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Beyond carbon accounting:
A landscape perspective on measuring and monitoring tropical forest degradation

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Lucía Morales-Barquero

PhD 2015

Beyond carbon accounting: A landscape perspective on measuring and monitoring tropical forest degradation

A thesis for a joint degree of

Doctor of Philosophy

By

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June 2015

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ABSTRACT

Human activities have modified a significant part of the tropical forest landscapes across the globe, affecting their ecological characteristics and their capacity to provide ecosystem services. In order to counter act the current decrease in tropical forest quality, avoiding and reversing forest degradation has been included as one of the goals of multiple international agreements; it is of particular importance for the climate change mitigation scheme for Reduced Emissions from Deforestation and forest Degradation, forest conservation and enhancement of carbon stocks known as REDD+. In this thesis, I investigated the challenges and feasibility of measuring and monitoring tropical forest degradation in human modified landscapes, focusing on two types of human activities: shifting cultivation and logging.

In Chapter 2, I built a conceptual framework that analyses the applicability of the international definitions of forest degradation, and their contrast with the complexity of tropical forest ecosystems and monitoring capacity in tropical countries. I proposed that given the current data and technological limitations, a quick start option to measure forest degradation is to use a benchmark that can be directly linked with the type and intensity of disturbance processes found in an area. Then in Chapter 3, I further studied disturbance processes by analysing the dynamics of shifting cultivation systems and the use of forest resources by communities. I found through a detailed mapping of high resolution data (10X10 m), that similar amounts of forest cover in tropical dry forests (TDF) were lost and gained between the study period (2004-2010), both at the regional and at the community level. This provides evidence that at least in terms of the above ground biomass pool, shifting cultivation systems in TDF could be considered carbon neutral, which implies that these systems have potential to participate in REDD+. The probability of changes in TDF cover in shifting cultivation systems was found to be dependent on the elevation, slope, amount of TDF available per person within a community, and to the amount of livestock and fence posts used by the communities.

The use of forest resources and its relation with forest degradation is further studied in Chapter 4. In this Chapter, I evaluated a series of disturbance indicators that best explain the response of forest attributes to human disturbance, and used these indicators to establish four levels of forest degradation. The feasibility of separating four levels of degradation based on two types of high spatial resolution remote sensing data (SPOT 5 and RapidEye satellite data) was assessed. I found that at the landscape level, based on the use of forest resources it was possible to classify TDF into low and high

degradation levels. The capacity to classify the landscape into disturbance levels is further explored in Chapter 5, by using historical logging concessions and multi-temporal time series of medium spatial resolution (Landsat) in tropical moist forest. Through the integration of previous land use information with an analysis of the relation of the amount of green vegetation with respect to soil and shadow that compose a pixel, I determined that almost one third of the forest in the study area has experienced disturbance processes.

This work supports the need to advance monitoring of forest cover analysis by incorporating forest condition, which has particular implications for the determination of forest carbon stocks. Overall, this research strengthens the concept that the definition, measuring and monitoring of forest degradation should be tailored to the particular dynamics of disturbance processes; and moreover that a direct link between monitoring capacity of a country and policy formulation is clearly needed to improve tropical forest stewardship.

ZUSAMMENFASSUNG

Bedeutende Teile der global verbliebenen tropischen Wälder sind menschlichen Einflüssen mit oft gravierenden Auswirkungen auf ökologische Eigenschaften und Ökosystemdienstleistungen ausgesetzt. Um der anhaltenden Verschlechterung des Zustands tropischer Wälder entgegenzuwirken wurden die Vermeidung von Waldschäden und die Wiederherstellung geschädigter Wälder in die Ziele internationaler Abkommen aufgenommen. Insbesondere ist hier das Klimaschutzinstrument REDD+ zu nennen, das für die Verringerung von Emissionen aus der Entwaldung und Schädigung der Wälder steht.

In dieser Doktorarbeit habe ich in vier Aufsätzen die Herausforderungen und Möglichkeiten untersucht, um tropische Waldschäden in anthropogen überformten Landschaften zu messen und zu überwachen. Das Augenmerk lag hierbei auf zwei Formen von Landnutzungen die Wälder schädigen können: Wanderfeldbau und Holzeinschlag.

Der erste Aufsatz (Kapitel 2) präsentiert einen konzeptuellen Rahmen inwieweit internationale Definitionen von Waldschäden in der Praxis anwendbar sind und wie diese im Kontrast stehen mit der Komplexität von Waldökosystemen und der begrenzten Überwachungsmöglichkeiten in tropischen Ländern. Angesichts begrenzter technischer Möglichkeiten und mangelnder Verfügbarkeit von Daten schlage ich als „Schnell-Start-Option“ zur Messung von Waldschäden die Verwendung eines Vergleichsmaßstabes vor, der direkt mit dem Typ und der in der Fläche gemessenen Intensität des Störungsprozesses in Bezug gesetzt werden kann.

Im zweiten Aufsatz (Kapitel 3) untersuche ich Störungsprozesse die von dynamischen Wanderfeldbausystemen und der Nutzung von Waldressourcen durch lokale Gemeinschaften ausgehen. Durch detaillierte Kartierungen von hochaufgelösten (10x10m Pixelgröße) Satellitenbildern konnte ich nachweisen, dass zwischen 2004 und 2010 ähnlich große Flächen an tropischen Trockenwäldern (TTW) verloren wie hinzugewonnen wurden und zwar sowohl auf regionaler als auch auf lokaler Ebene. Dies werte ich als Hinweis darauf, dass - zumindest in Hinblick auf die Menge des in oberirdischer Biomasse gebundenen Kohlenstoffs - Wanderfeldbausysteme in TTW als Kohlenstoffneutral angesehen werden können und damit potentiell in den REDD+ Mechanismus aufgenommen werden könnten. Die Wahrscheinlichkeit von Veränderungen in TTW war abhängig von Höhenlage, Hangneigung, verfügbarer TTW-Fläche pro Person in der Dorfgemeinschaft, der Anzahl der Weidetiere und der Anzahl der Zaunpfosten als Indikatoren für Holznutzung.

Die Degradierung von Wäldern durch die Nutzung von Waldprodukten ist auch Thema im dritten Aufsatz (Kapitel 4). Dieser untersucht für eine Reihe von Störungsindikatoren, wie geeignet sie sind um die Reaktion des Waldcharakters auf menschliche Störungen abzubilden, mit dem Ziel unterschiedliche Stufen von Waldschädigungen zu identifizieren. In dieser Studie untersuche ich die Machbarkeit, diese Störungsstufen anhand von hochaufgelösten Fernerkundungsdaten (SPOT 5 und RapidEye Satellitenbilder) zu identifizieren. Auf der Landschaftsebene war es möglich TTW mit hoher und niedriger Störung durch Nutzung von Waldressourcen zu differenzieren.

Die Möglichkeiten Landschaften anhand ihrer Störungsstufen zu unterscheiden ist auch Thema des vierten Aufsatzes (Kapitel 5), in diesem Fall anhand von tropischen Feuchtwäldern, basierend auf Daten zu historischen Holzeinschlag-Konzessionen und multitemporalen Zeitreihen von Landsat-Bildern mittlerer Auflösung. Die Integration von Informationen zu vorherigen Landnutzungen erfolgte hier durch die Analyse wie sich jedes Pixel aus dem Verhältnis von grüner Vegetation, offenem Boden und Schatten zusammensetzt. Die Ergebnisse zeigten dass fast ein Drittel des Waldes im Untersuchungsgebiet eine vorherige Störung durchlaufen war.

Diese Doktorarbeit illustriert den dringenden Bedarf an Weiterentwicklung der Überwachung von Walddeckung unter Einbezug des Waldzustandes, was von unmittelbarer Bedeutung für die Bemessung der Kohlenstoffvorräte ist. Insgesamt zeigt die Arbeit auf, dass Definition, Messung und Überwachung von Waldschäden auf die spezielle Dynamik von Störungsprozessen in einem Gebiet abgestimmt werden müssen und dass es einer direkten Verbindung zwischen der Politikgestaltung eines Landes und der Überwachungsmöglichkeiten bedarf um langfristig Verantwortung für tropische Wälder zu übernehmen.

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I dedicate this work to Rubén, and to my parents, Miriam and Julio.

ABBREVIATIONS

ACOSA	Osa Conservation Area
AD	Activity Data
AGB	Aboveground Biomass
AIC	Akaike Information Criteria
AUC-ROC	Area under the receiver's operational curve
BA	Basal Area
Bi	Brightness index
CBD	Convention on Biological Diversity
CI	Canopy Index
CONAFOR	National Forestry Commission - México
CONAPO	National Population Council - México
CV	Cross validation
DBH	Diameter at Breast Height (1.3 m)
EAGB	Estimated aboveground biomass
EF	Emission factor
EVI	Enhanced Vegetation Index
FAO	Food and Agriculture Organization of the United Nations
FMP	Forest Management Plans
FONAFIFO	Fondo Nacional de Financiamiento Forestal - Costa Rica
GFOI	Global Forest Observations Initiative
GHG	Green House Gas
GNDVI	Green Normalized Difference Vegetation Index
GOFC-GOLD	Global Observation of Forest and Land Cover Dynamics
GV	Green Vegetation
IGN	National Geography Institute of Costa Rica
INBio	National Biodiversity Institute of Costa Rica
INEC	National Institute of Statistic and Census - Costa Rica
INEGI	National Institute of Statistic and Geografía - México
IPCC	Intergovernmental Panel on Climate Change
IPCC GPG	Good Practice Guidance
ITTO	Internation Tropical Timber Organization
JIRA	Intermunicipal Board of the Ayuquila River Catchment
LDA	Linear Discriminant Analysis
LF	Logged Forest
LULUCF	Land use, land-use change and forestry
MINAET	Ministerio del Ambiente y Energia - Costa Rica
MMU	Minimum mapping unit
MRV	Monitoring Reporting and Verification
MSAVI2	Modified Soil Adjusted Vegetation Index 2
NDVI	Normalised Difference Vegetation Index
NIR	Near Infrared

NTFPs	Non-timber forest products
OOB	Out of the bag error
OSAVI	Optimized Soil-Adjusted Vegetation Index
PCA	Principal Component Analysis
PES	Payment for Environmental Services
PROCAMPO	Program of Direct Payments to the Countryside - México
REDD+	Reducing Emissions from Deforestation and Forest Degradation
REL	Reference emissions level
RF	Random forests
RFGD	Golfo Dulce Forest Reserve
RMSE	Root Mean Square Error
RONV	Range of natural variation
SAVI	Soil Adjusted Vegetation Index
SEC	Counterfactual second angle movement
SEMARNAT	Secretaría de Medio Ambiente y Recursos Naturales - México
SFM	Sustainable Forest Management
SINAC-FGIS	National System of Conservation Area - Forest Geographical Information Systems - Costa Rica
SMA	Spectral Mixture Analysis
SR	Simple Ratio
SWIR	Short wave Infrared
TC	Tasseled cap
TDF	Tropical Dry Forest
TNDVI	Transformed Normalized Difference Vegetation Index
UF	Undisturbed Forest
UNFCCC	United Nations Framework Convention on Climate Change

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Chapter 1. Introduction

1.1. Introduction

About 60% of the world´s tropical forests have experienced, to some extent, disturbance due to human activities that has altered their original ecological characteristics (ITTO, 2002). But does this mean that most of the world's forests should be considered to be degraded? How can forest degradation be defined and in what context is a definition relevant? Moreover, how can it be measured in a way that is useful for decision making? With the increasing interest in forest carbon markets and forest biomass becoming a commodity, these questions have gone beyond the ecological realm to have important social and economic implications (Putz & Redford, 2010).

Measurement and monitoring of degradation in tropical forests are important from both scientific and policy viewpoints. Degradation of forests is associated with carbon emissions and biodiversity loss, contributing to a decrease in both the social and environmental functions of forests. With regard to policy, this thesis has been carried out in the context of recent United Nations Framework Convention on Climate Change (UNFCCC) policy on Reduced Emissions from Deforestation and forest Degradation (REDD+), under which countries may be rewarded financially on the basis of their national achievements in reducing carbon emissions, not only from deforestation but also from forest degradation. This policy is firmly rooted in payment by performance, which means that reliable, quantitative estimates of degradation will be necessary, and countries are searching for appropriate methods to provide such data. Although it is well established in academic literature that much tropical forest is degraded, and that it is expected to increase (Blaser *et al.*, 2011), in reality estimation of the extent of degraded areas is highly uncertain (Mollicone *et al.*, 2007; Asner *et al.*, 2009; Potapov *et al.*, 2009). Likewise there are major challenges in estimating the intensity of forest degradation (the extent of the loss of biomass and/or capacity to provide environmental services in a given area), and the rate at which different types of disturbance lead to degradation. Therefore, methods for this assessment need to be improved (Herold *et al.*, 2011; Mertz *et al.*, 2012; Bustamante *et al.*, 2016; Pfeifer *et al.*, 2016).

The concept of forest degradation is complex, and needs to be approached from the perspective of multiple disciplines (Visseren-Hamakers *et al.*, 2012). An initial *conundrum* is the definition of forest degradation itself, because it is an inherently constrained concept based on judgment using a range of criteria (those of ecologists, policy makers, foresters, communities, logging companies, non-governmental organizations, economists etc.) according to what “we” think an undisturbed tropical forest ecosystem should be. Clearly this judgment varies between different stakeholders, the many disciplines involved in the study of tropical forest degradation and, moreover, between different forest ecosystems

(Guariguata *et al.*, 2009). What would be considered by some as an example of degraded forests, would for others be characteristic of improved forest management (Putz & Romero, 2015). Thus, there is a lack of agreement about the exact definition of forest degradation, and there is a tension between conceptually broad definitions and those that make the level and spatial extent of degradation amenable to practical measurement and monitoring. One consequence of this lack of agreement is that research on forest degradation is to a great extent exploratory and contestable. Furthermore, generalizations can be limited, in the sense that findings about degradation of forests from one type of disturbance, will have particularities to that specific type of forest and management system restricting its applicability to others (Mertz *et al.*, 2012). Despite these constraints, the successful creation and implementation of global view in which environmental degradation policies are being created, calls for an advance in our knowledge and conceptual framework of forest degradation.

That being said, in this thesis I attempt to study the complexity around forest degradation by conceptualizing it within the frame of the human-induced disturbance processes that act over a landscape, specifically on its carbon stocks. It is at the landscape scale that so much human decision making which results in either an increase or decrease in rates of forest degradation, that the study of forest degradation is most applicable (Thompson *et al.*, 2012; Sayer *et al.*, 2013). Thus, the main premise is that to advance assessment of forest degradation, in a way that is feasible to measure and that can be used effectively to reduce the extent of forest degradation, it needs to be modelled spatially. Achieving such improvements in the spatial modelling of forest degradation depends on improving the understanding of disturbance types, frequency and intensity that occur in the different landscapes, and how they relate to forest degradation. These spatial models of changes in forest cover extent and state as a result of disturbance processes, can be clearly linked to changes in forest carbon stocks (Goetz *et al.*, 2009; Pelletier *et al.*, 2012a; GOFC-GOLD, 2013). Focusing on carbon stocks, apart from being relevant to international policy, is also a feasible way to address forest degradation as it provides an indirect link to quantifying estimates of changes in the delivery of many ecosystem services in an area (Simula, 2009).

