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Forest degradation, a methodological approach using remote sensing techniques: A review

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ABSTRACT: Measuring all carbon stock changes caused by forest degradation within a country at the same level of detail and accuracy will likely not be efficient. In particular the considerations of IPCC source category analysis, and the fact that many degradation activities are focused on specific areas within the country help to make the monitoring more targeted and efficient to capture the most important components with priority.
To estimate forest degradation, countries need to assess carbon stock changes and the total area undergoing degradation, ideally for different types of degradation (i.e. fire, logging, and fuel wood harvesting). The assessment of changes in carbon stocks requires consistent ground data while the evaluation of the total area undergoing degradation is more reliably measured through remote sensing for the major degradation processes, in particular for developing countries. The particular problem of measuring forest degradation is the lack of field based forest data for developing countries.

KEYWORDS: Forest degradation, remote sensing techniques.

1 INTRODUCTION

Forest degradation is a serious problem, environmentally, socially and economically particularly in developing countries. It is estimated that as much as 850 million hectares [24] of forests and forest lands are degraded. Yet it is difficult to quantify the scale of the problem since at national and sub-national levels forest degradation is perceived differently by the various stakeholders who have different objectives.

Forest degradation has adverse impacts on forest ecosystems and on the goods and services they provide. Many of these goods and services are linked to human well-being and some to the global carbon cycle and thus to life on Earth.

Policy makers and forest managers need information on forest degradation. They need to be able to monitor changes happening in forests. They need to know where forest degradation is taking place, what causes it and how serious the impacts are in order to prioritize the allocation of scarce human and financial resources to the prevention of degradation and to the restoration and rehabilitation of degraded forests [35].

In addition, analyzing forest degradation is required to demonstrate efforts to tackle the problem and meet global objectives and targets. The proposed new Biodiversity Target includes a target on reduction of forest degradation. The agreement to establish a mechanism under the UNFCCC aimed at reducing emissions from deforestation and forest degradation (REDD) in developing countries has added a political dimension and the potential availability of substantial funds to reard developing countries that manage to reduce the level of forest degradation.

Accurate and up-to-date land use/cover assessments are important to define natural resource management strategies and policies for conservation especially in forest areas. Understanding the causes and consequences of land cover change and their cascading effects on many components of functional ecosystems, are the case for identifying negative effects on biological resources and human development [17], [42].

To measure forests worldwide, satellite imagery is a practical necessity. Aerial observations are expensive at present and only cover small areas at a time. Ground measurements are also expensive and are logistically challenging and spatially restricted. Neither aerial nor ground observations are well suited to continuous measurement of the entire global forest. Satellite mapping is necessary to detect forest degradation and regrowth in remote tropical forests [11]. The greatest strengths of satellite-based measurements are their unparalleled, unbiased measurements, their monthly to daily frequency, and above all their synoptic nature. Satellites provide a general view of the whole Earth that is not possible with any other forest measurement method.

Satellite remote sensing provides a meaningful method for detecting vegetation or land cover changes [5] Changes in the composition and spatial distribution of forest cover are a major environmental concern, affecting many biological, biochemical and ecological processes. Remotely sensed data are widely used to understand and manage environmental resources by determining land cover/use changes such as quantification of forest degradation. By comparing the images taken in different times, the changes in landscape level can be easily detected. Monitoring land cover and land cover change at regional and global scales often requires sensors data to identify and map landscape features and patterns with sufficient detail [50]Detailed and updated resource inventories are needed to support land use planning and sustainable management.

This literature review addresses how remote sensing techniques can be used to assess forest degradation directly or indirectly by means of different types of degradation process occurring in the forest area.

2 REMOTE SENSING: AN OVERVIEW

2.1 DEFINITIONS

Remote sensing can be defined as learning something about an object without touching it. As human beings, we remotely sense objects with a number of our senses including our eyes, noses, and ears [46]. For [19]remote sensing is the science and art of obtaining information about an object, area, or phenomenon through the analysis of data acquired by a device that is not in contact with the object, area or phenomenon under investigation.

The field of remote sensing can be divided into two general categories: analog remote sensing and digital remote sensing. Analog remote sensing uses film to record the electromagnetic energy. Digital remote sensing uses some type of sensor to convert the electromagnetic energy into numbers that can be recorded as bits and bytes on a computer and then displayed on a monitor.

2.1.1 ANALOG REMOTE SENSING

The field of analog remote sensing can be divided into two general categories: photointerpretation and photogrammetry. Photo interpretation is the qualitative or artistic component of analog remote sensing. Photogrammetry is the science, measurements, and the more quantitative component of analog remote sensing. Both components are important in the understanding of analog remote sensing.

2.1.2 DIGITAL REMOTE SENSING

While analog remote sensing has a long history and tradition, the use of digital remote sensing is relatively new and was built on many of the concepts and skills used in analog remote sensing.Digital remote sensing effectively began with the launch of the first Landsat satellite in 1972.Since the launch of Landsat 1, there have been tremendous strides in the development of not only other multispectral scanner systems, but also hyperspectral and digital camera systems. However, regardless of the digital sensor there are a number of key factors to consider that are common to all. For [26] these factors include: (1) spectral resolution, (2) spatial resolution, (3) radiometric resolution, (4) temporal resolution, and (5) geographic extent.

- **Spectral resolution**

Spectral resolution is typically defined as the number of portions of the electromagnetic spectrum that are sensed by the remote sensing device.These portions are referred to as “bands”. A second factor that is important in spectral resolution is the width of the bands. Traditionally, the band widths have been quite wide in multispectral imagery, often covering an entire color (e.g., the red or the blue portions) of the spectrum. If the remote sensing device captures only one band of imagery, it is called a panchromatic sensor and the resulting images will be black and white, regardless of the portion of the spectrum sensed. More recent hyperspectral imagery tends to have much narrower band widths with several to many bands within a single color of the spectrum.

