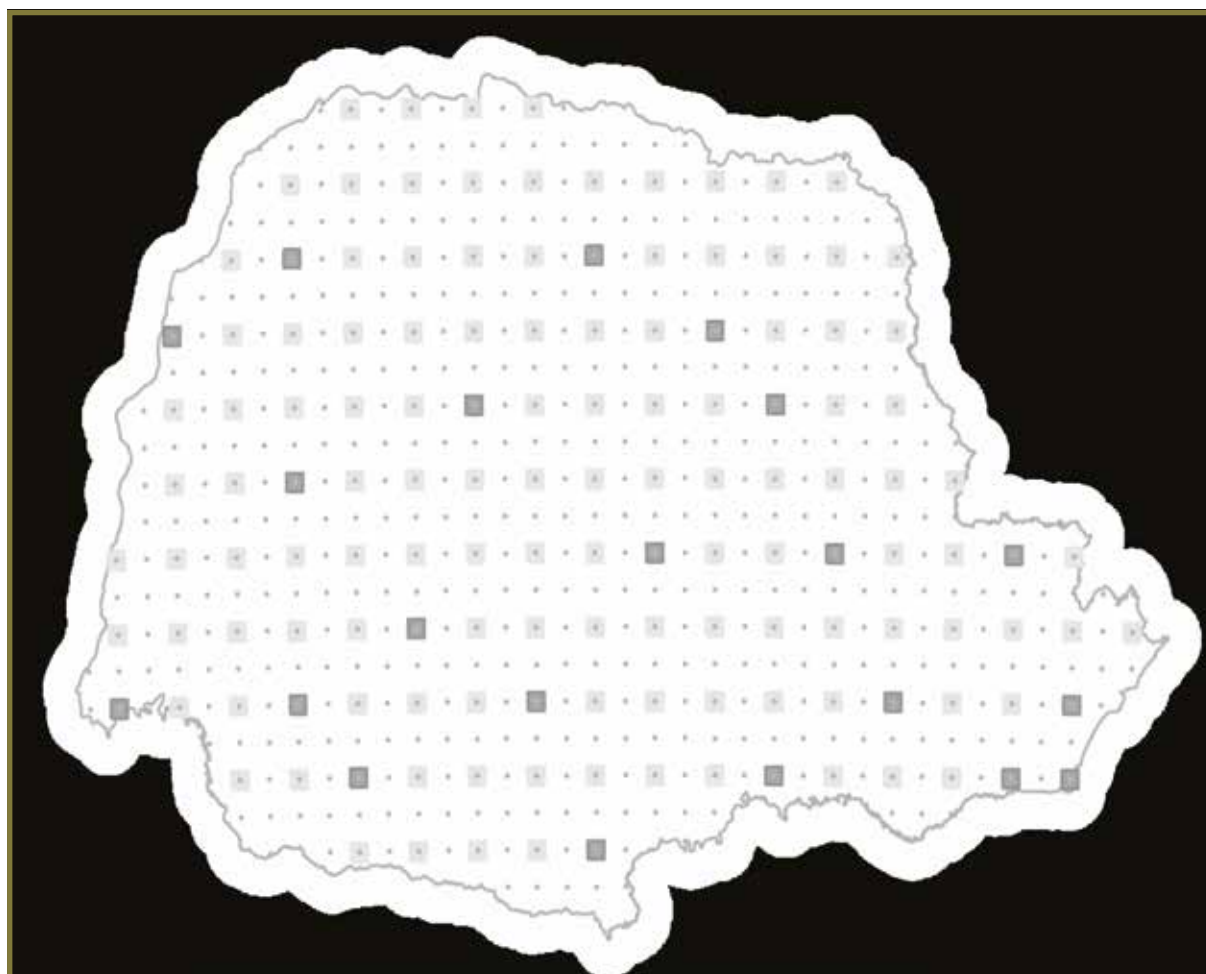
In addition to field data collected every 20 km × 20 km over the entire territory, the NFI also includes a Geospatial Component, which provides information at landscape level through Landscape Sample Units (LSUs), Land Use/Land Cover (LULC) mapping and spatial analysis (Luz *et al.*, 2015b). The Geospatial Component LSU methodology was developed as a joint effort between the FAO/BFS team¹⁰ and the Embrapa Forestry team¹¹. As stated by Freitas *et al.* (2006), the sampling design to collect data at landscape level must be based on the same systematic grid used for the fieldwork, although using a systematic subsample with an interval of 40 km × 40 km (figure 4). The size of each LSU is of 10 km × 10 km (100 km²), the geometric centre of which corresponds to the location of a field cluster.