In this thesis, rather than just analyzing forest degradation by quantifying carbon stocks *per se,* I approach it from the perspective of the disturbance agents, focusing on two human activities, namely shifting cultivation and timber exploitation (i.e. selective logging) to evaluate the areal extent of forest degradation. My approach to this analysis is from a technical perspective that aims to evaluate the feasibility of measuring and monitoring forest degradation in relation to shifting cultivation and timber exploitation in human modified

landscapes, in order ultimately to spatially model and quantify degradation at the landscape scale.

1.2. Considerations in the definition of forest degradation[1]

In broad terms forest degradation can be defined as a reduction of one or more forest attributes that do not result in a permanent change in land cover class (i.e. forest areas that remain forest areas) (FAO, 2011). Thus forest degradation is conceptualized as a reduction in forest quality; the magnitude of this reduction will depend on the intensity and extent of the disturbance processes that cause it. The variability in the extent and duration of disturbance processes implies that forest degradation results in a continuous range of degrees of degradation (and/or successional stages) (Denslow, 1987; Lambin, 1999; Eckert *et al.*, 2011) and is thus not a permanent state (Attiwill, 1994). These characteristics create major challenges in the definition, measurement and monitoring of forest degradation. At one end of this continuum lies the reference state, against which the reduction of forest attributes or functioning is compared. Defining reference states is highly subjective , mainly because it depends on what measures of forest quality are consider important and also because, in an era of high anthropogenic change, almost all forests have been altered to some degree by human use (Chazdon, 2008).

As a possible solution to deal with the dynamic nature of forest ecosystems and the ambiguity associated with it, Ghazoul *et al.* (2015) proposed that forest degradation should be framed within ecosystem resilience, stating that an area should be considered degraded only if it enters arrested succession, and cannot recover to its pre-disturbance state without human intervention. However, such a conceptualization ignores the temporal scale of decision making, as it implies that degraded forests can only be identified once it has become apparent that a forest system cannot recover. Furthermore, given the many trajectories that forest recovery can take (Norden *et al.*, 2015), it is complex to draw a line between any state of succession and the pre-disturbance state. Therefore, from both policy and utilitarian viewpoints, a major criticism of defining degradation based on resilience capacity is that significant amounts of carbon and biodiversity would be lost from the system before an area could be categorized as degraded. Such an approach, although scientifically sound as it truly captures the fact that tropical forests are constantly changing, would be very hard to make

[1] A more in-depth description of the limitations of defining forest degradation is elaborated in

operational within a carbon mitigation or biodiversity conservation context[2] that aims to implement activities or policies to reduce forest degradation.

Other widely used ecological-based definitions of forest degradation are based on biophysical parameters. Forest degradation is most often defined as changes or alterations in forest structure, composition, biodiversity, ecosystem functions and services that result from disturbance processes (Schoene *et al.*, 2007; Simula, 2009). Reduced biodiversity, reduction of primary productivity, changes in the dominance of species and their population structure, increases in non-native species or light demanding species etc. are among the ecological effects that are used to determine if a forest should be labelled as degraded (Parrotta *et al.*, 2012). Despite consensus that biodiversity is a key component for defining forest degradation, knowledge on biodiversity responses to human-induced disturbances remain limited (Gardner *et al.*, 2009), which has restricted its utility for measuring forest degradation. Clear examples are the difficulties in establishing biodiversity loss, e.g. measured as species richness, in forest areas that are under transition or in logged areas (Gardner, 2010; Ramage *et al.*, 2013). Although measurement of changes in biodiversity remain very challenging, it has been argued that narrowing the view on forest degradation within climate change mitigation schemes only to carbon could potentially have negative effects on biodiversity conservation, and ultimately on the ability of ecosystems to recover through restoration and enhancement (Stickler *et al.*, 2009; Strassburg *et al.*, 2010; Gardner *et al.*, 2012).

With regard to policy, definitions of forest degradation have attempted to accommodate the spatial and temporal complexity surrounding its ecological aspects, by defining it as a decrease in forest attributes (FAO, 2011). Different international agencies have applied definitions that serve specific policy purposes, tend to be generic and might or not comply with the reality of different types of disturbance or of forest ecosystems. The apparent efficiency of using remote sensing for vegetation monitoring over a large area has prompted a focus on identifying changes in canopy cover (or tree crown cover) (FAO, 2007; GOFC-GOLD, 2013). One issue is that using this criterion, the substitution of natural forest by many tree crops will not qualify as degradation, which is contrary to objectives of many

[2] Nonetheless, this approach can potentially be useful for identifying areas on arrested succession in order to explore the possibility of payments for carbon enhancement.

concerned about biodiversity conservation. Likewise, if only canopy cover is used to define degradation, remote sensing cannot tell apart degradation from forest management (Putz & Redford, 2010) so, clearly, complementary information will be needed. The majority of international agencies use definitions related to reduction in the delivery of ecosystem services (Simula, 2009), with a particular emphasis given to carbon stocks[3]. As argued by Cadman (2008), such an approach would avoid many of the practical assessment problems that result from measurement of forest attributes or biodiversity to quantify forest degradation.

In summary, multiple attempts have been made to define forest degradation and what is a degraded forest (Cadman, 2008; Sasaki & Putz, 2009; Simula, 2009; Thompson *et al.*, 2013; Ghazoul *et al.*, 2015). Many have noted the importance of linking the concept to the Millennium Development Goals and the ecosystem services framework. Thus, forest degradation has been considered to be a reduction in the capacity of forest to deliver ecosystem services in a given area. In this context the extensive research-based evidence about the relationship between forest biodiversity and ecosystem function has led some to emphasise the key role of biodiversity as a component of the natural capital that underpins the capacity of forests to deliver ecosystem services (Thompson *et al.*, 2012). Nonetheless, as explained above, measures of forest biodiversity are of limited utility to define forest degradation, as its response to disturbance is not always clear with total levels of biodiversity (e.g. species richness) sometimes being similar in areas under different degrees of disturbance or different stages of recovery (Gardner, 2010). Others have emphasised the conceptual linkage between forest degradation and the ecological concept of forest resilience (e.g. Ghazoul *et al.,* 2015). All of these considerations present major challenges for developing a definition amenable to measurement and monitoring of forest degradation, as the provision of ecosystem services and resilience are concepts that are not directly quantifiable using a single methodology. Therefore they are of limited use in providing evidence on the implementation of forest policy, such as REDD+. In contrast, a focus on the ecosystem service of climate regulation (through carbon storage) presents a direct link to forest biomass, a variable that is far more amenable to measurement and monitoring. Moreover, although a formal definition has not yet been adopted, it is clear that under

[3] Please refer to Table 2.2 for a list of the definitions used by international agencies.

REDD+ a narrow definition of degradation is likely to be used since the emphasis in this policy is on carbon stocks and change in carbon stocks (Goetz *et al.*, 2015).

Numerous studies have demonstrated the link between lower forest biomass (a surrogate for carbon stocks) and disturbance processes that lead to forest degradation (Gerwing, 2002; Urquiza-Haas *et al.*, 2007; Álvarez-Yépiz *et al.*, 2008; Lawrence *et al.*, 2010). It has been demonstrated that, on average, undisturbed forests have larger carbon stocks than degraded ones, and maintain these stocks during the cycle or mortality of individual trees and their replacement through natural regeneration (Luyssaert *et al.*, 2008; Rutishauser *et al.*, 2010). As there is increasing evidence that forest biomass takes decades to recover after human-induced disturbance (Martin *et al.*, 2013; Poorter *et al.*, 2016), degraded forest can be defined as a state of lower forest biomass (or carbon) stock resulting from-human induced disturbance of natural forests. With this definition, the forest carbon stock is lower than what would be expected for the same area if the disturbance process had not occurred. As the carbon stock is directly linked to forest structure, using it as a variable to measure forest degradation would provide an indirect measurement of the structural state of the forest including canopy cover, tree density and other attributes, all indicators that have commonly been included in definitions of forest and forest degradation and are related to the habitat quality of the forest for biodiversity (Grainger, 1996; Simula, 2009; Thompson *et al.*, 2012). As with any other definition of forest degradation, such an approach is not without problems, nor is it likely to be adequate for all applications. Nonetheless, it has the advantage that it is linked to the disturbance processes, making possible its integration within decision-making processes. Also, it can be spatially modelled and therefore monitored, allowing the areal extent of forest degradation to be estimated. Therefore, the conceptualization of degradation as a forest state with lower levels of carbon stock as a consequence of human-induced disturbance is used in this thesis as the definition of forest degradation.

1.3. What are degraded forests in tropical landscapes?

Forest degradation in tropical countries is caused both by natural and human-induced disturbance processes. The most conspicuous and widespread of the former are wildfires (Alencar *et al.*, 2015), and the latter includes shifting cultivation, selective logging, and extraction of fuelwood and non-timber forests products (Murdiyarso *et al.*, 2008a). Although the importance of natural disturbance in the tropics must be acknowledged, and it is recognized that there is feedback between natural and anthropogenic disturbances that makes this division artificial, this work is limited to forest degradation caused by human-induced disturbances. These disturbances reduce the structural complexity and alter the composition of tropical forests, and their biomass density (Kauffman *et al.*, 2003; Chazdon, 2008;

Gourlet-Fleury *et al.*, 2013; Chazdon *et al.*, 2016). At the landscape scale they result in vegetation loss, transitions in vegetation type and reductions in vegetation cover and density (Lambin, 1999; Joseph *et al.*, 2010). Consequently, human-modified landscapes are usually composed of agricultural and forest land areas under different levels of human use (Fig. 1), that are difficult to quantify and categorize (Putz & Redford, 2010). Although most of the literature and policy making has focused on defining forest degradation as a reduction in ecosystem services (e.g. Thompson et al., 2013), in practice attempts at categorizing tropical forests by this criterion have generally used the type of disturbance processes that act over an area to define forest degradation. For example, Grainger (1996) proposed that tropical degraded forests should be grouped as: a) selectively logged forests and forests used for other extractive purposes; b) regenerated forests, defined as short- and long-rotation shifting cultivation, and forests managed to increase the production of commercial timber; c) damaged forests, areas that suffer unusual disturbances such as fire, drought, and pollution; d) planted forests, which include tree plantations and agroforestry; e) arrested succession forests; and f) dispersed forests, which include all the other categories but at a landscape level.

Likewise, the International Timber Organization (ITTO) (2002) provides what is perhaps the most comprehensive framework for categorizing tropical forest landscapes that can be applied to conceptualize forest degradation as a state, by characterizing tropical forest lands into three broad main categories: primary forests, modified natural forests and planted forests. Within modified natural forests, two types are recognized: primary forest areas under improved management and degraded forest lands; this thesis focuses on this latter category (Fig. 1.1). Degraded forest lands include secondary forests (areas of forest regrowth) and exploited natural/primary forests (i.e. forests without any management or only poor management that results in a loss of carbon stocks and delivery of other ecosystem services).

Secondary forests, in this framework, are those areas dominated by woody vegetation that grows back (from now on called regrowth in this thesis) after clearance of their original forest cover, due to intensive disturbance processes such as shifting cultivation, conversion to pasture or failed tree plantations. Forests without management are those that, due to disturbance (mainly intense harvesting of timber and non-timber products or other extractive activity), have their structure, and ecological processes and functions, altered to a point that compromises their capacity to fully recover from exploitation in the short-medium term. Under this model, forests well managed for timber production, should not fit into the degraded land category (Fig 1). Although, from a carbon perspective, such forests have reduced carbon content and an altered structure, this will be a temporary state, as it has been shown that under improved forest management such as reduced-impact logging forests will

recover carbon and generate about 30% less emissions than under conventional logging practices (Putz *et al.*, 2008b). Hence, such improved logging practices will most likely be considered under the category of sustainable forest management within the REDD+ context, not under the category of forest degradation that is restricted to forest subjected to poor management (as indicated, for instance, by bad management plans, illegal logging, uncontrolled harvesting, premature reentry logging), which compromises the recovery capacity of forest ecosystems (Putz *et al.*, 2012) and causes a more permanent state of low carbon content.

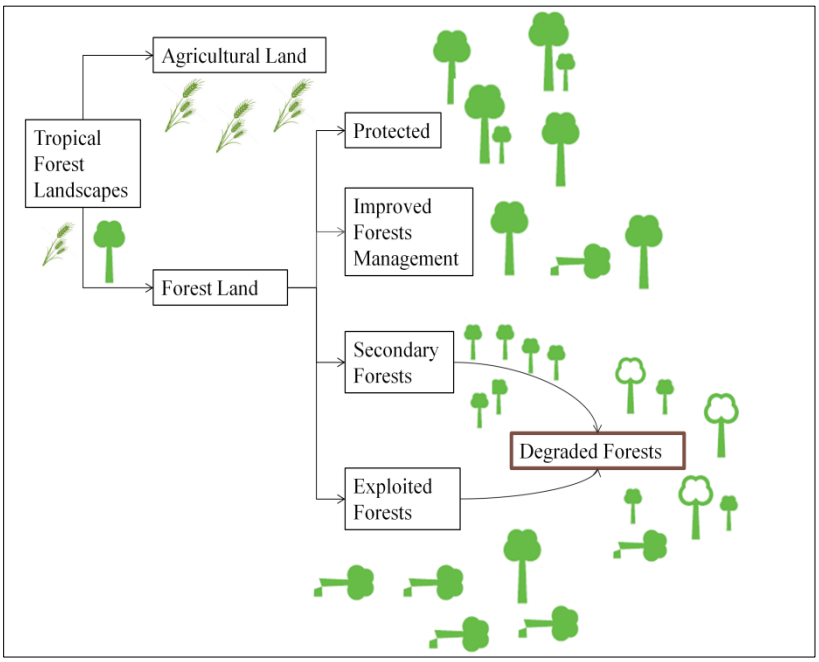


Figure 1.1. Scheme of a tropical forest landscape showing the classification of forestland uses.

Trees with white crowns represent under-stocked forests and small trees represent re-growth after disturbance

1.4. The importance of degraded tropical forest areas

Degraded tropical forests can provide multiple benefits to society, and are particularly important to local populations that depend on them for their livelihoods (van Vliet *et al.*, 2012; Edwards *et al.*, 2014a; FAO, 2014). Activities which enable humans to benefit from

forest resources, but which in turn lead to their degradation in the tropics, include selective logging, shifting cultivation, cattle grazing, charcoal production, large-scale forest fires and sub-canopy fires, fuelwood collection, and extraction of other non-timber forest products (NTFPs) (Murdiyarso *et al.*, 2008a; Hosonuma *et al.*, 2012). Most of the approximately 20% of the world's population that depends on forests for their livelihoods, building material for shelter and food security (Chao, 2012), and the 12% that use fuelwood as their main source of energy (FAO, 2014), are located in the tropical belt (Chao, 2012). Moreover, one quarter of the global forest area is designated as production forest (Blaser *et al.*, 2011). Consequently, it is foreseeable that degraded tropical and subtropical forest landscapes will continue to increase in the future, which will have important consequences for biodiversity conservation, ecosystem resilience, livelihoods and climate change.