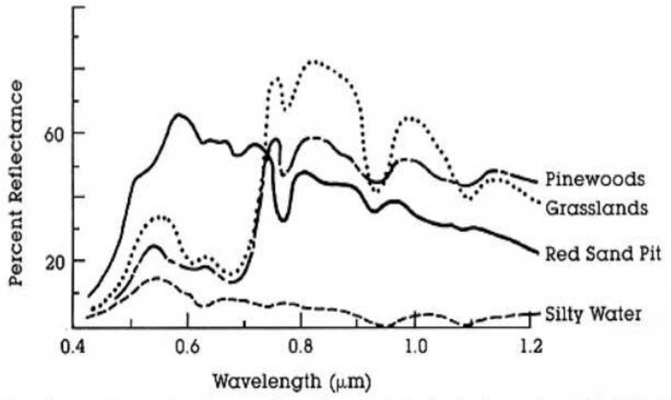

Figure 1.Comparison of spectrums of vegetation,bare soil,snow and water (Source: Asner et al,2004)

- **Spatial resolution**

Spatial resolution is defined by the pixel size of the imagery. A pixel or picture element is the smallest two-dimensional area sensed by the remote sensing device. An image is made up of a matrix of pixels. The digital remote sensing device records a spectral response for each wavelength of electromagnetic energy or “band” for each pixel. This response is called the brightness value (BV) or the digital number (DN). In [46] the range of brightness values depends on the radiometric resolution. If a pixel is recorded for a homogeneous area then the spectral response for that pixel will be purely that type. However, if the pixel is recorded for an area that has a mixture of types, then the spectral response will be an average of all that the pixel encompasses. Depending on the size of the pixels, many pixels may be mixtures.

Figure 2. Spatial resolution of different types of sensors, respectively for Spotand Ikonos(Source: Canada center for remote sensing,2003)

- **Radiometric resolution**

The numeric range of the brightness values that records the spectral response for a pixel is determined by the radiometric resolution of the digital remote sensing device. These data are recorded as numbers in a computer as bits and bytes [28] A bit is simply a binary value of either 0 or 1 and represents the most elemental method of how a computer works. If an image is recorded in a single bit then each pixel is either black or white. No gray levels are possible. Adding bits adds range. If the radiometric resolution is 2 bits, then 4 values are possible (2 raised to the second power equals 4). The possible values would be 0, 1, 2, and 3. Early Landsat imagery had 6-bit resolution (2 raised to the sixth power equals 64) with a range of values from 0 to 63. Most imagery today has a radiometric resolution of 8 bits or 1 byte (range from 0 to 255). Some of the more recent digital remote sensing devices have 11 or even 12 bits.

- **Temporal Resolution**

Temporal resolution is defined by how often a particular remote sensing device can image a particular area of interest. Sensors in airplanes and helicopters can acquire imagery of an area whenever it is needed. Sensors on satellites are in a given orbit and can only image a selected area on a set schedule. Landsat is a nadir sensor; it only images perpendicular to the Earth's surface, and therefore can only sense the same place every 16 days. Other sensors are pointable and can acquire off-nadir imagery.

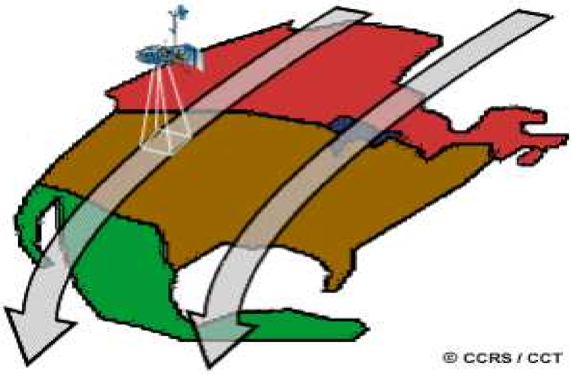

Figure 3 temporal resolution movement of a sensor

(Source: Canada center for remote sensing, 2003)

Table 1. Digital characteristics of some satellites are given below, personal compilation

Satellite	Sensor	Ground resolution	Radiometric resolution	Temporal resolution
Landsat	MSS	80m	-	18 days
Landsat	Thematic Mapper	30 m	6 bits	16 days
Spot	XS(multispectral)	20 m	6 bits	6 days
Spot	panchromatic	10 m	6 bits	5 days
Ikonos	Multispectral	4 m	11 bits	2.9 days
Ikonos	Panchromatic	1 m	11 bits	2.9 days
Quickbird	---	0.5 m	11bits	1 to 3.5 days

2.2 DIGITAL IMAGE ANALYSIS

Digital image analysis in digital remote sensing is analogous to photo interpretation in analog remote sensing. It is the process by which the selected imagery is converted/processed into information in the form of a thematic map. Digital image analysis is performed through a series of steps. These steps include: (1) image acquisition/selection, (2) pre-processing including image enhancement, (3) classification, (4) post-processing, and (5) accuracy assessment.

2.2.1 IMAGE ACQUISITION/SELECTION

Selection or acquisition of the appropriate remotely sensed imagery is foremost determined by the application or objective of the analysis and the budget. Once these factors are known, the analyst should answer the questions presented previously. These questions include: what spectral, spatial, radiometric, temporal resolution and extent are required to accomplish the objectives of the study within the given budget? Once the answers to these questions are known, then the analyst can obtain the necessary imagery either from an archive of existing imagery or request acquisition of a new image from the appropriate image source.

2.2.2 PRE-PROCESSING

Pre-processing is defined as any technique performed on the image prior to the classification. There are many possible pre-processing techniques. However, three of the most important techniques include: geometric registration, radiometric/atmospheric correction, and numerous forms of image enhancement.

There are many types of digital image processing enhancements that can be applied to remote sensor data. The enhancements can be applied to individual bands of imagery (e.g., the application of a low-pass filter) or to all bands of the imagery (e.g., principal components analysis).

2.2.3 CLASSIFICATION

Classification of digital data has historically been limited to spectral information (tone/color). While these methods attempted to build on the interpretation methods developed in analog remote sensing, the use of the other elements of photo interpretation beyond just color/tone has been problematic. In addition, digital image classification has traditionally been **pixel based**. A pixel is an arbitrary sample of the ground and represents the average spectral response for all objects occurring within the pixel. The earliest classification techniques tended to mimic photo interpretation and were called supervised classification techniques. These methods were followed by statistical clustering routines that were called unsupervised classification techniques. Both techniques were based completely on the spectral (color/tone) data in the imagery.

2.2.3.1 SUPERVISED VS. UNSUPERVISED CLASSIFICATION

Supervised classification is a process that mimics photo interpretation. The analyst "trains" the computer to recognize informational types such as land cover or vegetation in a similar way that the photo interpreters train themselves to do the same thing. However, the interpreter uses the elements of photo interpretation while the computer is limited to creating statistics (means, minimums, maximums, variances, and co-variances) from the digital spectral responses (color/tone).

Unsupervised classification uses a statistical clustering algorithm to group the pixels in the imagery into spectral clusters. These clusters are spectrally unique, but may not be informationally unique. In other words, a single cluster may be a combination of a number of informational types (e.g., cluster 4 may be a combination of white pine and grass). The analyst decides how many unique clusters are to be extracted from the imagery.