9 The Brazilian National Forest Inventory is led by Joberto Veloso de Freitas and Claudia Melo Rosa.

10 Naissa Batista da Luz and Jessica Maran.

11 Maria Augusta Doetzer Rosot, Marilice Cordeiro Garrastazú and Yeda Maria Malheiros de Oliveira.

FIGURE 4. LOCATION OF THE LANDSCAPE SAMPLE UNITS OF THE BRAZIL NFI FOR THE STATE OF PARANA.



Recently, the Brazilian Government has issued a recent regulation on the use of and changes to natural resources, under the umbrella of the new Brazilian Forest Law. The Rural Environmental Cadastre (CAR) is one element of this legislation. To implement this new regulation, the Ministry of the Environment acquired RapidEye (RE) imagery covering the entire country, annually, since 2011. As this imagery is available to other governmental agencies, in 2013, the Embrapa Forestry team, BFS and FAO initiated the NFI Landscape Study as a pilot project, using the available RapidEye and Landsat 8 (L-8) imagery. RapidEye orthorectified imagery was used as the basis for an object-based image analysis approach (implemented in Definiens software). Polygons generated from RapidEye segmentation were then classified with the aid of several ancillary layers, such as enhanced vegetation indices, temporal series statistical layers (one year mean, minimum, maximum, and standard deviation) and information derived from the Global Forest Change (GFC; such as tree cover percentage for 2013) and processed using the Google Earth Engine Code Editor. Pixel-based RapidEye and L-8 unsupervised classification, performed using the IMPACT Toolbox software (developed by the JRC), were also included as ancillary information for RapidEye polygon classification (Luz *et al.*, 2015b).

Within the Brazilian NFI, landscape can be considered as a heterogeneous group of ecosystems embodied in different LULC types interacting with one another (Luz *et al.*, 2015a). The mosaic of LULC classes – in which natural and anthropogenic components contribute to the quality of existing forest resources – were defined as: (a) tree/shrub cover; (b) planted forest; (c) natural grasslands; (d) agriculture and pasture; (e) urban areas; (f) bare soil; and (g) water bodies.

After the first phase concerning the LULC mapping involving the aforementioned classes, a second step is performed, the landscape structural analysis of each LSU. The methodology, which is tailored specifically to the NFI's LSUs envisages innovative aspects relating to landscape spatial patterns, LULC mosaics and habitat fragmentation, connectivity and interface. The design incorporates traditional indicators, such as landscape composition, but also addresses fragmentation in a different manner, adopting a normalized and comparable index based on the habitat's overall Euclidean distance. Another approach involves the quality assessment of riparian zones, based on the structural connectivity of these environments such as vegetation corridors, the degree of anthropogenic pressure and scenario simulations for riparian protection zones, as well as their ranking (Clerici and Vogt, 2012) with reference to conservation priorities. This is especially important in light of recent changes occurring in the Brazilian Forest Law concerning the extent of forest vegetation to be restored along rivers and water bodies. Trees Outside Forest (TOFs) are a specific theme within LSU analysis, and different approaches were tested to discriminate between and classify them using RapidEye imagery. The relevant definitions and premises were established by FAO, in partnership with the *Institut de Recherche pour le Développement (IRD)* (De Foresta *et al.*, 2013).