As noted at the outset of this chapter, estimates of the global extent of degraded forests are highly uncertain (Asner *et al.*, 2009; Potapov *et al.*, 2009), probably due to the difficulties of defining and measuring forest degradation. Although only coarse estimates are available, it is commonly stated that in the tropics the area covered by degraded forests is large (Herold *et al.*, 2011) and increasing. In the tropics the areas that experienced canopy cover reduction > 20% between 2000 and 2012 have been estimated to be 6.5 times higher than that deforested since 1990 (Sloan & Sayer, 2015) and logging alone affects 20% of the tropical forest biome (Asner *et al.*, 2009). Moreover, while emissions from deforestation are decreasing, those from forest degradation have increased from an average of 0.4 Gt CO_2 yr^{-1} for 1991-2000 to 1.1 Gt CO_2 yr^{-1} for 2011-2015 (Federici *et al.*, 2015). However, these estimates do not separate natural from anthropogenic causes, thus new analysis is needed that is focused on human causes of forest degradation at a regional or country level to provide a more accurate picture of its magnitude and causes. For the Amazon, it has been estimated that carbon emissions from selective logging represent 60-123% of the carbon emissions due to deforestation (Asner *et al.*, 2005). Annual forest degradation rates during 2005-2010 in the Democratic Republic of Congo (which holds about 60% of the forest of the Congo Basin, the second largest tropical forest in the world) have been estimated to be 2%, which is double the deforestation rate for that area (Zhuravleva *et al.*, 2013).

Even though the above estimates need to be improved, it is clear that forest degradation affects vast areas of the tropics, which in addition to generating carbon emissions can result in species loss due to alteration of the natural habitat (Stickler *et al.*, 2009; Strassburg *et al.*, 2010; Barlow *et al.*, 2016). The extent of degraded forest areas, in conjunction with the magnitude of rural populations that depend on them, and its importance for biodiversity conservation, have led to the inclusion of avoiding and reversing forest degradation as one of the goals of multiple global agreements, including the Aichi Biodiversity Targets, the Four

Global Objectives on Forests, and REDD+ (CBD, 2010; UNFCCC, 2010; FAO, 2011; Parrotta *et al.*, 2012). Advances in the assessment of tropical forest degradation are a high priority (GFOI, 2013), and are particularly urgent in the context of this last policy.

1.5. Forest degradation on the global international stage: REDD+

The role of tropical forests in the global carbon cycle has long been recognized (Houghton *et al.*, 1993; Defries *et al.*, 2002), as well as the need for policies to regulate carbon emissions from tropical deforestation and forest degradation to mitigate climate change (Brown *et al.*, 1993). Assessing tropical forest degradation is particularly important in the context of climate change mitigation for two reasons. Firstly, disturbance processes such as logging, shifting cultivation and forest clearing are widespread throughout the tropics (Blaser *et al.*, 2011; FAO, 2014) and, as explained in section 3, they generate important quantities of carbon emissions (van der Werf *et al.*, 2009; Houghton, 2013). Secondly, avoiding further degradation of tropical forests by achieving sustainable use, has the potential to turn tropical forests from carbon sources into carbon sinks for long time periods (Grace *et al.*, 2014). Indeed, to reduce greenhouse gas (GHG) emissions from the land use, land-use change and forestry sector (AFOLU), parties to UNFCCC are currently developing and implementing REDD+, which was included in the new international climate change agreement signed in December of 2015[4]. REDD+ is an international mechanism in which economic remuneration will be paid to landowners, projects, or countries in tropical regions, if they demonstrate that GHG emissions are reduced below a reference level, i.e. the level that could be expected if the mechanism was not in place (Angelsen *et al.*, 2012).

In 2013, the use of the latest Inter-governmental Panel on Climate Change (IPCC) guidelines to measure and monitor carbon stocks and carbon stock changes became official within the Warsaw Framework for REDD+ (the Warsaw Agreement)[5]. The IPCC Good Practice Guidance (IPCC, 2006) describes a methodology to account for emissions coming from the five carbon pools defined for areas classified as forest. These five carbon pools in the ecosystem are: above-ground biomass (AGB), below-ground biomass, litter, deadwood,

[4] Article 5 of the Paris Agreement. https://unfccc.int/files/meetings/paris_nov_2015/application/pdf/paris_agreement_english_.pdf

[5] Decision 11/CP.19 .https://unfccc.int/resource/docs/2013/cop19/eng/10a01.pdf

and soil organic carbon, that are normally converted into carbon stock estimates considering that biomass comprises 47-50% carbon (GOFC-GOLD, 2013).

To determine the carbon stocks associated with forest degradation and deforestation, the IPCC methodology states that their estimation for a specific region or country is the result of a simple equation that multiplies the activity data by the emission factor (IPCC, 2003). The emission factor refers to how much carbon is found per area; it quantifies the emissions/removals per unit area (t C ha^{-1}) of the different carbon pools found in the ecosystem. The activity data is defined as the change in extent (ha) between land cover categories, for instance from forest to degraded forest. This implies that a pre-requisite for any carbon stock accounting is a spatially-explicit identification of the forest area that was cleared in the case of deforestation or in the case of degradation the extent of degraded forest lands. Although the rules for carbon stock accounting are well established, in reality determining activity data and emission factors to acceptable levels of certainty is extremely challenging (Pelletier *et al.*, 2011; Pelletier & Goetz, 2015; Reimer *et al.*, 2015), especially for forest degradation (Herold *et al.*, 2011; Pearson *et al.*, 2014). Until recently, studies that measured emission factors or the forest carbon stocks of tropical forests subjected to different levels of human disturbance were rare (Berenguer *et al.*, 2014; Griscom *et al.*, 2014; Pearson *et al.*, 2014). In addition, the land cover dynamics of tropical forest ecosystems are complex, particularly for degraded landscapes that are formed by forest patches at different stages of disturbance and recovery that create large variability in carbon stocks within the landscape (Eckert *et al.*, 2011; Mertz *et al.*, 2012; Pelletier *et al.*, 2012b; Miettinen *et al.*, 2014).

The IPCC suggest three methodological levels that are defined according to the data quality and level of accuracy that is produced. Tier 1 uses default values for emission factors, while Tiers 2 and 3 provide greater accuracy of carbon stock estimates by using more detailed mapping and modelling approaches for carbon stocks and forest cover change (Gibbs *et al.*, 2007; Goetz *et al.*, 2009; Birdsey *et al.*, 2013). Given that REDD+ is performance-based, national and sub-national level initiatives would benefit from reporting at higher tiers, as Tier 1 will assign a conservative carbon value per ha that will be lower than local estimates obtained from forest inventories and spatial modelling (GOFC-GOLD, 2013; Langner *et al.*, 2014).

Reporting using Tier 2 and 3 implies that countries and/or projects will need to define in a measurable, meaningful, but also practical manner, what will be included as forest degradation. For this, the activities that are reducing the carbon density of their forest ecosystems need to be properly characterized, which means defining the temporal and spatial scales over which the reduction of carbon density in the forest is happening. This will require

countries to improve the detection of the area affected by disturbance, in order to improve their estimates of activity data both on degradation and on deforestation, as a large proportion of the uncertainty in REDD+ relates to the spatial distribution of forest cover (Mitchard *et al.*, 2013; Goetz *et al.*, 2015).

Apart from the accounting of forest carbon stocks, any REDD+ project or action needs to address 'safeguards'. This means that any reduction of emissions should avoid negative effects on local communities and on biodiversity (Gardner *et al.*, 2012), or that it should seek to achieve co-benefits in addition to carbon mitigation, e.g. by empowering local people, enhancing their livelihoods and conserving biodiversity, in addition to carbon emissions mitigation (Visseren-Hamakers *et al.*, 2012). Maintaining forest carbon stocks is often regarded as an umbrella-approach since, if achieved, it will at the same time preserve other ecosystem services (e.g. forest biodiversity and hydrological regulation functions) (Strassburg *et al.*, 2010; Donato, 2014). Even though there is considerable debate about this (Venter *et al.*, 2009; Phelps *et al.*, 2012; Martin *et al.*, 2013), increasing the delivery of ecosystem services and fostering healthier and more resilient tropical forest ecosystems are ultimately what should be achieved by enhancing carbon stocks in degraded natural forests and by avoiding forest degradation.

1.6. Theoretical framework: the interface between disturbance ecology, landscape ecology and land use change science to study forest degradation

The study of tropical forest degradation is grounded in the interaction/interface of three closely related disciplines: land cover change science, landscape ecology and disturbance ecology. Disturbance ecology studies disturbance processes that are the cause of forest degradation (Attiwill, 1994). These processes are reflected in the landscape patterns of land use and land cover (Lambin, 1999), and the study of spatial patterns caused by disturbances is one of the main streams of landscape ecology and land cover change science (Müller & Munroe, 2014). Forest degradation, as well as deforestation, are determined by a series of socio-economic factors and environmental policies (e.g. REDD+ and payment for ecosystem services) that interact in numerous ways with the ecological characteristics of forest ecosystems (Lambin, 1997). Land cover change science and landscape ecology are applied to monitor those interactions by extracting and analyzing spatial patterns that are created by deforestation, forest degradation and other disturbance processes (Lambin, 1999; Lambin & Meyfroidt, 2010). However, these three disciplines have only recently been integrated, due to the need to understand complex transitions in tropical ecosystems in human-dominated landscapes or socio-ecological systems (Uriarte *et al.*, 2010).

The level of forest degradation observed in a tropical forest landscape depends on the intensity, frequency and extent of the disturbance events that have affected the area. Disturbance events, either natural or human-caused, by definition result in removal of biomass from the forest ecosystem hence reducing carbon storage. Along with environmental factors, disturbance processes are responsible for the spatial and temporal heterogeneity of forest cover and biomass found in degraded forest landscapes (Chazdon, 2003; Berenguer *et al.*, 2014). In particular, two forms of human-induced disturbance events, shifting cultivation and logging, create complex forest landscape mosaics that differ in their structure, composition and biomass content (Mertz *et al.*, 2012). The reduction in carbon storage in complex landscape mosaics, as a result of shifting cultivation or logging alone or in combination with other disturbance events, has been relatively well documented in the tropics (Marín-Spiotta *et al.*, 2008; Ziegler *et al.*, 2012; Delang & Li, 2013). It has been estimated that, on average, each cycle of agricultural cultivation reduces biomass accumulation by 9.3%, and that secondary forest may not re-grow after approximately 10 cycles (50-200 years), although this will be very site-dependent (Lawrence *et al.*, 2010). Factors such as soil, climate, disturbance intensity and fallow length affect the rate of recovery of biomass and the ecological characteristics of the forest regrowth (Kauffman *et al.*, 2009; Dalle *et al.*, 2011; Becknell & Powers, 2014). In the case of logging the loss of biomass and the recovery time are also very variable depending on its intensity and the techniques used (Berry *et al.*, 2010; Putz *et al.*, 2012; Edwards *et al.*, 2014a; West *et al.*, 2014; Rutishauser *et al.*, 2015). For instance, it has been estimated that conventional logging can damage, for every tree logged, 10-20 surrounding trees (Putz *et al.*, 2008a), which produces substantial loss of biomass. In most tropical forests, above-ground biomass (AGB) is the carbon pool most affected by both shifting cultivation and logging (Thompson *et al.*, 2012), and is also the one that produces the most detectable spatial patterns. It is therefore the only carbon pool included in this thesis.

Spatial patterns and processes are not directly "interchangeable". Nonetheless, understanding and linking the temporal and spatial characteristics of disturbance events caused by human activities, such as shifting cultivation or selective logging, provides an indicator of ecological processes, such as carbon sequestration. Remote sensing has provided a way to estimate approximately the spatial and temporal characteristic of deforestation and forest degradation by providing data on the frequency and extent of these disturbance processes and the associated spatial patterns that they produce (Joseph *et al.*, 2010). It is an essential tool for forest monitoring and a key element in any forest carbon management strategy (Petrokofsky *et al.*, 2012).

1.7. Background on measuring and monitoring the extent of forest degradation in the tropics

It is generally considered that monitoring and measuring forest degradation is more difficult, and thus substantially less accurate, than monitoring deforestation (Mertz *et al.*, 2012; Bustamante *et al.*, 2016). Ambiguity in the definition of forest degradation, along with the variety of human activities that can lead to forest degradation, are the reasons behind this difficulty (GOFC-GOLD, 2013). Despite this wide variability in activities, that range from timber harvesting in moist forest to fuelwood collection in dry areas; assessment of the extent of forest degradation has been done through various combinations of remote sensing analysis and field-based measurements.

1.7.1. Remote sensing

There are a number of reviews of the application of different remote sensing data to the monitoring of deforestation, forest degradation and carbon stocks, particularly in the context of REDD+ (Gibbs *et al.*, 2007; Goetz *et al.*, 2009, 2015; Joseph *et al.*, 2010; De Sy *et al.*, 2012; Petrokofsky *et al.*, 2012). Other reviews have focused on methodological considerations for monitoring and reporting requirements within REDD+ (Herold *et al.*, 2011; Birdsey *et al.*, 2013). New guidance on quantification of land cover and carbon stocks has been recently developed and is being constantly updated (e.g. GOFC-GOLD, 2013; GFOI, 2014). Thus, in this section I do not aim to provide an exhaustive review of remote sensing techniques applied to land cover change assessment but rather I focus on relevant studies that have applied these techniques to the study of forest degradation in the tropics. The general consensus of these reviews is that, although significant advances in remote sensing have been achieved in terms of forest cover change, monitoring the different types of forest degradation is still at an early stage. Furthermore, these reviews suggest that to advance forest degradation monitoring innovative methods are needed that couple satellite data with ground-based observations to produce spatially explicit information in accordance with the type of disturbance that is leading to forest degradation.

1.7.1.1. Remote sensing for assessment of forest cover and forest cover change

Land cover and land-cover change are two variables that can be estimated with remote-sensing techniques (from now on called remote sensing in this thesis), which provide critical information about land-management activities and natural disturbances, and are fundamental to estimate emissions and removal of CO_2 at regional and national scales (Gibbs *et al.*, 2007; GOFC-GOLD, 2013). Analysis of land cover change through remote sensing is commonly used for forest monitoring in the tropics, mainly focusing on deforestation processes (Achard

et al., 2007; Hansen *et al.*, 2013). Satellite data is arguably the most consistent source for the derivation of activity data and to improve the precision of emissions factors by means of stratification of the landscape into more homogeneous units (Gibbs *et al.*, 2007; Goetz & Dubayah, 2011; Joseph *et al.*, 2013). Moreover, it is considered to be the most cost-effective way of measuring and monitoring forest cover and forest carbon stocks over large geographical regions (Strand *et al.*, 2007; Böttcher *et al.*, 2009), although there are important differences between results obtained through different approaches to classify satellite data (Olofsson *et al.*, 2014).