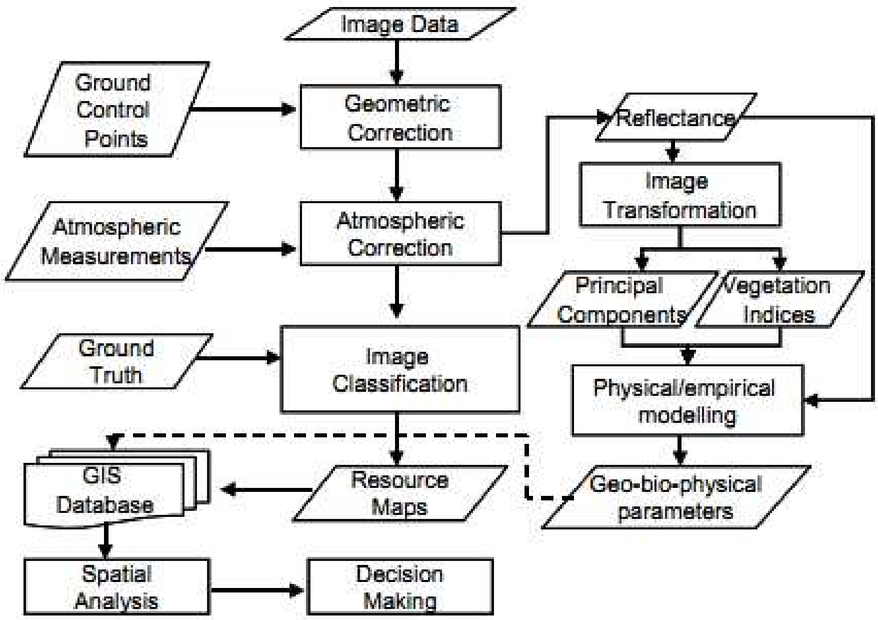

Figure 4. A schematic diagram of general image processing procedures, (Source: Campbell, 2007)

2.2.3.2 COMBINED APPROACHES

Many remote sensing scientists have attempted to combine the supervised and unsupervised techniques together to take the maximum advantage of these two techniques while minimizing the disadvantages. Many of these examples can be found in the literature. A technique by [28] 2.2.3.3. Advanced approaches

Using supervised or unsupervised classification approaches only work moderately well. Even the combined approaches only improve our ability to create accurate thematic maps a little more than using each technique separately. Therefore, a large amount of effort has been devoted to developing advanced classification approaches to improve our ability to create accurate thematic maps from digital remotely sensed imagery. While there are many advanced approaches, this paper will only mention three: (1) classification and regression tree (CART) analysis; (2) artificial neural networks (ANN); and (3) support vector machines (SVM).

2.2.3.3 Object-based approaches (polygon approach)

By far the greatest advance in classifying digital remotely sensed data in this century has been the widespread development and adoption of object-based image analysis (OBIA). Traditionally, all classifications were performed on a pixel basis. Given that a pixel is an arbitrary delineation of an area of the ground, any selected pixel may or may not be representative of the vegetation/land cover of that area.In the OBIA approach, unlabeled pixels are grouped into meaningful polygons that are then classified as polygons rather than individual pixels. This method increases the number of attributes such as polygon shape, texture, perimeter to area ratio, and many others that can be used to more accurately classify that grouping of pixels [53].Polygons are created from pixels in OBIA using a method called segmentation. There are a number of current image analysis software packages that provide the means of performing OBIA. In all these algorithms, the analyst must select a series of parameters that dictate how the segments or polygons are generated. Depending on the parameters selected, it is possible to create large polygons that may incorporate very general vegetation/land cover types or very small polygons that may divide even a specific cover type into multiple polygons. The power of the segmentation process is twofold. First, the imagery is now divided into polygons that can, in many ways, mimic the polygons that may have been drawn by an analyst that was manually interpreting this same image. In this way, some of the additional elements of manual interpretation mentioned earlier in this paper become relevant for digital image analysis. Secondly, as previously mentioned, the creation of polygons results in a powerful addition of attributes about the polygons that can be used by the classification algorithm to label the polygons. Both these factors significantly add to our ability to create accurate thematic maps.

2.2.4 Post-processing

Post-processing can be defined as those techniques applied to the imagery after it has been through the classification process—in other words, any techniques applied to the thematic map. It has been said that one analyst's pre-processing is another analyst's post-processing. It is true that many techniques that could be applied to the digital imagery as a pre-processing step may also be applied to the thematic map as a post-processing step. This statement is especially true for geometric registration. While currently most geometric correction is performed on the original imagery, such was not always the case. Historically, to avoid resampling the imagery and potentially removing important variation (information), the thematic map was geometrically registered to the ground instead of the original imagery.

One of the most important uses of remotely sensed data is the identification of change through time. Images can be used to simply identify binary "change versus no-change"or "from-to change" in which the change from one land cover category to another is carefully recorded and mapped. There are a significant number of change detection algorithms and methods that can be used [29]

2.2.5 Accuracy assessment

Accuracy assessment is a vital step in any digital remote sensing project. The methods summarized here can be found in detail in [47] historically, thematic maps generated from analog remotely sensed data through the use of photo interpretation were not assessed for accuracy. However, with the advent of digital remote sensing, quantitatively assessing the accuracy of thematic maps became a standard part of the mapping project.

Once the error matrix is generated, some basic descriptive statistics including overall, producer's, [46]and user's accuracies can be computed. In addition, there are a number of analysis techniques that can be performed from the error matrix. Most notable of these techniques is the Kappa analysis, which allows the analyst to statistically test if one error matrix is significantly different than another.

2.3 DIGITAL IMAGE TYPES

2.3.1 MULTI SPECTRAL IMAGERY

The dominant digital image type for the last 40 years has been multispectral imagery, from the launch of the first Landsat in 1972 through the launch of the latest GeoEye and DigitalGlobe sensors[9] Multispectral imagery contains multiple bands(more than 2 and less than 20) across a range of the electromagnetic spectrum. While there has been a marked increase in spatial resolution, especially of commercial imagery during these 40 years, it should be noted that there continues to be a great demand for mid-resolution imagery. The importance of continuing to obtain imagery with a spatial resolution of 20–30 meters and with a good spectral resolution that includes the visible, near -, and middle-infrared portions of the electromagnetic spectrum cannot be understated. There is a special niche that this imagery fills that cannot be replaced by the higher-spatial-resolution imagery that costs significantly more to purchase. There will be increased uses of the higher-spatial-resolution data that continue to improve all the time, but this increase will not reduce the need for mid-resolution multispectral imagery.