A group of landscape indicators (and respective indices) is currently being calculated. These are the following:

- Landscape composition (proportion of tree/shrub cover that includes natural forest, other wooded lands and TOFs) and proportion of other natural/seminatural areas, which include natural grasslands and planted forest;
- Landscape taxonomy defined by the degree (percentage) of the presence of each LULC class;
- Habitat morphological spatial pattern analysis (MSPA) implemented by Soile and Vogt (2008) in the Guidos Toolbox software (Vogt *et al.*, 2007; Saura *et al.*, 2011), which encompasses possible categories or classes, as core, edge, perforation, bridge, loop, branch and islets;
- Forest landscape mosaic, which envisages various classes and indices (and classifies a given location according to the surface of intensive agriculture and urbanized areas surrounding it) and is implemented in the Guidos Toolbox.
- Edge interface model, which generates various indices and considers the importance of fragmentation related to the change of LULC in the forest edges, and is implemented in the Guidos Toolbox;
- Landscape connectivity encompasses landscape connections priorities, based on the MSPA and Conefor¹² software (Saura and Torné, 2009); a ranking of the structural corridors under pressure in the landscape is also presented;
- Landscape fragmentation, an indicator that introduced innovative concepts to quantify forest fragmentation (in the Guidos Toolbox); it enables comparison of the degree of fragmentation in different locations, the measurement of changes in fragmentation and its monitoring over time;
- Riparian zones analysis, based on the structural connectivity of those environments as vegetation corridors, on the degree of anthropogenic pressure acting upon them and on scenario simulation for riparian protection zones based on the concepts elucidated by Clerici *et al.* (2011) and Ivits *et al.*, (2009).

The LSUs' structural quality is assessed against these indicators, represented by groups of indices. The linear weighted combination of selected indices generate a single score by LSU, which allows for analyses and comparisons between them, aiming to restore and monitor certain aspects of the landscape.

The efforts made by the Brazilian NFI constitute an essential contribution to the Brazilian Government's commitment to sustainability. In 2010, Brazil voluntarily committed to reduce emissions by 80 percent in the Amazon and 40 percent in the Cerrado (Savannah region) by 2020. The country plans to integrate existing instruments and to promote coordination and synergies between them to maximize the REDD+ results. The NFI provides tools that can contribute to those decisions. The NFI programme can also benefit the implementation and monitoring of other national policies on planted forests and on the integration of agriculture, livestock and forestry (iLPF-agroforestry), among others.

¹² <http://www.conefor.org>.

Brazil's intended Nationally Determined Contribution – or iNDC – is considered a highly ambitious project. Regarding the spheres of forestry and LULC, it was proposed to strengthen compliance with the new Brazilian Forest Law at all levels; strengthen policies and measures to achieve, in the Brazilian Amazon, zero illegal deforestation by 2030 and compensation of greenhouse gas emissions from legal removal of vegetation by 2030; restore and plant 12 million ha of forest by 2030 for multiple uses; expand the range of sustainable management systems of native forests through georeferencing and traceability systems applicable to the management of native forests, to discourage illegal and unsustainable practices. Additionally, the commitment relating to the agricultural sector was to strengthen the Low-Carbon Agriculture Plan (ABC Plan) as the main strategy to ensure sustainable development in agriculture, including the further restoration of 15 million ha of degraded pastures by 2030 and the increment by 5 million ha of iLPF-agroforestry projects, by the same year. Therefore, the Brazilian NFI will play an important role in the fulfillment of country goals and targets by providing valuable data sets on forest resources, LULC and landscape quality.

The landscape analysis complements the other two components of the IFN-BR, which consist in a field data collection exercise and a socio-economic survey. The adopted strategy has been to develop the methodology of all Brazilian NFI components, aiming at their integration and subsequent joint analysis. Thus, aspects of the physical and biological environment obtained in the field survey (ecosystem approach), integrated with spatialized information on LULC and the socio-economic environment may conform that which in contemporary terms is known as the landscape approach.