1.7.1.2. Remote sensing of tropical forest degradation

Monitoring of forest degradation with remote sensing is challenging for several reasons, as mentioned above. Unlike deforestation, forest degradation is a continuous variable, so its spectral variability within forest areas is not as contrasting as the differences between areas covered by forest and bareland areas. Therefore, different approaches are needed either to enhance the spectral variability to assess degraded areas directly or to determine human activities to estimate the approximate extent of degraded areas indirectly (Herold *et al.*, 2011; GOFC-GOLD, 2013). The latter approach is based on image interpretation, and degraded areas are most commonly inferred as a function of the distance from roads (or other infrastructure). This approach has been applied, for example, by mapping logging roads and estimating landscapes that have been transformed from intact or undisturbed forest to logged forest (Laporte *et al.*, 2007; Gaveau *et al.*, 2014; Kleinschroth *et al.*, 2015). Although this non- automated approach can be effective, its main disadvantage is that it is subjective, as it depends on the decision of the distance of the edge of the buffer area from the road, and on the interpreter's capacity to delineate roads.

More sophisticated techniques, such as sub-pixel analysis and the fusion of data from various types of sensors, have emerged in the last decade enabling spectral information to be used to model forest degradation directly. All these analyses seek to detect small clearings and gaps within the canopy and/or a reduction of canopy cover (e.g Negrón-Juárez *et al.*, 2011; Langner *et al.*, 2012), and attempt to link them to the human activity causing the disturbance. Time series of yearly Landsat data have been successfully used to detect forest degradation caused by logging operations and fire in the Brazilian Amazon, by analyzing the different materials that compose a pixel –subpixel analysis (Asner *et al.*, 2002, 2005, Souza *et al.*, 2005, 2013; Matricardi *et al.*, 2010; Alencar *et al.*, 2011). However, these approaches have rarely been applied in other tropical areas and require further testing. Subpixel analysis of optical data, in combination with active sensors (e.g. Lidar), is a promising approach to improve the detection of forest degradation resulting from logging, fires and mining, because

such methods provide data on forest height and can indirectly estimate forest carbon stocks (Asner *et al.*, 2010; Birdsey *et al.*, 2013), and is an area of active research (De Sy *et al.*, 2012). In general, for the detection of forest degradation the availability of remote sensing data with adequate temporal, spectral and spatial resolution is critical (Joseph *et al.*, 2010). Nonetheless, this is seldom the case, as data with higher resolution are usually much more expensive to obtain, and tropical forest areas are characterized by high cloud cover, at least for much of the year, which often hampers data acquisition. To date, the main limitation of combining data from active and optical sensors to monitor forest degradation due to logging is cost (De Sy *et al.*, 2012). Lidar data acquisition is especially expensive, therefore it is usually only obtained for small regions, and used for calibration and validation, in combination with data from optical sensors (Tokola, 2015). The other problem is that since their use is very recent, there are no historical Lidar data for analyzing forest cover change dynamics. It is highly probable that their use will increase in the near future, but as most tropical regions do not have any data from active sensors, they are not yet an available option for regular forest monitoring (De Sy *et al.*, 2012; Zolkos *et al.*, 2013; Pfeifer *et al.*, 2016).

While the use of remote sensing methods to assess forest degradation caused by logging has had some positive results, as outlined in the paragraph above, development of new methods for analyzing forest degradation resulting from other drivers such as shifting cultivation has not been so successful (Mertz *et al.*, 2012). Therefore, regrowth dynamics associated with shifting cultivation continues to be a major source of uncertainty in quantification of activity data in the tropics (Houghton, 2012; Berry & Ryan, 2013). A major constraint on method development has been the lack of availability of frequent high resolution spatial data (10 X 10 m or less) able to capture the complex dynamic features of shifting cultivation systems (Li *et al.*, 2014). Nevertheless, time series analysis of medium-resolution multispectral data has been applied to map dynamics associated with shifting cultivation, using subpixel analysis techniques developed for logging by Pelletier *et al.* (2012b). Image analysis of single-date high spatial resolution data, in combination with indices based on image texture, has been used to delineate shifting cultivation landscapes (Hurni *et al.*, 2013). Delineation of shifting cultivation landscapes has also been attempted using coarse optical satellite data (250 m X 250 m); in this case dense time series provided information on the dynamics of shifting cultivation by linking its presence to fire occurrence (Müller *et al.*, 2013). Different degrees of success have been achieved with these methods, indicating the need for further research into this approach, particularly in drier environments where leaf phenology further affects the detection of small clearings.

The availability of remote sensing data with higher resolution, different sensors and more frequent data acquisition is expected to keep increasing in the near future, becoming key for

tropical forest monitoring systems (Mora *et al.*, 2012; Goetz *et al.*, 2015). There are several planned satellites specially designed for monitoring vegetation, (e.g. the first Sentinel-2 satellite was launched in 2015) that will provide continuity with previous satellite sensors (e.g. Landsat 8) (GFOI, 2014). With the availability of new data and new research methods, improvements in the detection of forest degradation are expected. Detection of forest degradation based on multi-date analysis that incorporates information on land use history, such as the approaches presented in this thesis, are of particular interest. As more frequent images become freely available, coupled with better image analysis methods, they will enable improvements in the temporal characterization and in the assessment of activity data of forest degradation (Joseph *et al.*, 2010). Improvements in the activity data will provide a better basis for land cover stratification, which will improve precision in biomass estimation at the landscape scale (Gibbs *et al.*, 2007; Goetz & Dubayah, 2011). Nonetheless, a prerequisite for making use of all this newly available information to improve activity data is to understand the types of disturbance that are acting on the forest system, their frequency and the scale at which the effects are happening.

1.7.2. Forest inventories

Field-based forest inventory using sample plots has been the traditional technique for monitoring forest resources, especially for the assessment of forest biomass (Brown, 1997). Ground-based measurements are also used to provide information to calibrate and validate remote sensing analyses (GOFC-GOLD, 2013; Hill *et al.*, 2013). Field-based assessment over a range of scales is important for collecting data on forest biodiversity and on disturbances occurring over an area (Thompson *et al.*, 2013; Berenguer *et al.*, 2014). Thus, they are an essential component of forest monitoring systems, especially for quantifying forest degradation (e.g. as indicated by the amount of timber extracted or fuelwood collected) (Herold *et al.*, 2011; GFOI, 2014; Salvini *et al.*, 2014). While ground-based forest inventories provide the only means of obtaining direct information on forest carbon stocks or other changes occurring below the main canopy, they are expensive, time consuming, and therefore restricted in terms of the area they can cover (Birdsey *et al.*, 2013). Moreover, most tropical countries lack a comprehensive programme of forest inventory, although this situation has improved in the last few years (Mora *et al.*, 2012). Having forest inventories performed by communities or through a citizen science approach can make an important contribution to overcoming these limitations (Danielsen *et al.*, 2011; Skutsch *et al.*, 2011). As communities are often the end users of tropical forest resources, and dependent on the sustainability of their production, community monitoring can potentially provide a direct link to locally-based project interventions directed to reduce forest degradation. However,

questions remain about how to integrate local community monitoring, particularly data about disturbances, into quantification of rates of forest degradation over larger areas and national-level accounting systems (Skutsch & Balderas-Torres, 2012; Pratihast *et al.*, 2013). Integration will require the development of better links between remote sensing and ground inventories that include data on the effects of disturbance on biomass and on drivers of biomass loss (Salvini *et al.*, 2014).

1.7.3. Non spatial approaches

It has also been suggested that forest degradation can be modeled by using socioeconomic variables, such as population density or timber exports, to predict biomass density (Grainger, 1999). However, such an approach is based on aggregated country data (Tier 1) and therefore will not represent an improvement towards more accurate methods (Tier 2 and 3) that are based on spatial analysis of forest degradation.

1.8. Research statement

From a methodological perspective I have identified, that there are currently three major approaches in which forest degradation in tropical areas can be measured and monitored. First, there is the "theoretical" oriented approach, in which the focus is on the *reduction in forest stocks and functions that are likely to reduce the delivery of ecosystem services* (FAO, 2011; Thompson *et al.*, 2013) The limitation here is that, while there can be consensus that reduction in the capacity to retain forest carbon and biodiversity stocks, and regulate water cycling, is degradation, it cannot be directly quantified. Models based on indicators that can relate ecosystem stocks and functions to readily measurable forest attributes need to be developed in order to assess the state and change of forest capacity to deliver ecosystem services. Development of models designed to meet this need requires understanding of the context of the disturbance processes causing the reduction, but model uncertainty is normally high and models are usually context-specific.

A second approach is based on defining *forest degradation based on biophysical parameters* and tracking their changes over time. On-the-ground forest inventories, repeated over time, are needed to monitor changes in forest attributes (Birdsey *et al.*, 2013; Chidumayo, 2013). This approach tends to be costly and time consuming, and can therefore only assess a very small proportion of the landscape. Depending on the inventory design, it may or may not be possible to link it to the causes of forest degradation. Through spatial modelling, forest attributes such as canopy cover can also be assessed with remote sensing, at least to some extent. However, the success of such an approach is highly dependent on the remote sensing resources that are available, and model uncertainty tends to be high. Most

importantly this approach does not necessarily provide a link to human activities that cause the disturbances leading to forest degradation.

A third approach is based on *land-use change*, with forest degradation only being assessed as changes in the land cover matrix, for example as changes from old-growth to post-agricultural secondary forests, or from forests classified spatially as intact to non-intact (Mollicone *et al.*, 2007; Bucki *et al.*, 2012). This approach relies almost entirely on remote sensing to provide information on activity data and changes in forest cover. Nonetheless, if this approach is used in isolation its resolution is too spatially coarse to improve estimations of forest degradation, as changes within forest classes are ignored.

To date, none of these three approaches is without limitations, hence a compromise is needed between how forest degradation is conceptualized, what evidence is required for policy making and implementation, and what can be measured and monitored with available technological resources and capacity. A new way forward to improve current capacity to measure and monitor forest degradation within the science-policy interface, is therefore to better integrate these three approaches.

This research is based on the practical consideration that our capacity to conceptualize, measure, monitor and ultimately avoid forest degradation is highly determined by the type of use that human populations make of tropical forest resources at the landscape level. Hence, for both scientific and policy reasons, measurement of degradation should take into account the drivers that cause the disturbances. To explore the temporal and spatial dynamics of forest degradation, I used a land cover change science approach in combination with elements of landscape and disturbance ecology to forest degradation. The combination of these approaches enables: (i) detection of spatial patterns in forest cover over time, (ii) linking of patterns of change in forest cover to forest condition, (iii) linking of spatio-temporal patterns to disturbance agents, (iv) exploration of the implications of scale in the detection of spatial patterns and forest condition. The approach adopted in this study involves exploring forest cover and condition within two different types of human-modified landscapes (or socio-ecological systems), as well as conceptualizing forest degradation as the state of the forest, rather than just a process, that is tightly coupled with the disturbance history of an area.

Through the use of these closely related approaches the following overarching questions are addressed throughout the thesis:

1. How does the most appropriate operational definition of forest degradation vary with the type of landscape dominated by different socio-ecological systems?

2. To what extent is focusing on human-induced disturbance processes at the landscape level useful both to conceptualize and measure forest degradation?
3. Given the spatial and temporal heterogeneity of tropical forests, how can multiple scales be integrated to provide effective measurement and monitoring of forest degradation?

1.9. Study areas

In this thesis I study forest degradation in two human-modified landscapes, one located in the dry forest of western Mexico (in the Ayuquila Watershed, Jalisco, near the Pacific coast) and the other in the moist forest of the southern Pacific coast of Costa Rica (Osa Peninsula, Puntarenas) (Fig. 1.2). Both countries share several characteristics that have partly defined their forest monitoring needs and strategies. Mexico and Costa Rica both have well-established Payment for Ecosystem Services (PES) programmes, clearly defined land tenure systems and legal frameworks that regulate forest land use change (FONAFIFO & CONAFOR, 2012). Both countries are well advanced in developing and implementing their REDD+ strategies, and have submitted reference emission levels to the UNFCCC.[6]

Analysis of forest degradation due to shifting cultivation is studied in dry forests in Mexico, while disturbance due to logging was researched in moist forests in Costa Rica (Fig 2). Both study areas are complex landscapes comprising forest mosaics, where patches of old-growth forest are found alongside areas under different levels of forest degradation due to human use. Further description of the study areas are provided in each chapter. Here I described general characteristics of these forest types, focusing on the neotropics because this is the most relevant context for this study.

[6] http://redd.unfccc.int/fact-sheets/forest-reference-emission-levels.html

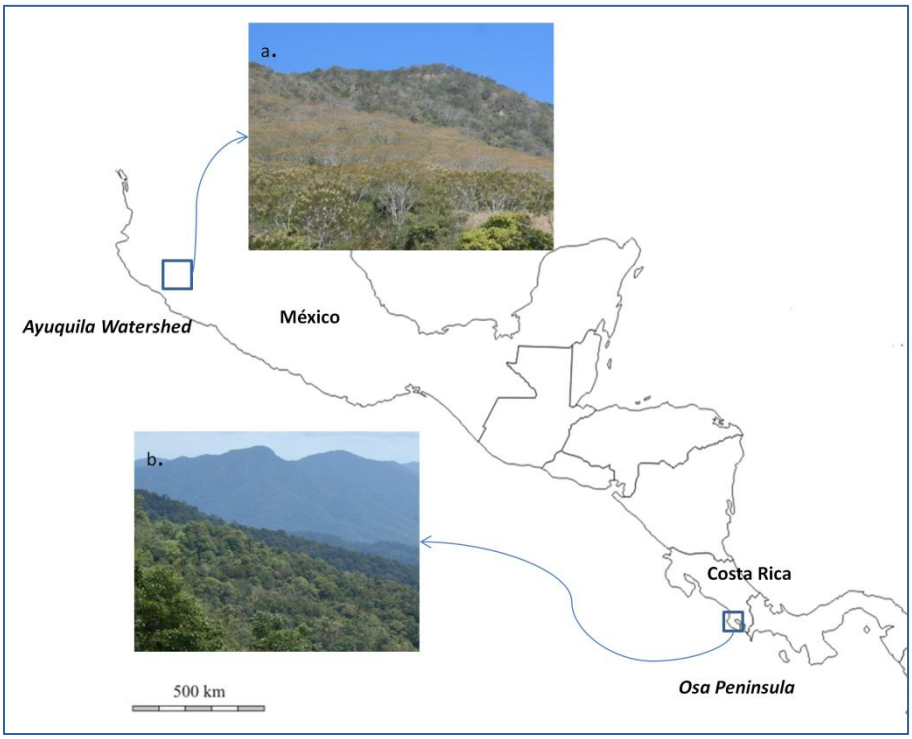


Figure 1.2. The study sites in Mexico and Costa Rica illustrating the vegetation type in each area: a. tropical dry forest landscape, b. tropical moist forest landscape (photos credit: L Morales).