2.3.2 HYPERSPECTRAL IMAGERY

Hyperspectral imagery is acquired using a sensor that collects many tens to even hundreds of bands of electromagnetic energy. This imagery is distinguished from multispectral imagery not only by the number of bands, but also by the width of each band. Multispectral imagery senses a limited number of rather broad wavelength ranges that are often not continuous along the electromagnetic spectrum. Hyperspectral imagery, on the other hand, senses many very narrow wavelength ranges (e.g., 10 microns in width) continuously along the electromagnetic spectrum [34] Hyperspectral imagery has changed the way we perform digital image analysis. Given this imagery collected over narrow bandwidths across a large portion of the electromagnetic spectrum, it is possible to create spectral libraries of various information types and compare these for identification on the imagery. These libraries exist for a variety of rock and mineral types and have even been created for some simple land cover/vegetation classifications. These detailed spectral patterns also allow for the analysis of the chemical content of vegetation and other land cover. For [10] the uses of hyperspectral imagery for environmental studies, especially related to pollution and other hazards, have tremendous potential. Currently, significant research is occurring in this field. As the costs associated with this technology continue to decline, more and more uses of hyperspectral imagery will be developed.

2.3.3 DIGITAL CAMERA IMAGERY

Most digital camera imagery is collected as a natural color image (blue, green, and red) or as a color infrared image (green, red, and near infrared). Recently, more projects are acquiring all four wavelengths of imagery (blue, green, red, and near infrared). The spatial resolution of digital camera imagery is veryhigh with 1–2 meter pixels being very common and some imagery having pixels as small as 15 cm.

2.3.4 OTHER TYPES OF IMAGERY

There are other sources of digital remotely sensed imagery that have not been presented in this paper. These sources include RADAR and LiDAR. Both these sources of imagery are important, but they fall beyond the scope of this paper. RADAR imagery has been available for many years. However, only recently has the multifrequency component of RADAR imagery become available (collecting frequencies of imagery simultaneously and not just multiple polarizations) that significantly improves the ability to create thematic maps from this imagery. LiDAR has revolutionized the collection of elevation data (e.g., 45 and is a valuable source of information that can be used in creating thematic maps (e.g., [2]). In the last few years, these data have become commercially available and are being used as a vital part of many mapping projects.

3 FOREST DEGRADATION

3.1 KEY CONCEPTS TO FOREST DEGRADATION

[23] developed a way for understanding forest degradation as followed, common indicators for monitoring and assessing forest degradation can be developed for the following key elements to be used in assessing forest degradation(Biodiversity (e.g. species composition and richness, habitat fragmentation);

- Biomass (e.g. growing stock, forest structure);
- Forest goods obtained (compared against sustainably managed forests);
- Forest health (e.g. fire, pest and diseases, invasive and alien species);
- Soil quality (as indicated by cover, depth and fertility).

For [35] the term degradation refers to a change process within the forest, which negatively affects the characteristics of the forest. The combination of various forest characteristics (forest quality) can be expressed as the structure or function, which determines the capacity to supply forest products and services Forests may be degraded in terms of loss of any of the goods and services that they provide (wood, food, habitat, water, carbon storage and other protective socio-economic and cultural values.

According to [18] degradation is typically caused by disturbances, which vary in terms of the extent, severity, quality, origin and frequency. The change process can be natural (caused by fire, storm, drought, pest, disease) or it can be human induced (unsustainable logging, excessive fuelwood collection, shifting cultivation, unsustainable hunting, overgrazing). The latter can be intentional (direct) through for example excessive logging, overgrazing, too short a fallow period or it can be unintentional (indirect) for example through spreading of an invasive alien species or pestilence or road construction that might open a previously inaccessible area for encroachment [35].

Perceptions regarding forest degradation are many and varied, depending on the driver of degradation and the main point of interest. In relation to REDD, it is likely to entail a reduction in the capacity to sequester carbon, but a forest may also be degraded in terms of loss of biological diversity, forest health, productive or protective potential or aesthetic value.

Forest degradation is generically defined as the reduced capacity of a forest to provide goods and services [18]. However, in the context of climate change, the International panel on climate change, [23] developed a definition of forest degradation that focuses on human-induced changes in the carbon cycle in the long run:

A direct human-induced long-term loss (persisting for X years or more) of at least Y% of forest carbon stocks [and forest values] since time T and not qualifying as deforestation or an elected activity under Article 3.4 of the Kyoto Protocol [24]

MAIN CAUSES OF FOREST DEGRADATION

Many natural factors and human activities can affect forest health and vitality leading to a gradual or sudden decrease in forest growth, tree mortality and to a decline in the provision of forest goods and services. Wild or human-induced fires, pollution, floods, nutrients and extreme weather conditions such as storms, hurricanes, droughts, snow, frost, wind and sun are among abiotic agents that may be responsible for a loss of health and vigor of forest ecosystems. Biotic influences of forest conditions include insect pests, diseases and invasive species and can either consist of fungi, plants, animal or bacteria. Humans are also a major factor of forest health deterioration as overexploitation, competing land uses, poor harvesting techniques or management can negatively impact forest ecosystems.

In the study of forest degradation can have any number of causes, dependent on resource condition, environmental factors, socio-economic and demographic pressure and “incidents” – e.g. pests, disease, fire, and natural disasters. The understanding and separation of different degradation processes is important for the definition of suitable methods for measuring and monitoring. Various types of degradation will have different effects on the forest carbon storage and result in different types of indicators that can be used for monitoring degradation using *in situ* and remote methods (i.e. trees being removed, canopy damaged, etc.).

In this review, the emphasis is on those forms of forest degradation that are caused by direct human impacts on the forests (i.e wood removal) or indirect human impacts on the forests(i.e. long term forest management that favors the occurrence of fire).

4 Mapping Forest Degradation

4.1 Remote Sensing And Global Forest Measurement

For any worldwide forest monitoring effort to succeed, there must be consensus on forest definitions, past reference maps (so that change can be detected), and selected forest metrics. We have chosen the Forest Identity [44] as an organizing principle for the central metrics of this study. The Forest Identity relates four forest attributes (area, volume [density of growing stock], biomass, and sequestered carbon) that provide a useful starting point for global forest monitoring. Current maps of forest area have medium to high accuracy. Monitoring volume, biomass, and carbon on a regional to global scale is possible with current technology. Similarly, we can develop past reference maps for forest area (maps of what an area once looked like), but past reference maps for volume, biomass, or carbon will require innovative reprocessing of old imagery. For forest area, “accuracy” is roughly defined as the percentage of pixels in the remote sensing imagery that correctly identify land-cover type. For forest volume, biomass, and carbon, accuracy refers to the match between predictions from remote imagery and observed ground measurements.