7.4.3. The FAO Global Forest Survey project

Objectives of the Global Forest Survey project

The main objective of the Global Forest Survey (GFS) project is to provide global and regional estimates of forest inventory data for specific forest ecosystems. Forest inventory data is to be collected through a global network of field plots. The project is intended to be implemented on a global scale.

The specific objectives of the GFS project are to:

- develop a global network of permanent field sample plots, which will utilize existing field plots where possible, but will also include new field sample plots as required;
- Produce detailed, georeferenced global estimates of forest carbon, forest health, and other forest characteristics based on the field sample plots and remote sensing data;
- Develop an information portal and data sharing policy to make all data and results freely available; and
- Demonstrate the value of a single, permanent, freely available, web-based repository.

The data collection exercise is intended to be based on a multiscale sampling design and measurement protocols will be developed to assess forests, from basic (for example, tree cover percentage) to complex (such as land use types) parameters. Data will be collected by partner organizations, local authorities and communities and, where necessary, by FAO staff directly. All of the data collected in the context of the GFS will be freely available and accessible through a web-based GIS-enabled portal.

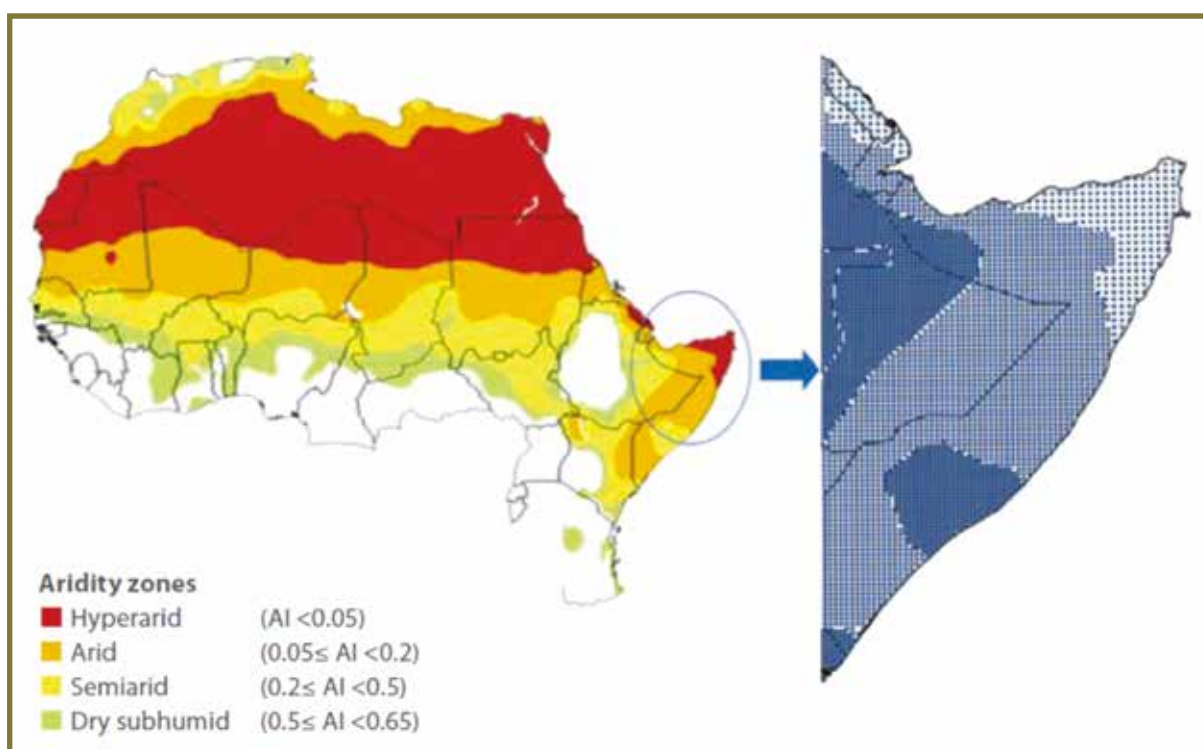
The first Global Drylands Assessment

The Global Drylands Assessment (FAO, 2016) is a pilot action within the World Forest Open Data project that focuses solely on drylands and on the use of satellite images from publicly available repositories (such as Google Earth Engine and Bing Maps). For the first Global Drylands Assessment, more than 200 experts with knowledge of the land and land uses in specific dryland regions were involved.