1.9.1. Tropical dry forests

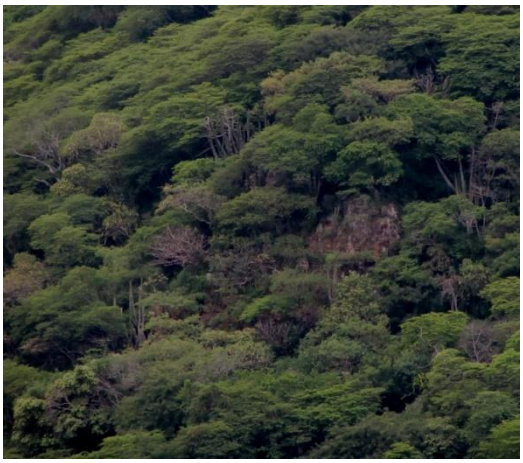
Over 42% of tropical forests globally are classified as tropical dry forests (TDF) (Murphy & Lugo, 1986). The definition, and therefore the extent, of this vegetation type varies depending on the environmental threshold values used, mainly mean annual precipitation and length of the dry season (Miles *et al.*, 2006). Dry forests can be defined as tropical forests characterized by having several months of drought (between 4-8) due to pronounced rainfall seasonality, with an annual precipitation range that varies between 500 and 2000 mm and annual potential evapo-transpiration greater than one (Holdridge, 1967; Martinez-Yrizar, 1995). Unlike open woodlands and savannas, TDF have a continuous tree cover layer (Hughes *et al.*, 2013; Dexter *et al.*, 2015; Banda-R *et al.*, 2016). Most TDF are dominated by deciduous trees, but there are extensive areas of dry evergreen forest (Murphy & Lugo, 1986). The main TDF areas are found in western Mexico extending through Central America, the Brazilian caatinga, the dry forests of India, and parts of the miombo woodland of central-southern Africa that are dominated by tree cover. The majority of TDF globally,

about 60%, is in the Neotropics (Olsen *et al.* 2001, Miles *et al.* 2006). The above-ground biomass of neotropical mature TDF ranges from 39 to 334 Mg ha^{-1}, with the lowest value found in Chamela-Cuixmala Mexico and the highest in Guanacaste, Costa Rica (Becknell et al. 2012).

It is commonly stated that TDF are critically endangered ecosystems (Miles *et al.*, 2006; Portillo-Quintero *et al.*, 2014); it has been estimated that about 48.5% of their area has been converted to other land uses (Becknell *et al.* 2012). Tropical dry forests have had a long history of human use (Murphy & Lugo 1986); they are three times more densely populated than moist and wet forests probably because of their seasonal climate and fertile soils. As a source of food, medicine, building and handicraft material, and most importantly of fuelwood, TDF are crucial to sustain the livelihoods of their local populations (Dirzo *et al.*, 2011). Thus, degradation and conversion processes are more widespread in TDF than in moist forests, and very few areas remain that serve as examples of relatively undisturbed TDF (Sanchez-Azofeifa *et al.*, 2014b). Unlike savannas, fire is not a natural disturbance agent, but shifting cultivation, cattle grazing, fence post extraction and fuelwood collection are prevalent processes that have altered the structure of this vegetation type resulting in degraded forests (Dirzo *et al.*, 2011; Dexter *et al.*, 2015) (Fig. 1.3.b).

1.9.1.1. The dry forests of western Mexico

The TDF of western Mexico are characterized by a mean annual rainfall of 750 mm, concentrated in a period of four to six months. Located at the most northern boundary of the range of TDF these forests are amongst the driest of its type. In undisturbed areas the estimated mean canopy height is 10 m and average basal area 23 m^2 ha^{-1} (Castellanos *et al.* 1991, Martinez-Yrizar *et al.* 1992). With a density of 790 trees ≥ 10 cm DBH per hectare, these forests are described as dense (Gentry, 1995). They have amongst the highest plant species density over small scales in the Neotropics, having on average 940 plant species > 2.5 cm DBH per ha, which is double the amount found in other dry forests with the same precipitation (Lott *et al.*, 1987). Throughout western Mexico the vast majority of areas of TDF have been heavily used for shifting cultivation (Trejo & Dirzo, 2000), thus they consist of forest patches at different levels of degradation and recovery (Fig. 1.3)



a.

b.

Figure 1.3 Examples of tropical dry forest in western Mexico: a. undisturbed with a largely closed canopy; b. degraded forest subject to shifting cultivation and grazing with a more open canopy (photo credits L Morales).

1.9.2. Tropical rain forests

Lowland tropical rainforests are closed canopy forests with canopy heights generally between 30 and 60 m. They are structurally complex ecosystems, in which three or four strata may be recognised in their vertical profile, with a generally sparse understory, high abundance of epiphytes, lianas and, in many sites, emergent trees above the main canopy (Whitmore, 1998). Tropical rainforests are considered to be the most species rich ecosystem in the world having, for example, an average 1520 plant species >2.5 cm per 1 ha (Gentry, 1995). Except on very unfertile soils, these are highly productive ecosystems (carbon sinks), leading to a high carbon stock density (e.g. Langner *et al.* (2014) reported an average of 273$\pm$ 25 Mg ha^{-1} for undisturbed rainforests using global estimates). As a consequence deforestation or degradation of tropical rain forests through conversion to agricultural land, logging, mining, shifting cultivation, grazing and fire is a major source of global C emissions (Defries *et al.*, 2002; van der Werf *et al.*, 2009; Houghton, 2012). Many classifications have been applied to tropical rainforests categorising them on the basis of floristic, phenological and/or bioclimatic characteristics. Here we followed the life zone system of Holdridge (1967) to characterize the study area, as it is the most commonly used system in Central America.

1.9.2.1. The tropical moist forest in the southern Pacific coastal zone of Costa Rica

These forest ecosystems of the southern Pacific coastal zone of Costa Rica are characterized by a very humid and warm climate, having a mean annual precipitation of

5500 mm and an average temperature of 25 °C. The young soils have a high nutrient content, which enhance the productivity of the forests. These forests harbour a particularly high biological diversity, a total of approximately 750 tree species have been recorded in the Osa Peninsula (Quesada et al., 1997). The tree flora is notable for its high levels of endemicity to the southern part of Mesoamerica (Costa Rica and Panama) (Quesada et al., 1997; Thomsen, 1997; Cornejo et al., 2012). With emergent trees often exceeding 60 m in height, these forests are unusually tall for the neotropics (Taylor et al., 2015). These forests experienced a high rates of deforestation during the 1980s and 1990s due to conversion for cattle ranching and agricultural production (Vaughan, 2012). Subsequently government policy greatly reduced the rate of deforestation but it was replaced by selective timber harvesting in many areas as the main human impact on the forests (Barrantes *et al.*, 1999; Lobo *et al.*, 2007; OTS, 2008). As a result the area is a mosaic of forests subject to different levels of degradation (Fig. 1.4).

a. **b.**

Figure 1.4 Examples of tropical rain forest in the southern Pacific coastal zone of Costa Rica: a. undisturbed forests with dense closed canopy cover; b. forest that had been logged 15 years previously (photo credits L Morales).

1.10. Thesis structure

This thesis presents research into the definition, measurement and monitoring of forest degradation linked to human activities. It develops methods based on spatial analysis of the disturbance processes through combining field-based measurements, historical data and remote sensing data. It analyses forest degradation from the perspective of the disturbance

agents, rather than just the quantification of carbon stocks *per se*. The thesis is organized into four central chapters that have been prepared as stand-alone research papers. Each of these chapters is self-contained, having an introduction that provides its background information and detailed methodology. Chapters 2 and 3 have already been published (the references are provided below), while chapters 4 and 5 are in preparation to be submitted for publication. Chapter 1 provides an overview of the context of this study, introducing key concepts of the main disciplines integrated in the research. The last chapter (6) reflects critically on the results and provides some overarching conclusions.

Chapter 1: Introduction

Chapter 2:"Operationalizing the Definition of Forest Degradation for REDD+, with Application to Mexico" (paper published in Forests)

Chapter 2 analyses the context in which forest degradation has been internationally defined and evaluates the utility of field-based forest inventory and remote sensing data for detecting degradation of tropical forests. The idea that forest degradation can only be defined using local reference conditions is introduced. In order to obtain meaningful estimates of these local reference conditions for forest carbon stocks, an approach that links the potential biomass of a landscape with the common degradation agents acting on that landscape is proposed.

Morales-Barquero, L. *et al.* 2014. Operationalizing the definition of forest degradation for REDD+, with application to Mexico. Forests 5(7):1653–81.

Chapter 3: "Identification and quantification of forest degradation drivers in seasonally tropical dry forests: a case study in Western Mexico" (paper published to *Land Use Policy*)

Chapter 3 evaluates the factors that can be linked to forest degradation in TDF landscapes that are used for shifting cultivation. It explores the approach of measuring and monitoring the local communities' livelihood activities that can be associated with a decrease in forest biomass (rather than focusing exclusively on forest carbon stocks). It also elaborates on the need for analysis to be carried out at a sufficient landscape spatial scale to characterize the phenomena associated with forest degradation. From this, the importance and challenges of incorporating complex mosaic landscapes in TDF biomes into REDD+ are assessed. The study of forest degradation in TDF is then developed further in chapter 4.

Morales-Barquero, L. *et al.* 2015. Identification and quantification of drivers of forest degradation in tropical dry forests: a case study in western Mexico." *Land Use Policy* 49:296–309.

Chapter 4: "Assessing forest degradation on the ground and from space: Developing indicators to evaluate the state of tropical dry forests in Mexico"

In chapter 4 I focus on how variation in forest structure and composition that result from human-induced disturbance can be assessed to establish levels of forest degradation, and their utility for monitoring. It explores the use of locally relevant indicators measured in the field that are clearly linked to the human activities causing disturbance processes, in order to determine degrees of forest degradation. Then, it assess if the degree of forest degradation determined in the field can be modelled at the landscape level by using remote sensing indices as predictor variables. The approach presented in this chapter associates measures of disturbance with more conventional measures of forest degradation, with the aim of providing methods to monitor forest degradation that are directly linked to interventions that can avoid degradation and enhance recovery in TDF.

Chapter 5: Forest degradation and deforestation dynamics in a tropical moist forest over 40 years: a case study of the Osa Peninsula, Costa Rica

In Chapter 5 I further develop practical approaches to assessment of forest degradation through comparison with undisturbed forests, in this case in a closed-canopy moist forest landscape subject to commercial selective logging. Following the approach of analysing the human activities that cause forest degradation, inventory and mapping data from historic forest management plans are used to determine degraded areas, and to track the conversion of an undisturbed forest landscape into a series of degraded patches, using medium-resolution satellite data.

Chapter 6: Discussion and synthesis

Chapter 6 synthesises the main findings, conclusions and implications of the preceding chapters.

Together these chapters present an overview of the main issues surrounding the concept of forest degradation and provide a new framework to guide the development of methodology for assessment of forest degradation caused by a range of human activities, using the range of data sources that are currently widely available for evaluating human modified landscapes.

Chapter 2. Operationalizing the definition of forest degradation for REDD+, with application to Mexico

This chapter is based on: Morales-Barquero L, Skutsch M, Jardel-Peláez E, Ghilardi A, Kleinn C, Healey J (2014) Operationalizing the definition of forest degradation for REDD+, with application to Mexico. *Forests*, **5**, 1653–1681.

Abstract

The difficulty of defining and quantifying forest degradation is a major constraint in the implementation of the international mitigation mechanism Reduced Emissions from Deforestation and forest Degradation (REDD+). Our aim is to develop an operational framework for defining and measuring forest degradation at a local level for early REDD+ projects and for national REDD+ programmes, through a ground level approach. We critically review and discuss national and international definitions of forest and of forest degradation, and then analyse the main difficulties in making these operational, evaluating the key elements and threshold values that are used and contextualizing them using Mexico as a case study. We conclude that given the lack of historical biomass data and the limited capability for monitoring degradation using remote sensing, forest degradation is best measured against a local benchmark that represents areas of low or no degradation that have comparable biophysical characteristics. Use of benchmarks of this type could offer a quick-start option for local assessment and construction of reference levels for forest degradation. These could be refined as more data become available and could eventually be integrated into national monitoring systems.

Keywords: forest monitoring; Mexico; community-based monitoring; remote sensing; tropical dry forests; deforestation; benchmark

2.1. Introduction

There has been considerable debate about how to define and measure forest degradation in the context of the United Nations Framework Convention on Climate Change (UNFCCC) policy on Reduced Emissions from Deforestation and forest Degradation (REDD+) (Simula, 2009; FAO, 2011). Many contrasting views have been presented on this subject (IPCC, 2003; Cadman, 2008; Sasaki & Putz, 2009; Putz & Redford, 2010) and it has even been suggested that a definition is not required (Guariguata *et al.*, 2009).

An important part of the discussion on the definition of forest degradation at the international level has assumed that it is necessary to establish thresholds and/or indicators that allow forests in non-Annex I countries to be classified as degraded or non-degraded; on the grounds that such a system is required for the purpose of generating carbon credits under REDD+ (Bucki *et al.*, 2012). However, the estimation of net greenhouse gas (GHG) emissions implies not only the identification of areas that have been subject to degradation in a given period but also the assessment of the annual rate of loss of carbon stocks within these

forests, which requires more than simple thresholds, as it implies quantification of degradation over space and time. In addition, REDD+ schemes are required to assess more than just carbon stocks, so projects are expected to demonstrate positive outcomes in terms biodiversity and local livelihoods.

Thompson *et al*. (2013) have called for a broad definition of degradation that includes five criteria, of which carbon storage is only one. They emphasize that forest degradation is a wide and complex concept, that can be quantified using several indicators that range from those focused on biodiversity to those most linked to stored carbon. Variation in the definitions proposed for forest degradation is highly dependent on the interests of the corresponding stakeholders. Until now, the climate change mitigation aims of REDD+ have given the highest priority to carbon storage, even though concerns have been raised that if this is the sole focus of REDD+ it could promote actions that have a negative effect on biodiversity (Gardner *et al.*, 2012). Even though a more integrated approach is desirable, it is not clear that a multi-criteria definition of degradation, with the associated complexity of its indicators, would satisfy the requirements for monitoring REDD+ projects in which funding is primarily linked to demonstrated improvements in carbon stocks compared with the case of "business-as-usual". Therefore, in this paper we focus on the application of the kind of broad framework proposed by Thompson *et al*. (2013) for an operational definition relevant to the less developed countries that have an immediate need to develop quantitative carbon-based forest degradation methods applicable at the landscape level.

Considerable uncertainty remains about the amount of GHG emissions that can be linked to forest degradation and the amount of degraded forest worldwide. It is estimated that around 850 million hectares of tropical forests are degraded (ITTO, 2002). Depending on how it is defined and what drivers are considered in the analysis, forest degradation was estimated to represent a wide range of between 10 and 40% of the 1.4 PgC y^{-1} of the estimated net carbon emissions from tropical forests between 1990 and 2010 (Houghton, 2012). By analyzing regional-scale emissions derived only from wildfires and unsustainable logging, several other studies have estimated values over a similar range between 22% and 57% of the total forest GHG emissions (Asner *et al.*, 2010). These estimates would probably further increase if other degradation processes such as extensive cattle grazing and unsustainable fuel wood collection were also included, indicating that forest degradation could be an even larger source of GHG emissions. These figures must be regarded with some skepticism; mainly because the methodology used by individual countries to calculate area of forest degradation varies greatly. Also, most countries have very poor data on carbon stocks, as few have carried out systematic national forest inventories.