Designing a satellite-based, worldwide forest monitoring system requires choices in budgeting, processing logistics, sampling frameworks, and the collection of validation (or “ground-truth”) data from forest inventories and high-resolution imagery. Collection of ground-truth data is typically necessary as a means of determining the accuracy of remote sensing. According to [47] these data are particularly essential when attempting to estimate forest volume, biomass, and carbon using remote sensing technology. Archiving and standardizing global ground-truth data for forests would be a significant contribution to global forest science. Ground data, aerial imagery, and high-resolution satellite imagery are expensive and require coordination in a sampling hierarchy for efficiency.

In current coarse-resolution world forest maps, forest area is measured with medium accuracy as two classes (forest/non-forest) [12]) or categorized with low accuracy into homogenous forest types based on leaf persistence (for example, evergreen forest).Recent improvements in classification techniques and the combination of distinct types of satellite imagery (called imagery fusion) have allowed moderate-resolution mapping of forest types with high accuracy (80–90 percent). Currently, complete forest clearing can be detected with the highest accuracy. With current technology, it remains difficult to distinguish primary forests from tree plantations and older secondary forests in remote sensing images. It is also challenging to detect forest degradation in which a forest is partially cleared by human activity. Significant progress on these problems has been made in certain geographic regions, but accurate global forest maps with multiple classes remain elusive. In the years between 2009 and 2015, we can expect to see numerous improvements that promise to address many of these challenges. Some of the anticipated advances include: active and passive satellite imagery is sensitive to forest structure (both vertical and horizontal), and forest structure can be used to estimate forest volume, biomass, and aboveground carbon. Both SAR and LIDAR are directly sensitive to forest volume. SAR images tend to saturate or fail to penetrate in dense forests but they can cover large areas. Conversely, LIDAR data do not saturate but can only measure small areas. In open forests, stereo and high-resolution imagery can also measure forest height and canopy structure and have the potential to aid LIDAR and SAR measurements of forest volume and biomass.

Future satellite launches of LIDAR, long wavelength SAR, and In SAR sensors will significantly improve estimates of biomass, forest volume, and carbon in the near term and may provide information crucial to the development of a global, ground-level elevation model. If such a model were available, scientists could create accurate, worldwide maps of forest height and, in turn, generate global reference maps that estimate historical forest biomass as far back as the mid-1990s.

4.2 Forest change detection analysis

Measuring forest area is distinct from measuring changes in forest area, for both practical and quantitative reasons. Practically, increases in forest area often result from land-cover types that are quite spectrally distinct from the original forest and would not be classified as forest area. In temperate and tropical areas, woody encroachment into grasslands creates spectrally and structurally distinct forests in unexpected areas, and forest regrowth on abandoned farms creates distinct secondary forests [49] Deforestation results in the conversion of forests to a variety of agricultural land covers, including spectrally similar tree plantations. Tropical forest regrowth is very rapid, making ten- to twenty-year-old forests difficult to distinguish from primary forest on a satellite image.

Since early days of earth observation systems, various techniques of change detection have been developed for forest monitoring using high resolution optical remote sensing. These approaches are focused on the identification of forest cover change, described by [23] including among others forest clearing, regrowth, damage and disease. Different reviews have been proposed in the literature for summarizing and comparing these different approaches [4] Coppin and [16], [38][44] However, as new change detection methods are still designed and with the recent development of image segmentation applications, change detection approaches are regrouped into three categories: (1) visual interpretation,(2) pixel-based and(3) object-based methods.

4.3 METHODS TO EVALUATE FOREST DEGRADATION WITH REMOTE SENSING

- Direct detection of degradation processes (forest canopy damage);
- Indirect approaches (observation of human infrastructure).

4.3.1 REMOTE SENSING METHODS TO MEASURE CHANGES IN FOREST LAND USES

While most countries have been reporting their changes in forest area affected by degradation based on their National Forest Inventories, the measurement and monitoring of forest change land use through remote sensing offers a series of advantages: i) it represents an operational, consistent, coherent, transparent and fairly accurate way of reporting on change in forest land-use, which allows for near-real reporting on land use changes, ii) it is cost and time effective, iii) it offers data over remote and logistically complicated regions, iv) it offers a high frequency of data that help minimize seasonality problems, v) it is the only approach that objectively offers information on historical trends, and iii) it favors the control of leakage and permanence issues.

However, it also has several disadvantages: i) it is hampered by clouds, ii) it is limited by the technical capacity to sense and record the change in canopy cover with small changes likely not to be apparent unless they produce a systematic pattern in the imagery, iii) optical remote sensing is not useful to identify sub-canopy changes and therefore it is insensitive to under-canopy forest degradation (i.e. certain fire types, certain overgrazing, certain logging activities), and iv) not all degradation processes can be monitored with high certainty using remote sensing data. Table 2 offers a list of degradation processes that are best detected through remote sensing. Of course, a mixed approach would be desirable.

Table 2: Forest degradation activities and their degree of detection using Landsat-type data, (Source: Peres et al., 2006).

Highly Detectable	Detection limited & increasing data/effort	Detection very limited
• Deforestation • Forest fragmentation • Recent slash-and-burn agriculture • Major canopy fires • Major roads • Conversion to tree monocultures • Hydroelectric dams and other forms of flood disturbances • Large-scale mining	• Selective logging • Forest surface fires • A range of edge-effects • Old-slash-and-burn agriculture • Small scale mining • Unpaved secondary roads (6-20m wide) • Selective thinning of canopy trees	• Harvesting of most non-timber plants products • Old-mechanized selective logging • Narrow sub-canopy roads (<6m wide) • Understorey thinning and clear cutting • Invasion of exotic species

Independently of the approach chosen, the development of a monitoring system for degradation first requires that the causes of degradation be identified and the likely impact on the carbon stocks be assessed. FAO, together with the Members of the Collaborative Partnership on Forests (CPF) undertook a special study on forest degradation to identify the parameters of forest degradation and the best practices for assessing them.

Mapping forest degradation with remote sensing data is more challenging than mapping deforestation because the degraded forest is a complex mix of different land cover types (vegetation, dead trees, soil, shade) and the spectral signature of the degradation changes quickly (i.e., < 2 years) [14]). High spatial resolution sensors such as Landsat, ASTER and SPOT have been mostly used so far to address forest degradation. However, very high resolution satellite imagery, such as Ikonos or Quick bird, and aerial digital imagery acquired with videography has been used as well. Methods for mapping forest degradation range from simple image interpretation to highly sophisticated automated algorithms [40].