The global assessment draws on information from 213 795 sample plots in the world's drylands. Each plot measured 70 m x 70 m (approximately 0.5 ha), a size corresponding to the smallest patch that qualifies as forest according to the forest definition used by the FAO Global FRA (FAO, 2015a).

In locating sample plots in a grid across the drylands, each aridity zone was treated as an independent stratum. The relative sampling intensity assigned to each aridity zone was as follows: hyperarid = 0.5; arid = 1; and semiarid and dry subhumid = 1.5. The results are reported at the global and regional levels (FAO, 2016). The statistical sampling error for the estimate of the total forest land area for all drylands is about 1 percent.

FIGURE 5. ILLUSTRATION OF SAMPLING INTENSITY OF THE FIRST GLOBAL DRYLANDS ASSESSMENT



FAO, 2016

Data and tools used for the Global Drylands Assessment

The survey was set up using Collect, a software tool available in the Open Foris suite¹³ and then embedded in Collect Earth, which was developed in cooperation with Google Earth Outreach (Bey *et al.*, 2016).

Sample plot data were collected from online libraries of satellite images using Collect Earth. Typically, each plot was overlaid onto several images obtained through Google Earth Engine and Bing Maps. Collect Earth is capable of visualizing reflectance values and user-defined indices such as the Normalized Difference Vegetation Index (NDVI) based on Landsat and MODIS satellite images. The visual interpretation exercise was facilitated by the temporal profiles of interannual vegetation indices, which were derived from lower-resolution satellite data (the ground resolution ranging from 30 to 250 m).

¹³ Open Foris is a suite developed by the FAO Forestry Department to facilitate flexible and efficient data collection, analysis and reporting; see <http://www.openforis.org/>.

Landsat imagery (having a resolution of 30 m) was available for all plots, and 89 percent of plots were also covered by finer-resolution images, more than half of which consisted in images from Digital Globe and having a spatial resolution finer than 1 m. The proportion of satellite image types was similar for all land-use categories.

Collect Earth projected each sample plot as a frame containing a grid of 49 control points, enabling users to make precise estimates of the proportion of plots taken up by trees, shrubs and other land elements. In the visual interpretation exercise, each expert used his or her knowledge of the location and information provided by remote sensing data to support the survey process.

Land use image interpretation

For each sample plot, data on over 70 characteristics were collected and recorded for the most recent point in time for which satellite images were available. The variables were selected to characterize land cover, land use, land use change and other significant land dynamics (such as desertification and greening), along with biophysical indicators. The year 2000 is used as the reference year, because it is considered to be first year for which consistent global coverage of satellite data (Landsat 7) is available.

The simultaneous use of low-resolution and very-high-resolution (VHR) satellite imagery facilitates the detection of land use and land-use change. For certain land elements (for example, distinguishing between trees and shrubs), satellite data and local knowledge sometimes proved to be insufficient; therefore, a decision rule based on the crown diameter of trees and shrubs was adopted. Elements with a crown diameter larger than 3 m were considered trees; elements with smaller diameters were considered shrubs. Collect Earth does not allow for the direct measurement of tree height; therefore, tree shadows (where visible) were used in addition to the crown diameter threshold to determine whether elements were sufficiently tall (in other words, 5 m or taller, consistently with the definition of forests used in the Global Drylands Assessment) to be considered trees.