Even though its contribution to GHG emissions is probably substantial, degradation has implicitly been held to be of secondary importance compared with deforestation and most early REDD+ projects have focused on avoiding deforestation (Lin *et al.*, 2012). In general, deforestation and forest degradation result from very distinct drivers, and are brought about by different groups of actors (Hosonuma *et al.*, 2012). Typically, deforestation occurs when a single actor makes a conscious decision to change forest to another land use. While it is wrong to make an inherent link between logging and degradation (as there is evidenced that planned forest management using reduced-impact logging recover carbon and will reduce carbon emissions (Putz *et al.*, 2008a; West *et al.*, 2014), degradation does often result from poorly regulated or managed logging, or other unregulated extractive activity often carried out at a small-scale by many actors. In the context of REDD+ degradation has been grouped together with deforestation, but in terms of monitoring it has more features in common with other "within-forest" activities (sustainable forest management and enhancement of forest C stocks) (Herold & Skutsch, 2011). In some cases degradation and deforestation are causally linked, e.g. creation of access routes for either illegal or legal timber extraction can increase the probability of subsequent deforestation through conversion of forest to agricultural land.

The availability of forest monitoring methods suitable to assess forest degradation is especially critical in certain countries. For instance, Mexico has experienced a much reduced deforestation rate during the last five years but has very high levels of human disturbance in its forests. The field survey of the National Forest Inventory of Mexico records indicators of human or natural disturbance for each plot in the field (e.g. stem damage due to fire, presence of tree stumps, grazing, illegal logging). In a simple analysis of these data we have found that a very high proportion of the inventory plots (70-80%) do have one or more of these disturbance indicators recorded. Although this does not provide a reliable quantification of the intensity or extent of degradation, it does provide evidence of how important it is for countries such as Mexico to monitor forest degradation. As forest degradation may contribute to an increasing proportion of net GHG emissions from forest land there is an urgent need for the development of operational approaches to quantify degradation for incorporation into REDD+ schemes. This will depend on having an unambiguous and operational definition of degradation based on measurable indicators. However, it has proven extremely difficult to find a definition that meets this criterion and that is appropriate to different geographical scales, as well as satisfying the perspectives and needs of different actors (IPCC, 2003).

This paper therefore aims to advance the definition and measurement of forest degradation within the context of the REDD+ discussions, following three main ideas:

1. Assessing the gap between international discourse on forest degradation and the practicalities involved in monitoring it at national and local levels.

2. Identifying the key elements that are necessary to assess forest degradation in both the national and the local contexts.

3. Proposing a new framework for the operationalization of a definition and quantification approach to forest degradation at a local level for early REDD+ projects and for national REDD+ programmes.

The approach taken in this study is first to examine the reasons why forest degradation has not yet been clearly defined and how this contributes to the considerable difficulties in finding adequate methods to measure it (section 2.2). After reviewing the international attempts at reaching a definition, in section 2.3, we take the case of Mexico and discuss what is possible both for definition and measurement of degradation (sections 2.4 and 2.5), summarising our conclusions in section 2.6.

2.2. The challenges involved in defining forest degradation

The absence of agreed definitions and clear criteria hinders global capacity for REDD+ policy and project development, as countries have not been able to assess the area of degraded forest or the level of its degradation in consistent ways. There are a number of reasons for the difficulties in adopting clear and consistent definitions, including the differences in perspectives and management goals amongst actors, the challenge of defining the counter-factual (what would the biomass density be if the forest were not degraded) when the natural condition and dynamics of forest ecosystems are so variable, and human disturbance impacts on forest vary so much in their intensity, spatial extent and frequency. An underlying challenge is the fact that ecosystems vary greatly in their capacity to recover to a pre-disturbance state, and complex transitions occur throughout the disturbance phases (Baker *et al.*, 2010).

2.2.1. Forest degradation can only be defined relative to a benchmark

An assessment of forest degradation necessarily implies a comparison, either with a previous state or with a contemporaneous reference condition (a benchmark), as proposed by Thompson *et al.*(2013). The first is analogous to standard measures of deforestation that compare forest cover at the end of a period with that at the beginning. However, in a practical project context, it is very rare that data are available of earlier biomass stock levels, or the condition of the forest during a previous period or before any human impacts took place. In the case of comparison with a contemporaneous benchmark, the problem for

degradation assessment is to define, identify and measure an appropriate benchmark or reference condition; a challenge directly analogous to that faced in ecological restoration or when trying to determine the degree of “naturalness“ of managed forests.

There is a lot of subjectivity and assumptions in the use of concepts such as “natural”, “primary”, "intact", “pristine” or “virgin” forests, all of which are associated with the concept of a reference condition (Bradshaw *et al.*, 2011). For example, Cadman (2008) proposed using "intact forest" as the reference (for any given ecotype/species mix), in which case any forest that has a carbon stock lower than that of "intact forest" should be considered degraded. However, use of this term does nothing to solve the fundamental problem of defining which forest falls within this category: in reality there are huge natural spatial and temporal variations in carbon stocks within forests in the same region or landscape, linked to differences in structure, productivity and species composition, due to variation in biophysical conditions (hydrology, soil etc.) and long-term natural, as well as anthropogenic, disturbance regimes. In addition such terms as “naturalness” or "intact" are likely to be very difficult to apply in practice: they have been a highly contested concepts, with some observers arguing that none of the world’s forests are natural (on the basis that all global forest has a history of human influence to a greater or lesser degree (White & Oates, 1999)). It seems very unlikely that adequate agreement could be reached about which indicators or thresholds should be used to define whether a given area of forest should be classified as “natural”, "intact" or "primary".

Definition of reference conditions or benchmarks using more pragmatic criteria needs to be based on understanding of the properties, patterns and processes of forest ecosystems, taking into account their complex dynamics. At a landscape level forests both heavily and lightly influenced by humans exist in a shifting mosaic of patches with variation in species composition, structure and biomass-carbon stocks. To some extent these patches may represent the successive phases of forest stand development (Oliver & Larsen, 1990) (Fig.2.1). An analysis of this mosaic and its land-use history should enable identification of areas that have been least subject to human disturbance for the longest time and which contain patches representing the range of forest development phases including old-growth, which would then be appropriate to use as the reference condition or benchmark. These can then be contrasted with the areas subject to greater human impact. The furthest extreme will be those areas that, while still meeting the criteria of being “forest”, have been most recently subject to intensive or frequent human disturbance and show attributes that depart widely from the benchmark. It is important to recognize that, while this approach assumes that the landscape includes areas with a range of levels of degradation, it does not depend on the least degraded areas being completely free of human impact.

A requisite for the selection of benchmarks based on chronosequences, - is to have an indication of the range of natural variation (RONV) of carbon stocks and other forest attributes, i.e. the range of values that would occur even without major human disturbance. Benchmarks should reflect the variation in potential stocking rates of different non-degraded areas. For example, even within a given vegetation type, sites higher up the slope with thinner soils, and those with an aspect receiving lower rainfall or greater wind exposure, are likely to have lower potential stocking levels than those in sheltered sites at the base of slopes receiving higher rainfall. Once the natural range of variation is known, information on land-use history and degradation agents that are acting locally should be used to classify areas into degradation level categories, and to estimate which areas are gaining or loosing carbon stocks. It is key to understand the processes and landuse history that are acting over the forest, to avoid for example misclassifying areas under reduced impact logging as degraded when compared with the benchmark, when in reality they are areas that are gaining carbon (West *et al.*, 2014).

The identification of a range of possible values by comparing forest stands over space, is interpreted as corresponding to the changes that may occur in a single stand over time (chronosequence). While this classical approach to research on vegetation succession is subject to serious criticism because of its underlying assumptions (Chazdon *et al.*, 2007; Feldpausch *et al.*, 2007; Johnson & Miyanishi, 2008), there is good empirical evidence that it can work in tropical forest landscapes (e.g. Chai *et al.* (2012)). Even if it depends on potentially unreliable assumptions, as pointed out by Johnson and Miyanishi (2008) and Quesada *et al.*(2009), the chronosequence is the most suitable approach for assessing the relation of current forest state and attributes to land use history in the usual situation where long-term monitoring has not been carried out. The relationship is especially strong for basal area and biomass accumulation, as demonstrated by Chazdon *et al.* (2007), suggesting its potential usefulness (provided that the assumptions are carefully considered) in assessing and predicting carbon stocks.

In its application, this approach leads to the assumption that there is a convergence of forest condition during the process of recovery: if a degraded area (as shown on the left hand side of the succession curve, Fig 2.1) is not further disturbed but allowed to recover naturally, it will eventually store similar amounts of carbon, and be able of delivering the same level of other ecosystem services, as areas of this forest type under similar biophysical conditions that have never been disturbed. While the uncertainty in this assumption must be acknowledged, it may offer the only realistic option to evaluate what carbon sequestration gains will result from elimination or reduction of human practices that are causing biomass loss.

There is likely to be a strong scale-dependency in these applications. While stage of forest recovery can be assessed for a given patch or stand of forest, this is much harder at the scale of a landscape, which will be composed of patches of a wide range of degradation/recovery states. If the landscape is clearly sub-divided into a defined classification system of degradation and recovery states, it would then be possible to use a threshold to classify the landscape as a whole based on the proportion of its patches/area that is in a degraded state. However, there may be a problem with applying the same threshold level between different landscapes. With increasing knowledge of the complex properties of ecosystem dynamics it is clear that forest recovery may not be a linear process over time and landscapes may be subject to regime shifts, following which they may remain in an altered state for a long time (Hobbs *et al.*, 2006). It is also important to recognize that the process of forest recovery is not simply the inverse of degradation, it may follow a different trajectory (e.g. towards a novel ecosystem state).

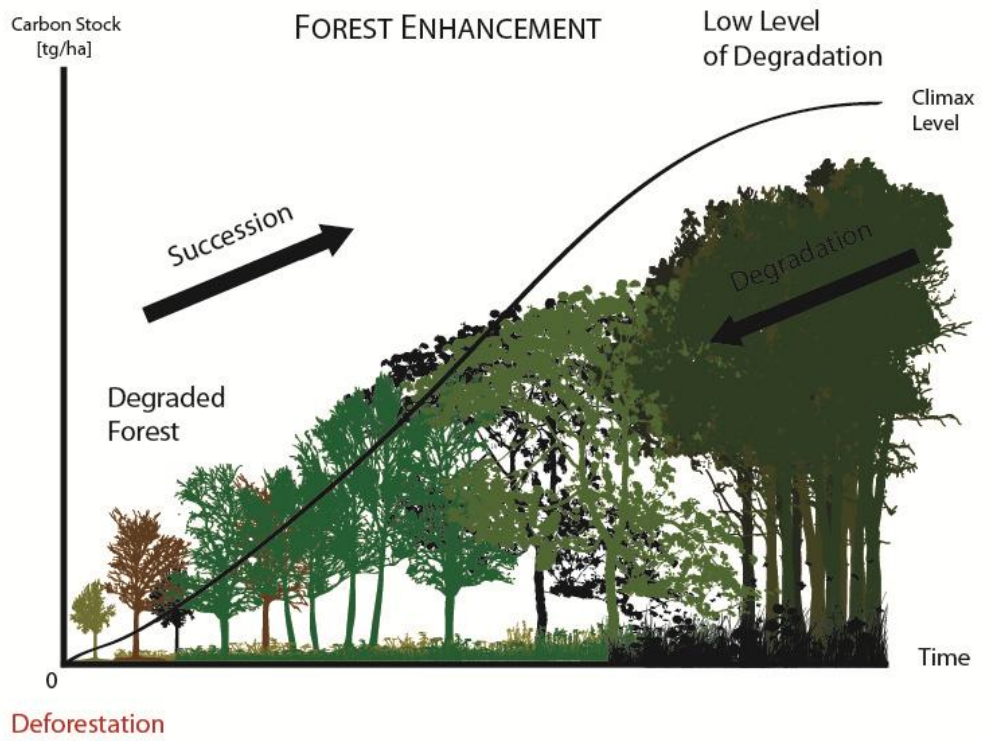


Figure 2.1 Forest succession curve (modified from Eckert *et al.* (2011))

2.2.2. Degradation is a process which is best assessed at the level of the landscape

Forest degradation is both a state ("degraded forest") and a process ("degradation of forest") (FAO, 2011), and in reality it can only be assessed adequately over whole landscapes (or series of management units), that could be defined in terms of property boundaries or coherent landscape units, depending on the activities involved. In many tropical areas, much of the forest is in a state of transition as a result of the combination of human activities and natural processes. This means that some areas may be recovering and increasing their carbon stocks, while others are losing them, as a result of cyclical agricultural practices, which include a woody fallow (i.e. secondary forest) phase or sustainable timber management, or as a result of periodic natural events such as fires. Such mosaics are very common in populated tropical forests (Mertz *et al.*, 2012). It is the overall carbon budget of each coherent landscape/management unit that should be assessed, not individual patches of forest within the unit, so that the temporary losses and gains are averaged out.

A wider geographical scale encompassing the range of management activities across the landscape needs to be used to assess whether it is suffering from net degradation, but defining the scale and boundaries of such units is very difficult, as the team charged by the IPCC with defining degradation has reported (IPCC, 2003). It would require on-the-ground knowledge of the organization of forest use, specific to each area. It is partly for this reason that it has been suggested that, not only degradation, but all forest carbon budgeting should be done at a landscape level, in a nested system of MRV) (Minang & van Noordwijk, 2013). In areas dominated by small-scale peasant agriculture, particularly shifting agriculture, where formal property boundaries may be difficult to map, it may make more sense to assess degradation over landscape units that represent the typical agricultural practices; these would be on the order of +/- 5000 ha (Thompson *et al.*, 2013). In areas that are subject to timber extraction (sustainably managed or not), an approach using property or concession boundaries may give a more accurate picture.

2.2.3. Biomass loss is difficult to quantify

In strict carbon accounting terms, degradation will only occur in a forest area if its rate of biomass loss is higher than the natural re-growth rate. As is well known, biomass assessment per se is an inaccurate and imprecise process unless very expensive, detailed inventory is conducted (Petrokofsky *et al.*, 2012). Determining loss and re-growth rates is a complex task that requires long-term observations and intensive research which are not usually available in developing countries (Herold *et al.*, 2011), or alternatively good statistical records (the "gain-loss" method). Unsustainable selective logging, slash-and-burn agriculture, fuel-wood collection, charcoal extraction and grazing, that are the main activities that induce gradual loss of carbon stocks, vary greatly and render generalizations difficult (Murdiyarso *et al.*, 2008a).

2.2.4. Fluctuations in forest carbon also reflect natural causes

Tropical forests are dynamic systems, that gain and loose biomass as part of natural cycles driven by disturbance events (fires, storms, floods, droughts and pests etc), that makes it difficult to establish strictly which losses are due to the influence of human activities (Herold & Skutsch, 2011). During these cycles there will be temporary reduction in carbon stocks that do not imply persistent loss (Attiwill, 1994). However, there can also be positive feedback between natural and anthropogenic disturbances, which can promote further loss of carbon stocks. Establishing whether or not this loss is human-induced is difficult in many cases, for example, there is often a higher frequency of forest fires and increased vulnerability to drought after logging events, related to forest fragmentation (Cochrane &

Barber, 2009). International negotiations and voluntary markets related to REDD+ will have to deal with the fact that there is an intrinsic level of uncertainty due to such natural causes (Grassi *et al.*, 2008; Baker *et al.*, 2010; Barlow *et al.*, 2012).