4.3.2 DIRECT METHODS OF MAPPING FOREST DEGRADATION

In the direct method, and under a degradation definition based on changes in carbon stocks, forest canopy gaps, small clearings, and the structural forest changes resulting from disturbance are the features of interest to be enhanced and extracted from the satellite imagery. Among the most classically used techniques are: i) visual interpretation, which can easily detect canopy damage areas in very high spatial resolution imagery; ii) automate segmentation; iii) spectral mixing analysis for logging disturbances [20], [45] and fire [11] lacunarity indices for canopy structural characterization [54] vi) hyper spectral automated canopy identification [34].

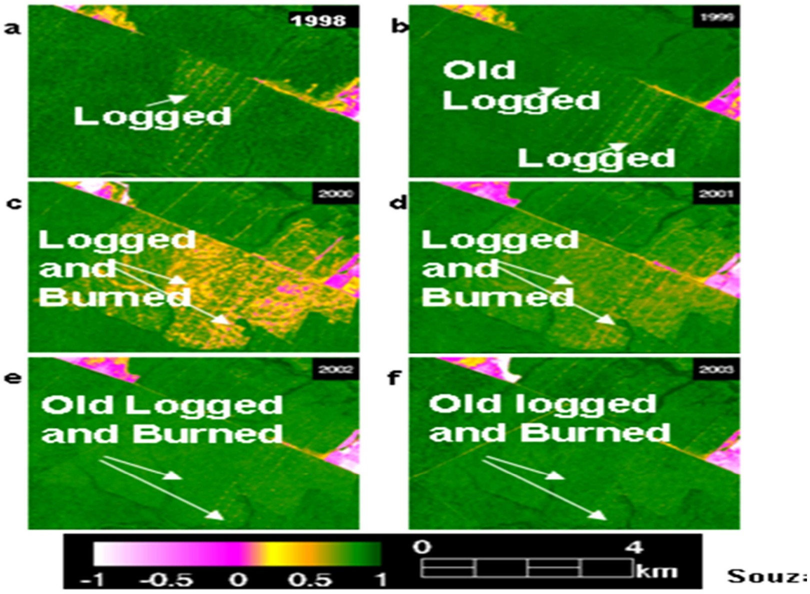

Figure 5: Spectral mixing analysis (SMA) as a way to follow the degradation dynamics of Amazonian lowland forests using Ikonos sensors [11]

There are limiting factors to be taken into consideration when mapping direct forest degradation [12] First, it requires frequent mapping, at least annually, because the spatial signatures of the degraded forests change after one year. Additionally, it is important to keep track of repeated degradation events that affect more drastically the forest structure and composition resulting in greater changes in carbon stocks. Second, the human-caused forest degradation signal can be confused with natural forest changes such as wind throws and seasonal changes. Confusion due to seasonality can be reduced by using more frequent satellite observations. Third, all the methods described above are based on optical sensors which are limited by frequent cloud conditions in tropical regions. Finally, higher levels of expertise are required to use the most robust automated techniques requiring specialized software and investments in capacity building.

4.3.3 INDIRECT METHODS OF FOREST DEGRADATION MAPPING

The indirect method is useful when degradation intensity is low and the area to assess is large, when satellite imagery is not easily accessible, or when the direct approach cannot be applied for whatever other reason. An example of a useful indirect approach is the “intact forest” approach where the spatial distribution of human infrastructures (i.e. roads, population centres) are used as proxies, so that the absence of these are used to identify forest land without anthropogenic disturbance (intact forests) so as to assess the carbon content present in the disturbed and non-disturbed forest lands [13], [41]Intact forests: fully-stocked (any forest with tree cover between 10% and 100% but must be undisturbed, i.e. there has been no timber extraction);

- ✓ Non-intact forests: not fully-stocked (tree cover must still be higher than 10% to qualify as a forest under the existing UNFCCC rules, but in our definition we assume that in the forest has undergone some level of timber exploitation or canopy degradation).

Scenario modelling for forest degradation would be another indirect method which could be applied to estimate both future and historical forest degradation dynamics. [7] published an example of a *deforestation modelling approach* for the Amazon Basin that produced annual maps of simulated future deforestation under user defined scenarios of highway paving, Protected Area (PA) networks, PA effectiveness, deforestation rates and deforested land ceilings. With the right support from field data, a similar modeling approach could be used for (re)constructing historical and future scenarios of forest degradation.