Land use is assessed on the basis of the six land-use categories established by the IPCC (IPCC, 2006): forest, cropland, grassland, wetlands, settlements, and other land. A predominant land use is assigned to each sample plot, based on the presence of key land-use indicators interpreted according to a hierarchical rule (Martinez and Mollicone, 2012). For example, a sample plot with a crown cover greater than 10 percent is not classified as forest unless the prevailing land use can also be identified as forest. Only one land use per sample plot can be assigned.

Results and lessons learned during the first Global Drylands Assessment

FAO has used this approach to produce a global assessment of the drylands (FAO, 2016) by analysing approximately 214 000 sample plots (Bastin *et al.*, 2017). This survey is the first statistical sampling-based assessment of land use, including the assessment of forests and tree cover, in the global drylands. Therefore, it provides a baseline for monitoring changes in dryland forests, tree cover and land use, globally, regionally and by aridity zone.

According to the first Global Drylands Assessment, the world's drylands contain 1.11 billion ha of forest. More than half of these (specifically, 566 million ha) are in the dry subhumid zone, mostly in the northeastern part of southern Africa and the western (pre-Andean) part of South America. Approximately two thirds of dryland forests (742 million ha) can be considered closed forests, because they have a crown cover density of more than 40 percent. More than half of these forests (most of which are in Europe and South America) have a crown cover of 90 percent or more.

The Global Drylands Assessment uses data from publicly and freely available online libraries of satellite images using a simple visual interpretation tool, and it engages people with land-use expertise in a systematic data collection exercise. This approach has the following advantages:

- A statistics-based assessment of a basic set of variables can be conducted rapidly and inexpensively to complement other methods, because sample plots are assessed using satellite images rather than in the field; and
- A large number of people can be engaged in the assessment process, thanks to the ease of use of the interpretation and because the software and data are both available free of charge.

The first Global Drylands Assessment produced results (FAO, 2016; Bastin *et al.*, 2017) in less than one year from conception, in a participatory and collaborative manner. The Global Drylands Assessment provided an opportunity to test the approach developed at a global scale. However, the methodology must be further developed for non-dryland areas, in particular to reduce interpretation errors.

A potential source of error is inconsistency: more than 200 people were engaged in the visual interpretation of satellite images, and the supply of images was not the same for all 213 795 sample plots assessed. The risk of inconsistency was mitigated by ensuring that all experts used the same training modules and tools. Additional measures to reduce inconsistencies and errors in interpretation will be implemented in a pilot assessment of all lands worldwide.

The methodology can be adapted to accommodate more intensive sampling for specific regional, national and landscape-scale needs, if required by countries and other users. For example, it is used at the regional scale for the baseline assessment of the Great Green Wall area over more than 20 countries both north and south of the Sahara, building on data already collected in North Africa, the Sahel and the Horn of Africa.

Future prospects

The results of the Global Drylands Assessment were reported in early 2017 (Bastin *et al.*, 2017), following supplementary ground measurements and analyses. The results were made publicly available. It is expected that the Global Drylands Assessment will be repeated every two years.

The use of Collect Earth and other relevant tools for baseline assessments and monitoring must be further promoted through capacity-development events and workshops at regional and national levels. These tools provide a new and economically feasible way of assessing trees, forests, land use and land-use change in all areas of the world, as shown by the first Global Drylands Assessment.

FAO intends to apply the methodology in a global pilot assessment of all types of land by adding approximately 250 000 sample plots to be visually interpreted through Collect Earth. Global estimates of forest areas will be produced from a total of approximately 500 000 sample plots each about 0.5 ha in size. These results will be integrated into the Global Forest Survey's project database.

7.5. COMPLEMENTARITY BETWEEN ESTIMATES OF CHANGES IN FOREST AND AGRICULTURE

The complementarity between estimates of changes in forest and agriculture areas is illustrated by the analysis carried out by VITO, IIASA, HIVA and IUCN NL in the study entitled “Comprehensive analysis of the impact of EU consumption on deforestation”, funded by the European Commission, hereafter EC Technical Report (European Commission, 2013).