2.2.5. Gray areas between deforestation and degradation

It is not clear if some effects of human interventions should be considered to be deforestation or forest degradation or a component of normal forest management. For example, if trees are clear-felled but forest immediately starts to regrow, this would generally be classified as degradation. However, if crops are temporarily cultivated and then farming is abandoned, for what length of time would this need to occur before the impact is classified as deforestation? Then, if classified as deforestation, at what point during subsequent secondary forest regrowth would the area be classified as degraded forest? This is an extremely critical point, especially in terms of slash-and-burn agricultural systems, because it seriously affects carbon accounting statistics. Depending on how woody fallow lands are viewed in this regard, forest degradation may account for anything between 10 and 40% of forest carbon emissions, while deforestation will represent between 10 and 90% (Houghton, 2012). If an area is defined as deforested only if it remains without trees for at least 20 years, then a great deal of what has been labelled "deforestation" should instead be categorised as "degradation".

2.2.6. Lack of historical data on forest carbon stocks for baselines

In order to evaluate possible reduction in GHG emissions both for deforestation and forest degradation, a baseline is required. A baseline or reference emissions level (REL) is built on rates of degradation (and deforestation) over a given historical period against which emissions due to future degradation can be compared. To build a baseline both emission factors (which for REDD+ are estimated as the amount of carbon that is lost per hectare per year as a result of degradation (IPCC, 2003) and activity data (i.e. the area that is affected by degradation and changes in this area over time) are needed.

In the case of deforestation, emission factors are calculated by assessing the total carbon stock per hectare that would be lost, in one go, if the area were deforested. With degradation, estimation of the emission factors is more complicated, as illustrated in recent work by Pearson *et al.* (2014) that developed an accounting method to estimate emission factors from selective logging of tropical forests. To this complexity, it must be added that baselines will require knowledge of the past annual rate of loss of carbon stock due to degradation in any given forest (e.g. in tonnes per hectare per year), so that the reduction due to the corresponding REDD+ activities can be compared with this.

Although significant advances have been (see for current status of methods (Herold *et al.*, 2011; Petrokofsky *et al.*, 2012; GOFC-GOLD, 2013)), determining activity data for degradation remains challenging, as explained in the next section.

2.2.7. The capability of remote sensing for detection of forest degradation is limited

Methods have long been developed using remote sensing to classify forest cover change between forest and non forest at a large scale, as for example required for reporting to the FAO's decadal Forest Resources Assessment. There has been no comparable development of methods to meet the greater challenge of quantifying forest degradation, and this inertia has led institutions to stick to the tried-and-tested approach of basing forest change assessments solely on deforestation. The spatial extent of degradation, and thus the rate of its expansion, is much more difficult to observe than deforestation using remote sensing data (GOFC-GOLD, 2013). It is particularly challenging to detect the intensity of degradation at any given point and assess the rate at which forests are losing carbon. Optical remote sensing faces a fundamental problem, that is that changes in canopy cover are not a direct measure of total biomass, or of degradation that is occurring to the forest below the canopy surface level (e.g. fuelwood collection or grazing) (Lambin, 1999; Peres *et al.*, 2006). Important advances have been made in detecting the area impacted by selective logging in the Brazilian Amazon, by means of spectral mixture analysis (SMA) (Asner *et al.*, 2005; Souza *et al.*, 2005). This method allows detection of canopy damage by assessing the combination of green vegetation, soil and non-photosynthetic vegetation found in each pixel. However, such studies have mostly been performed in Brazil on relatively flat and extensive terrain, with logging predominantly carried out at an intensity of 10- 40 m^3ha-1. Such conditions strongly enhance the detectability of the signal, and the success of these techniques where logging has occurred in more topographically complex terrain or in other types of forests, with less uniform canopy or with a more patchy or diffuse pattern has not been demonstrated.

A further constraint with low frequency monitoring using these optical remote sensing methods is that the kind of activities that cause detectible changes to the canopy cover, e.g. selective logging, may be missed or under-estimated if the resulting canopy gaps are rapidly filled within a few years (at least in part) by in-growth of the canopies of the adjacent trees or recovery of a lower stature of canopy through natural regeneration (but without full recovery to previous biomass levels, which will take several decades). Calculating degradation based on area estimates of logging or other degradation activity may also lead to underestimates since tree density change might exceed area change (le Polain de Waroux & Lambin, 2012). Monitoring systems need to take such factors into account, e.g. in terms of their frequency. Integrating optical remote sensing with lidar (which is discussed in section

4.1.3) has produced interesting results, however its cost is currently prohibitive. None of these remote sensing methods will meet the degradation monitoring need without having sufficient ground data and information on the historical context.

2.3. Definitions of forest degradation in the international context

A pre-requisite to defining forest degradation in the international context is an accepted definition of "forest". There are many (hundreds of) forest definitions, in part because of the wide range of purposes for which they are designed, from administrative-legal to land use planning, forest cover monitoring, biodiversity conservation and carbon budgeting (Lund, 1999). What should and should not be considered to be a forest is controversial (Schoene *et al.*, 2007). International organizations have produced a series of definitions to meet their own needs, and individual countries and institutions have adjusted definitions to their specific interests as illustrated by the case of Mexico in Table 2.1.

Most countries, for purposes of international agreements, follow the FAO definition (Simula, 2009). In this, forests are defined on the basis of thresholds values for three quantitative criteria: crown cover, area and height, all of which can be related to biomass and carbon stocks. However, the reference area to measure such criteria, mainly canopy cover, is usually not defined which results in major uncertainty in forest cover estimates (Magdon & Kleinn, 2013). Another problem with thresholds is that some tree-dominated land uses are classified as forest whereas others are classified as non-forest, through the application of commodity-based definitions of “land use” by FAO and other organizations. Thus tree plantations whose primary use is timber are classified as forest; but tree plantations whose primary use is harvesting of fruit (e.g. orchards or oil palm) are classified as non-forest, even though there may be no biophysical difference between these types of plantation. In the case of agroforestry systems, which involve joint production of timber and agricultural products, the classification by land use is particularly arbitrary. For the purposes of REDD+ there has been controversy about whether the increase in carbon stocks in such agroforestry systems, e.g. planting of shade trees, should be eligible for credits or not, and therefore whether increases in trees in such systems should count as a reduction in forest degradation. As a further complication, actions that increase the agricultural productivity of agroforestry systems can contribute positively to REDD+ by reducing pressure for additional deforestation to increase agricultural land area (Noponen *et al.*, 2013). There are many other examples of such grey areas about what should be classified as forest under REDD+ (and therefore would need to be monitored for degradation), that have not yet been resolved.

Table 2.1 Forest attributes used to define what is classified as "Forest" by relevant international policy bodies and Mexican national entities.

Institution	Minimum crown cover (%)	Minimum area (ha)	Minimum tree height (m)	Species/vegetation type
IPCC GHG for land use, land-use change and forestry (LULUCF)	Countries can decide on a threshold between 10-30% (or similar stocking level) at maturity.	≥0.05-1.0	Countries can decide on a value above ≥ 2-5 (at maturity in situ)	Includes closed or open forest, young natural stands and forest plantations that have the potential to reach 2- 5 m Includes harvested forest, that is below 10-30% canopy cover where they are considered to be temporarily unstocked.
FAO	≥10% (at maturity)	≥0.5	≥5 (at maturity in situ)	Does not include areas predominantly under “non-forest” land use such as agriculture or urban
CBD-Convention for Biological Diversity	≥10%	≥0.5	≥5	Only includes “natural” forest. Excludes areas under “non-forest” land use such as agriculture.
Mexico (under the Kyoto Protocol)	≥30%	≥1.0	≥4	Includes agricultural land and tree plantations
INEGI-Mexican National Institute of Statistics and Geography	>10%	≥25 (medium resolution, most of the country) ≥1.6 (area detectable using high resolution)	Not specified	Not clearly specified
CONAFOR-Mexican National Forestry Commission	>10% (at maturity)	≥0.5	>5	Excludes trees in agricultural lands, parks and gardens

It is evident that improvements in the clarity and completeness of forest definitions are needed in the context of international climate change mitigation programmes because this has a major impact on the estimation of the areas that are reported as deforested or degraded (Romijn *et al.*, 2013). The same holds for defining forest degradation. As we explained in section 2.2.2, there is no easy way of fixing temporal or spatial criteria for degradation

without specific reference to individual management units. The result is that it is generally agreed among parties that for the purposes of climate change mitigation, forest degradation simply involves lowering of carbon stocks in forests, in areas that are classified as forests (Simula, 2009).

Definitions of degradation used by the major agencies involved in REDD+, however, vary widely (Table 2.2). At one extreme the Convention for Biological Diversity (CBD) considers loss of biodiversity as the main sign of degradation. At the other end of the scale organizations directly concerned with carbon crediting systems (such as Voluntary Carbon Standard (VCS) and UNFCCC) favour definitions based solely on carbon stock loss. This relates to the need for a water-tight accounting system if credits are to be marketed. A possible resolution to this difficulty may be provided by the promulgation of "safeguards" tailored to the requirements of REDD+. Safeguards have received considerable attention in recent negotiations in response to concerns that other environmental and social values might be sacrificed to maximize carbon values. Conditions might be introduced such that degradation may be officially defined in terms of carbon loss, but credits would not be issued if there is evidence that there have been large biodiversity losses (or negative social impacts) associated with REDD+ interventions. This does not, however, resolve the problem of whether the definition of degradation should be based solely on carbon loss, or also include some reference to the "naturalness" of the forest (Guariguata *et al.*, 2009), which in the end is largely a political decision.

Table 2.2. Definitions of forest degradation proposed by relevant international policy bodies concerned with forestry.

Agency	Definition	Source	Main focus
FAO	Reduction in the capacity of forest to provide goods and services	FAO 2002 & FAO 2008	Ecosystem services approach
SBSTA/UNFCCC workshop on defining and measuring degradation for REDD	Proposal that degradation should be defined in terms of comparison with intact forest of the same vegetation type: "Forest degradation is the reduction of the carbon stock in a natural forest, compared with its natural carbon carrying capacity, due to the impact of all human land-use activities."	Cadman (2008/2009)	Carbon content
IPCC	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[7]	IPCC 2003.	Carbon content

[7] The parameters X , Y and T were left open, no agreement was reached in IPCC 2003a. As pointed out by Penman (2008) in (Murdiyarso *et al.*, 2008a) defining X, Y and T will be extremely difficult; mainly because these parameters depend on the activity causing degradation and on the particular ecosystem.

ITTO	Long-term reduction of the overall potential supply of benefits from the forest, including wood, biodiversity and other products or services. Also, a direct human-induced loss of forest values (particularly carbon), likely to be characterized by a reduction of tree crown cover. Routine management from which crown cover will recover within the normal cycle of forest management operations is not included.	ITTO 2002 ITTO 2005	Ecosystem services
CAN	From a climate change perspective, forest degradation needs to be defined to include the impact of all human land-use activity that reduces the current carbon stock in a natural forest compared with its natural carbon carrying capacity.	Mackey *et al*. (2008)	Carbon content
VCS	The persistent reduction of canopy cover and/or carbon stocks in a forest due to human activities such as animal grazing, fuelwood extraction, timber removal or other such activities, but which does not result in the conversion of forest to non-forest land (which would be classified as deforestation), and falls under the IPCC 2003 Good Practice Guidance land category of "forest remaining forest".	VCS 2011	Carbon content

2.4. Definitions of forest degradation for Mexico

In Mexico, as mentioned above, a large part of both the temperate and the tropical forests appears to be, to a greater or lesser extent, degraded. Much of the degradation is the result of unsustainable extraction of wood products, shortening of slash-and-burn cycles, and allowing cattle to graze within the forests. These drivers of degradation typically result in a landscape mosaic in which part of the forest area has lost biomass stock, part is depleted but stable, and other parts are recovering their biomass stocks, with the net result that the landscape's average stock is at levels below those expected in forests undisturbed by human uses.

Mexico has adopted the agreements and definitions established by FAO in the context of the Kyoto protocol, but has also made important advances towards developing a legal framework to regulate climate change related activities, including those in the forestry sector. In this context two different regulatory frameworks have proposed definitions relating to forest degradation: the Law on Climate Change and the Law on Sustainable Development of Forests[8].

Both of these laws refer to forest degradation as a reduction in delivery of ecosystem services, however the Climate Change Law only refers clearly to carbon sequestration services in relation to a reference value that reflects conditions in areas where no human interventions have occurred. On the other hand, the amendments to the Sustainable Development of Forests Law, which were made in the same year, present a wider view, referring to a reduction in the capacity to deliver ecosystem services, which is likely to be more difficult to measure and evaluate. To our knowledge, there have as yet been no challenges to this inconsistency in definitions, and we therefore have to assume that for purposes of reporting to UNFCCC, Mexico will apply the definition made in the Climate Change Law. There are, however, also inconsistencies relating to other aspects of the Mexican definition of forests and degradation, which we consider in discussing the operationalization of the degradation element of REDD+ below.

[8] Ley General de Cambio Climatico and Ley General de Desarrollo Forestal Sustentable, both promulgated in 2012

2.4.1. Elements to be considered in the definition and measurement of forest degradation in Mexico

2.4.1.1. The Canopy Cover Element in the Definition of Forest

As noted section 2.3, UNFCCC requires a definition of forest that relies on threshold values, of which canopy cover is the key element. The choice of a threshold value for canopy cover will, to a large extent, determine which areas in Mexico are allowed to participate in REDD+ activities. Mexican forest law states that a vegetation type is considered forest until the point at which it falls below a tree canopy cover threshold of 10%, while for the purposes of the Kyoto Protocol, it has adopted a 30% canopy cover threshold. This was probably to enable the promotion of CDM projects, which can only be carried out in areas which are not forest. This difference in definitions has so far not been resolved and it is not clear which one will pertain for the case of REDD+.

In the context of REDD+, however, the definition of canopy cover threshold has important implications (Romijn *et al.*, 2013). If Mexico assumes a 30% threshold, any open forests and woody vegetation formations with canopy cover below this level (such as *matorrales* (scrubland) would be ineligible. By the same reasoning, clearance of such open formations would not be counted as deforestation, and loss of biomass density within them would not be counted as degradation, against the national reference emissions level. A key question in this regard is whether areas that currently have a tree canopy cover between 10% and 30% do so as a result of past degradation processes (which could perhaps be reversed) or as a result of natural ecological characteristics. This has important implications for the selection of the minimum canopy cover threshold for REDD+. It would be important first to consider whether low carbon density ecological zones such as the *matorrales* offer any real opportunities to increase Mexico´s carbon stocks. Because of the cost of monitoring land areas for carbon stock changes in national REDD+ inventories it would be efficient to exclude from the forest definition those ecosystems with low potential for loss or gain in carbon stocks associated with changes in tree canopy cover. However, for the case of degraded ecosystems that currently have a low tree canopy cover, but have good potential for increase in carbon stocks through project interventions (e.g. tree planting or forest protection) it would be useful to include them within the forest definition so that such projects can be monitored as part of the REDD+ process. Additional information on the rate of potential carbon stock gains and monitoring costs is required to assess this trade-off. If areas with canopy cover down to 10% are included in the area to be monitored for REDD+ this would approximately double the area to be monitored compared with a minimum threshold of 30%. Knowledge of the proportion of total project costs comprised by monitoring (Rendón Thompson *et al.*, 2013) would then enable calculation of what value

from carbon stock gain from these areas would be required to generate a net benefit. It may well be that some ecosystems with 10-30% tree canopy cover are in biodiversity hotspots and should in any case be protected for that reason, but it is questionable whether REDD+ is the most appropriate instrument to do this.