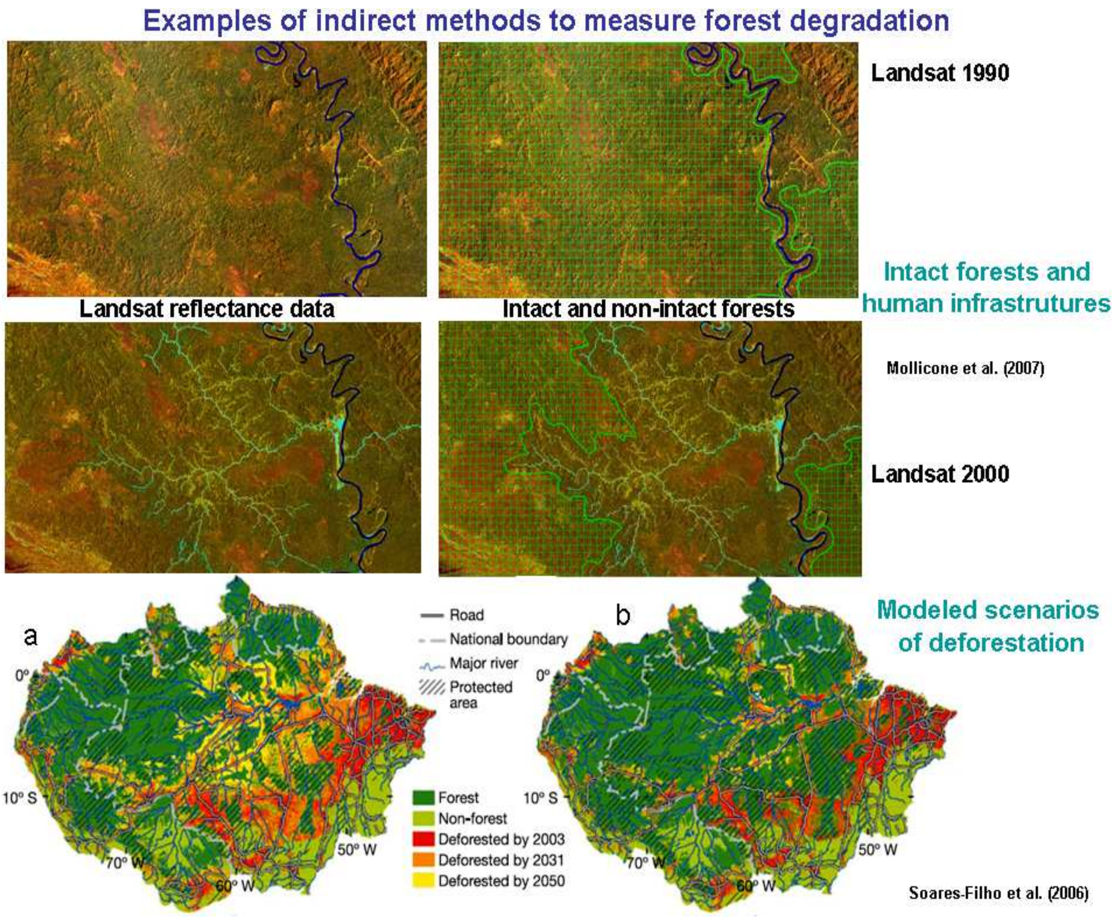

Figure 6: Estimation of intact and non-intact forests based on areas of influence (buffers) from human infrastructures (Soares-Filho et al., 2006).

4.4 RELEVANCY OF DIFFERENT FOREST DEGRADATION APPROACH

In the study of [33] they tried to develop a relevancy of different forest degradation assessment in Nepal (Table 3).

Table 3 Relevancy of different forest degradation approach, [33]

Methodology	Advantageous	Disadvantageous	Accuracy level	Costs	Implications for Nepal
Aerial photography	• Easy to understand to local community • Visible to demonstrate forest degradation such as crown cover change, shifting cultivation, forest fragmentation • Long experience • Infrastructure exits • Require low input on technology	• Difficulty in mountain area • High costs, • High time requirement, • Nearly abandoned and replaced by new technologies. • No latest aerial photographs available • Degradation elements such as grazing, fire damage, forest NTFPs and understorey damage, encroachment is not completely detectable	High	High	No recent aerial photographs available - less useful
Field survey	• Data available for comparison • More accurate, • Widely understood, • Cheap labour • Considerable experience • Simple technology • Capture all kinds of ecosystem services • National to local scale possible • Scattered case study and academic, research data available	• More resources, • Long time requirement • Difficult in mountain terrain • No recent data available	High (Std. Error for the top 4 "volume ranged from 2.61% to 6.66 %).	Medium	Considerable experience exists, labour is cheap- still a good option, community involvement is available, proposed FINNIDA assistance survey will generate new data
Satellite image analysis and GIS	• Global uniformity • Rapidly advancing technology • Easy interpretation in high resolution images • High resolution images usable as a map for demonstration • Requires low forest inventory	• Technical capacity and infrastructure demanding, • Cloud, shadow and slope in hilly areas, • Few control plots for ground verification, • Seasonal images availability, • Limited data to replace ground inventory • Difficult to assess under storey including NTFPs.	Medium to high (67 to 98% to distinguish in different stocking class)	Free to moderately expensive (Landsat to IKONOS) Low or medium	Difficult terrains support it. Needs capacity development, if combined with field survey, is one of the best option
Ecosystem service valuation	• Recognizes broader value of forest ecosystem	• Technically demanding • Outside forestry discipline	Medium to High	Low to Moderate	Community participation, true valuation of forest services.

5 METHODOLOGICAL APPROACH FOR FOREST DEGRADATION ASSESSMENT USING REMOTE SENSING

As we said before that common indicator for monitoring and assessing forest degradation could be developed for the following key elements to be used in assessing forest degradation:

- Biodiversity (e.g. species composition and richness, habitat fragmentation);
- Biomass (e.g. growing stock, forest structure);
- Forest goods obtained (compared against sustainably managed forests);
- Forest health (e.g. fire, pest and diseases, invasive and alien species);
- Soil quality (as indicated by cover, depth and fertility

The methodological approach for forest degradation assessment using remote sensing should focus in one of each key concept to explain the impact of remote sensing trough degradation.

5.1 THE USE OF VEGETATION INDICES AS NDVI CONCEPT TO ASSESS FOREST DEGRADATION

Vegetation indices are the quantitative measure of measuring biomass or vegetation vigor. They are usually formed by a combination of several spectral bands whose values are added, divided or multiplied in order to yield a single value that indicates the amount or vigor of vegetation. A variety of vegetation indices have been developed, with most commonly using red and near infrared regions of the spectrum to emphasize the difference between strong absorption of red electromagnetic radiation and the strong scatter of near infrared radiation. The simplest form of vegetation index is a ratio between near infrared and red reflectance and it is high for healthy living vegetation. Literature survey revealed wide disagreement regarding the biomass and vegetation indices relationship. Many studies report a significant positive relationship (e.g [21] while some results showed poor relationship [19].The normalized difference index (NDVI) is one of the most commonly used vegetation indices in many applications relevant to analysis of biophysical parameters of forests. Over the past two decades its utility has been well demonstrated in satellite assessment and monitoring of global vegetation cover [3] [43] The strength of NDVI is in its rationing concept which reduces many form of multiplicative noise present in multiple bands. However, conclusions about its value vary depending on the use of specific biophysical parameters and characteristics of the study area [21] It is computed by the product of the ratio of two electro-magnetic wavelengths (near infrared–red)/(near infrared+red). Vegetation has high near chlorophyll pigments and the value of NDVI tends to one. In contrast of this, clouds, water, snow etc. have a high red reflectance than near-infrared and these features yield negatives NDVI value. Rocks and bare soil also have similar reflectance and usually zero value of NDVI.

The saturation of the relationship between biomass and NDVI is also a well-known problem. This can be explained by the fact that as canopy increases, the amount of red light that can be absorbed by leaves reaches a peak while near-infrared (NIR) reflectance increases because of multiples scattering with leaves. The imbalance between a slight decrease in the red and high NIR reflectance results in a slight change in the NDVI ratio and thus, yield poor relationship with biomass [13] Further, [29] Observed that saturation level is also dependent on the tree species, forest types as well as the ground surface types. Therefore, a suitable relationship of vegetation indices and biomass is crucial in assessment of biomass in different circumstances and a matter of more research work. The usefulness of remote sensing in such work depends on the strength of the relationships developed with respect to a particular type of forests and its geographical location.