Worldwide gross deforestation from FAO Forest Resources Assessment 2010 for 1990–2008

For the period from 1990 to 2008, worldwide gross deforestation is estimated at 239 million ha (Mha), or about 13 Mha on average per year, with substantial regional variations, as reported in the FAO Forest Resources Assessment 2010. During the same period, gross deforestation was partially compensated by afforestation and by the natural expansion of forests, together counting for 115 Mha. Thus, net deforestation was of 124 Mha (FAO, 2010a).

In the EC Technical Report (2013), using FRA 2010 (FAO, 2010a) and FAOSTAT land use domain databases (FAOSTAT, 2011), gross deforestation is attributed to five main sectors: Agricultural Expansion, Logging (prior to agricultural expansion), Urban Areas Expansion, Natural hazards (especially wildfire), and Unexplained. Using a transition model, the land use changes reported in FAOSTAT for the above sectors are linked to the deforestation areas identified in the FRA 2010. Moreover, a fraction of the agricultural land expansion allocated to deforestation is reallocated to “logging for industrial round wood extraction”, to account for wood extraction preceding the conversion of forest land for agriculture.

Unexplained deforestation

When gross deforestation cannot be explained by agriculture, logging, built-up area increases or natural hazards, it is termed Unexplained in the EC Technical Report (2013). Of the 239 Mha of worldwide gross deforestation, approximately 58 Mha (24 percent) of reported deforestation cannot be conclusively linked to the conversion of forests for clear consumption purposes or other reported deforestation causes. The largest source of uncertainty relates to the data on deforestation. However, FAO considers even the 9 percent difference in forest area between the FRA 2010 assessment and the FRA 2010 RSS as a good result, considering the differences in the methods adopted (FAO and JRC, 2012). Furthermore, an accurate assessment of tree cover at lower canopy densities (from 10 to 30 percent) is difficult with both the country-level FRA 2010 assessment and the RSS. Therefore, uncertainties are particularly significant in dry regions and for degraded forests. Unlike the situation in Africa, no large discrepancies were found between the RSS survey and FRA 2010 with regard to the deforestation rates for South America. Agricultural production statistics and trade data were considered to be relatively reliable.

Unexplained deforestation can be partially attributed to erroneous deforestation figures (overreporting) and agricultural area data at the national level (underreporting), as demonstrated by the recent results of the FRA 2010 RSS. Second, the Unexplained category can be partially interpreted as the result of long-term degradation effects ensuing from several informal practices being carried out in forests, such as illegal logging and unsustainable fuelwood gathering. As consistent global data and clear cause-consequence relationships on the latter are non-existent, their impact is assumed to be taken into consideration in this category. Third, the conversion of forests into agricultural land may encompass more conversion than will actually result in productive (and reported) agricultural land.

Drivers of deforestation

For the remaining 182 Mha of worldwide gross deforestation, approximately 41 Mha (17 percent) were caused by natural hazards (mainly natural or man-made fires) that failed to result in reported agricultural land expansion (EC, 2013). The country of Indonesia alone lost 9 Mha of forest because of the 1997–1998 El Niño Southern Oscillation (ENSO). Furthermore, approximately 9 Mha (4 percent) were turned into built-up land and infrastructure. The remaining 132 Mha, or 55 percent of worldwide gross deforestation, can be clearly attributed to the conversion of forest land to land for crop production, ruminant livestock production and industrial round wood production (logging).

Of the 132 Mha (55 percent) of deforestation linked to the global production of agricultural and forestry products, only 4.5 Mha (or 2 percent) of deforestation was attributed to logging, representing only the impact of logging which precedes conversion into agricultural land (EC, 2013).

Additionally, within the overall impact of the agricultural sector (128 Mha or 53 percent), 69 Mha (or 29 percent) of forests were directly or indirectly cleared for cropland to meet the global human demand for food, feed for livestock, fuel and fibres from crops. Approximately 58 Mha (24 percent) of forests were cleared for pastures to raise livestock.

7.6. REFERENCES

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