5.2 FOREST CANOPY CHANGE AND REMOTE SENSING

Researchers have found relationships between vegetation properties and remotely sensed variables. In order to summarize these diverse experiments, basal area and canopy cover, and the “volume and productivity” variable includes age, height, volume, diameter and density. [31] found a significant relationship between green TM band (2) with basal area of trees.

More recent work by Fiorella and [33] found that ratios of near-infrared/red and near-infrared/middle-infrared correlated with structural forms. [1] discovered that vegetation productivity is more strongly related to band ratios than individual bands.

[48] analyzed (simulated) TM data, and concluded most information about vegetation was contained in the blue, near-infrared and middle-infrared. Thermal infrared was used by [37] to map broad forest type classes. Vegetation dieback and damage are best mapped by band ratios.

5.3 COMPARING FOREST INVENTORY AND REMOTE SENSING MEASUREMENT OF FOREST DEGRADATION

The same forest quantities (e.g., biomass) are estimated differently by ground forest inventory and by remote sensing. Forest inventory typically measures tree abundance, diameter, crown width, species, and height [10],[27].

Table4. How Forest Inventory and Remote Sensing Estimate the Forest Identity

Forest identity	Forest inventory	Remote sensing
Area	Measured locally, at one time, in one to a few forest types.	Measured regionally and repeatedly, distinguishing forest types and ages (Optical, SAR).
Volume	Estimated using diameter at breast height, tree height.	Estimated from measures of forest height/structure (SAR, LIDAR).
Biomass	Estimated from volume and wood density measurements. Extrapolated regionally.	Estimated from area and forest structure. Estimates are improved by measures of forest flammability, productivity, leaf area, phenology, and gas flux.
Carbon	Estimated from biomass and carbon density measurements. Extrapolated regionally.	Same as biomass. Estimates are site specific, across entire regions.

Remote sensing measures reflected spectra, forest area and the horizontal and vertical structure of forests can be measured directly from these reflected spectra. Fieldwork or higher resolution imagery can be used to generate ground-truth data to assess the accuracy of these forest area and structure measurements [29].

5.4 CLASSIFICATION APPROACH FOR FOREST DEGRADATION ASSESSMENT

Global forest area is often measured as two classes (forest/non-forest) or binned (that is, categorized) into homogenous forest types that does not distinguish tree plantations or disturbed forests ([37], [42].

5.5 ESTIMATING FOREST VOLUME USING REMOTE SENSING

Both the volume and the aboveground biomass (AGB) of forests can be estimated from allometric relationships with canopy width, structure, and/or height, the intensity of SAR backscatter, correlations with passive spectra, and various fusions of the above [16].

5.6 ESTIMATING FOREST BIOMASS USING REMOTE SENSING

Tree height and/or diameter, because of the unique constraints of plant structure, is positively correlated with tree biomass within a species ([27], [37] Using well-established allometric relationships, biomass can be calculated from tree diameter, height, and/or wood density [27]. Remote sensing cannot directly measure wood density, but correlative forest inventory data can use species-specific or region-specific allometric equations to provide accurate estimates of biomass.

Forest height can be measured from a variety of remotely sensed data and used to estimate biomass [30], [34], [15] Although diameter, height, and wood density are central variables, biomass estimates can be improved by using additional forest structure variables (e.g., canopy width, canopy volume) [17], [51].

5.7 ESTIMATING FOREST CARBON STOCKS FROM REMOTELY SENSED DATA

Satellite imaging can tell us much about global carbon stocks, but there are limits to its accuracy. Dry biomass is approximately 47–55 percent carbon by weight [23] so aboveground biomass estimates from remote sensing can be simply converted into aboveground carbon (AGC) stock estimates [22].

5.8 Landscapes indices

To investigate the relationship between landscape pattern and ecological processes, it is useful to describe these structures in quantifiable terms. This explains the development of a series of "landscape metrics" [8],[16],[25]The need to use several indices to characterize the spatial structure of a landscape seems logical and many clues are available to ecologists for this purpose. These measures are often an indicator of human impact on landscape morphology [25] Since no action can be summed up in itself all the complexity of the spatial arrangement of patches, a set of measures should generally be done [25],[34]This idea is at the base of the existence of an abundance of indices.

Landscape ecology is based on the idea that there is a link between spatial ecological pattern and processes. Spatial indices or metrics have been developed by community and population ecologists to study this link, using theoretical concepts of disturbance, island biogeography, and information theory [6],[34], [39] These indices are commonly related to patch size, complexity, diversity, and neighborhood structure. Size-related indices measure patch size characteristics. Complexity-related indices measure how complicated patch shapes are. Diversity-related indices measure how diversified patches are. Neighborhood-related indices measure the relationship of a patch with its neighbors. Detailed mathematical descriptions of these indices are available in [19].

6 Conclusions

From the preceding three sections of this review, quite a number of conclusions can be made. Measuring forest degradation and related forest carbon stock changes is more complicated and less efficient than measuring deforestation since the former is based on changes in the structure of the forest that do not imply a change in land use and therefore it is not easily detectable through remote sensing. There is not one method to monitor forest degradation. The choice of different approaches depends on a number of factors including the type of degradation, available (historical) data, capacities and resources and the potentials and limitations of various measurement and monitoring approaches.

Measuring all carbon stock changes caused by forest degradation within a country at the same level of detail and accuracy will likely not be efficient. In particular the considerations of IPCC source category analysis, and the fact that many degradation activities are focused on specific areas within the country help to make the monitoring more targeted and efficient to capture the most important components with priority.

To estimate forest degradation, countries need to assess carbon stock changes and the total area undergoing degradation, ideally for different types of degradation (i.e. fire, logging, and fuel wood harvesting). The assessment of changes in carbon stocks requires consistent ground data while the evaluation of the total area undergoing degradation is more reliably measured through remote sensing for the major degradation processes, in particular for developing countries. The particular problem of measuring forest degradation is the lack of field based forest data for developing countries. In general terms, forest degradation areas can be mapped through direct and indirect methods, the former approach is based on direct observations of forest structural changes (i.e. canopy gaps), while the second considers modelling approaches based on known drivers of forest degradation.

The major issue affecting the assessment and reporting of forest degradation emissions is the estimation of its uncertainty. Among the REDD+ activities, both forest degradation and deforestation will require high levels of accuracy and certainty since they are major contributors of countries´ GHG budgets for forests. While consistent measurements of forest carbon stock changes have not been of a high priority in many countries and monitoring programs in the past, this situation is changing now and new investments in systematic forest degradation estimates can help reduce uncertainties even for historical estimates. However, historical degradation estimates will necessarily come with large uncertainties due to the lack of available data to determine their accuracy.

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