2.4.1.2. The area element and the estimation of degradation activity data

In Mexico, as in many other countries, there is a mismatch between what area is actually observed and what is defined as forest by law. At a national scale and on an annual basis forest areas are mapped based on coarse resolution images (i.e. MODIS). This implies that the minimum area that can be identified is 6.25 ha, which is validated with mid-resolution imagery (i.e. Landsat or SPOT data) (Meneses-Tovar, 2011). The minimum forest area defined by law (1 ha, Table 2.1) cannot therefore be observed using this technology, although with the use of high resolution images, the area observable could be brought down to 0.5 ha (Velazquez *et al.*, 2011). When resolution is increased, the forest loss estimates may change significantly. For example, when comparing deforestation estimates between 1993 and 2010 derived from mid-resolution Landsat data with aerial photos for 2003 and high resolution SPOT 5 images for 2007 in a small area in Northwestern Mexico, the estimates of deforested area were increased by a factor of three, because many smaller patches of forest clearance could be seen when using higher resolution technology (Ghilardi *et al.*, 2012). The same general effect will hold for estimates of areas that are degraded. However, use of higher resolution technology implies much higher costs, not only for the images but for the skilled work in analysis (Böttcher *et al.*, 2009).

In the near future, a finer scale approach may be feasible using very high resolution images such as those from the RapidEye satellite, because Mexico, through its National Commission for Knowledge and Use of Biodiversity (CONABIO), has recently obtained full national coverage for 2010 and 2011. It is expected that with the higher spatial resolution of RapidEye data (> 6.5 m) it will be possible to map areas where canopy cover is increasing or decreasing (i.e. to obtain the activity data for degradation) (Franke *et al.*, 2012; Magdon *et al.*, 2014). Mexico plans to continue to receive updated RapidEye image data, but it will be at least 10 years before enough images are acquired in order to be able to construct baselines at a national scale for changes in area of deforestation and degradation (CONAFOR *et al.*, 2012). Thus in the short term, Landsat, in combination with MODIS and SPOT, will continue to be the backbone of national monitoring systems for land cover change detection, since it provides data over the last four decades at medium resolution and is relatively cheap (Birdsey *et al.*, 2013). This means that, for the time being, the de facto minimum measurable unit that could potentially be used in the construction of a baseline for change in area of

degradation will be based on pixel size that range between 10-250 m, that is probably too coarse to detect most degradation activities.

Although interesting results have been achieved for the impacts of logging and fires in rainforest by combining different remote sensing data sources (Souza *et al.*, 2005; Asner *et al.*, 2010; Franke *et al.*, 2012; Langner *et al.*, 2012), it is still challenging to identify and estimate the areas of forest that are losing carbon stocks due to other types of degradation, such as slash-and-burn agriculture, grazing within the forest, and extraction of fencing poles and fuelwood, which are the most common causes of degradation in Mexico (Bonilla-Moheno *et al.*, 2013). Considerable uncertainty remains in assessing activity data on forest degradation due to activities that do not produce obvious changes on canopy cover (Plugge & Köhl, 2012).

Meneses-Tovar (2011) attempted to define the areal extent of forest degradation in Mexico using the changes in NDVI from low resolution imagery (500x500 m MODIS data) and the plots from the National Forest Inventory. This work first obtained an average NDVI value over a five year period (2000-2005) for each vegetation type to derive a regression model using the above-ground biomass values from more than 15,000 National Forest Inventory Plots. Dry season (15 February -15 April) NDVI values for subsequent years were calculated for each plot. An increase, decrease or stable value of the dry NDVI was associated with biomass gains or loss. Although this study was valuable for establishing trends that helped understanding which plots have suffered biomass loss or gains and where these areas were located, due to its coarse spatial resolution it does not allow a proper quantification of biomass change nor to establish if these losses were due to human-related activities.

Bonilla-Moheno et al. (2013) used the EVI (enhanced vegetation index) derived from MODIS (at 250 m resolution) to assess biomass losses at the level of municipalities in Mexico. Although time series comparison of these indices allowed the identification of broad areas with reduced biomass levels, the resolution level is coarse (too coarse to superimpose an overlay for management units, for example). Moreover, it is not possible to distinguish clearly losses that are due to degradation from those that are due to deforestation, nor to directly quantify the biomass changes involved.

Other efforts have been made with medium spatial image resolution to make the quantification on the basis of changes in canopy cover. Velazquez *et al.* (2011) proposed the definition of areas subjected to degradation in Mexico as those in which tree canopy cover had dropped by more than 30%, e.g. from 70% to 40% (Velazquez *et al.*, 2011), simply because this is the minimum which they felt could be reliably detected using a sequential

series of Landsat images. However, the difference in biomass levels between a forest with 70% cover and one with 40% is huge. If degradation is to be included in REDD+, a much finer approach would be needed.

2.4.1.3. The ability to detect changes in biomass stocks over time and data availability for baseline

As explained in section 2.6, there is a lack of historical data for forest degradation on emissions factors (losses of biomass per hectare overtime). It is doubtful whether the losses of biomass per hectare over time (emissions factors) due to forest degradation can be accurately quantified solely using optical or radar remote sensing, even with high resolution data, since optical data do not measure biomass directly and tend to saturate on high biomass ecosystems (Gibbs *et al.*, 2007; Zolkos *et al.*, 2013). The same would hold for aerial photos, even high resolution photos taken from low flying unmanned aircraft (UAVs).

Recently, however, the remote sensing field has seen advances in assessing AGB by combining different types of optical sensors with lidar and/or radar data, which are able to sense and record forest structure metrics (e.g. maximum canopy height) and penetrate both cloud and canopy cover. Such surveys have been made at a national level for relatively small countries (e.g. Panama) with a high level of accuracy (Asner *et al.*, 2013) and allow quantification of a reference level of forest carbon stocks. This offers great potential for future monitoring of stock level change, although carrying this out for large areas of forest would be very expensive with current technology (Böttcher *et al.*, 2009).

Mexico would, ideally, need to carry out regular lidar surveys in combination with intensive field sampling to calibrate the lidar data in order to assess changes in carbon stocks. The costs of such a monitoring system will be large, but need to be compared with the benefit of improved assessment not only of changes in carbon stock, but also for other ecosystem services that could be linked to this remote sensing data. However, it will be many years before enough data are generated to create a credible baseline or reference emissions level, and therefore before carbon credits could be claimed for avoided or reduced degradation on this basis.

The best current approach to gathering adequate emissions factor data would be to base biomass density assessments largely on ground-level measurements that can later be used to analyse remote sensing data. Mexico has a well developed framework for monitoring its forest resources. The National Forest Inventory is based on 23,000 permanent plots, set out on a regular grid of 5 km across all forests in the country, i.e. an average of one plot per 2500 ha of forest. The plots are sampled once every five years and provide invaluable data on the forest attributes, structure, composition and state of the different types of forest at a national

level. When averaged over whole ecosystems, these data provide a good picture of national trends of losses and gains of biomass within forests, and set the distribution of biomass values that occur in each ecozone. However, the Inventory does not provide sufficient data to gain a definitive picture of degradation at local (landscape) levels. For this, much more intensive ground-level survey work would be needed.

2.5. Operationalizing the assessment of degradation at the landscape level

2.5.1. Use of local forest inventories

In areas where REDD+ pilot actions will be implemented intense monitoring will be required to access their impact (Herold & Skutsch, 2011). Accounting for carbon emissions coming from forest degradation could require methods that are extremely time consuming and complicated, especially those related to timber harvesting as explained in Griscom *et al.* (2014) and Pearson *et al.* (2014). Such detailed accounting, though desirable, will not be feasible to implement at a landscape level at different sites across the country, because it requires a high level of expertise. However, the results of local forest inventories done by communities have proved to be of comparable quality to those done by experts (Danielsen *et al.*, 2011) and could be used to assess forest degradation.

Forest owners could be expected to carry out regular ground-level surveys of biomass stock in the forests which they register under the REDD+ programme; monitoring could be considered as part of the management requirements. In Mexico, around 59% of all forest is owned by *ejidos* (communal agrarian settlements) or communities (Skutsch *et al.*, 2013), and is (at least in principle) managed communally; most of the remainder is in the hands of small property owners. It is hoped that the management practices they would need to follow under REDD+ would first reduce rates of degradation and then reverse them as forest enhancement takes place. Therefore, these surveys need to be designed to enable a sufficiently accurate assessment of the levels of degradation and enhancement within the property boundaries to quantify these management effects as a basis for reporting and payments. To enable this, communities and other land owners participating in REDD+ activities could be trained to carry out simplified forest surveys of aboveground biomass. Several projects, such as the "Kyoto: Think Global, Act Local" (Skutsch, 2011) have provided data and experienced to developed detailed field manuals (e.g. Honorio Coronado & Baker (2010), GOFC-GOLD (2013)) on how to design surveys and which variables to measure to assess forest resources, however there also need to be mechanisms to verify the resulting data (Larrazábal *et al.*, 2012; Pratihast *et al.*, 2013). Such extensive community-based monitoring would give a much denser coverage of data than is currently available from the National Forest Inventory,

and enable an analysis at the level of management units, of which areas are losing carbon stocks, which are degraded but stable and which areas are gaining stocks (Table 2.3).

At a national level, this information would not only be useful to assess current emission rates, but also to help determine the relative success of different REDD+ interventions in reducing emissions, because it can be directly linked to the drivers. Ground surveys could include information on land use history and the current use, such as amount of cattle, unsustainable logging or estimates of fuelwood collection, which could improve knowledge of the relationship between human activities and the observed biomass in an area. In addition to quantifying carbon stocks, ground surveys have the potential to informed national policy on the state of other ecosystems services, that are lost when forests become degraded.

Although it may be many years before the entire forest area of Mexico is included under REDD+ (since participation is voluntary) such local surveys would strongly reinforce knowledge about biomass stock levels and how they are changing as a result of REDD+, both at the local and, when summed, at the national level. Given adequate quality filters, local inventories could also serve as ground truth data for remote sensing analysis that will in turn reduce the uncertainty of the carbon estimates at regional and national levels. The combination of local inventories with high resolution remote sensing or lidar could help to develop a nested national MRV system. There is, however, no way that a historical baseline or reference emission level for degradation could be developed from these contemporary data. Rather, their value would be in creating the baseline for future assessment of carbon stock changes and calculation of resulting carbon credits. Given that such a large proportion of Mexico´s forests are degraded, this "room-to-grow" may in reality be the country´s greatest opportunity for carbon crediting under REDD+.

This kind of community-based “bottom-up” analysis of forest degradation would greatly benefit from the establishment of benchmarks which provide locally relevant indicators of carbon stocks for natural forest and forest under different conditions of contemporary or previous use and disturbance which lead to degradation of carbon stocks.

Table 2.3. Suggested activities under REDD+ appropriate to counter different phases of forest degradation

Category	Process	REDD+ mitigation aim	Means of achieving this goal
Degrading	Losing biomass and carbon annually due to human activities in which extraction or loss exceeds natural growth rates	Avoid further degradation When this is achieved, forest enhancement	Sustainable forest management, conservation, extended slash-and-burn cycles (especially woody fallow phase), restriction of off-take of different forest products, e.g. through quotas, removal of cattle.
Degraded but stable	With a low level of carbon, but small rate of losses or gains	Forest enhancement	Possibly through replanting if insufficient soil seed bank, seed rain or root stock exists for natural regeneration or sprouting. Fencing, removal of cattle.
Degraded or deforested but already recovering naturally	Forest re-growth or secondary succession.	In principle, this may not be credited under REDD+ because it is occurring naturally (it is not additional). However, rate of C accumulation may be increased through additional REDD+ measures	Stimulate faster re-growth by forest protection from further disturbance, eliminating sources of loss, enrichment planting etc.

2.5.2. The benchmark approach

As described in more detailed in section 2.2, we propose that a degradation scale could be made for regions that are relatively homogeneous in terms of natural ecosystem, biophysical conditions and land use, using a chronosequence approach. A gradient from least-degraded areas (the benchmark) to highly disturbed sites, with some range of uncertainty for each level can be established (as illustrated for two contrasting cases in figure 2.2). The range in values for the benchmark is important to reflect the variation with site environment (e.g. linked to vegetation type, topography and soils) in potential above-ground biomass stocking rates of areas without major human disturbance impacts.

The first step in operationalizing this approach would be to decide on the size of the region within which the benchmark would be applied. For Mexico, a possible approach would be to work at the watershed level, as watersheds tend to be made up of landscape units with relatively similar sets of biophysical characteristics, and moreover in some cases they

are the spatial basis of governance units, e.g. in Jalisco State where a number of inter-municipal juntas uniting up to 20 spatially contiguous municipalities have been created. These associations are already taking a strong lead in early actions for REDD+ in Mexico, particularly in Jalisco and Yucatán. A second step is to stratify the landscape into homogeneous units based on biophysical characteristics and then carry out the local forest inventories (see section 2.5.1). Selecting an adequate number of strata is not straightforward in most cases and it requires an in-depth knowledge of the area characteristics.

In Jalisco a first attempt to apply the benchmark concept was undertaken for the Junta Intermunicipal de la cuenca del Rio Ayuquila (JIRA), one of the REDD+ demonstrative actions selected by the Mexican Government. In this case a detailed forest inventory was carried out in the tropical dry forests area ("selva baja") (Jardel-Peláez *et al.*, 2013), where the main forest degradation drivers are shifting cultivation agriculture and grazing. Before the communities (*ejidos*), used to practice slash and burn all over the communal area. Currently only the specific areas are allocated for this type of agriculture, this has allowed forest regrowth, but at the same time has intensified the use of certain areas. If the data from four communities' plots are classified based on the land use history and altitude, as the basis to create homogeneous units, it is possible to distinguish four levels of degradation as shown in Figure 2.2. In this case it will be feasible to distinguish highly degraded areas in comparison with the benchmark; assessing intermediate categories (D2-D3) will be more difficult because there is a notable overlap between categories as shown by the error bars, especially for lower altitudes. This indicates that a more detailed classification, using biophysical variables such as slope, aspect or smaller altitudinal ranges, should be attempted, to reduce this variability.

The complexity of ecosystems and their dynamics makes the establishment of benchmarks difficult. However, with limited current capabilities and data constraints, the benchmark approach is still likely to be the best to help assessment of degradation and forest enhancement for the early implementation of REDD+. This will enable the design and monitoring of REDD+ activities to tackle the anthropogenic disturbance processes causing degradation, either through interventions to stop the processes or through behaviour change of the actors involved (Hosonuma *et al.*, 2012; Olander *et al.*, 2012). By using local inventories linked to degradation drivers, a benchmark system could also serve to scale up evaluation of the performance of REDD+ actions to evaluate the impact of REDD+ policy interventions on carbon stock changes (Skutsch & Balderas-Torres, 2012).

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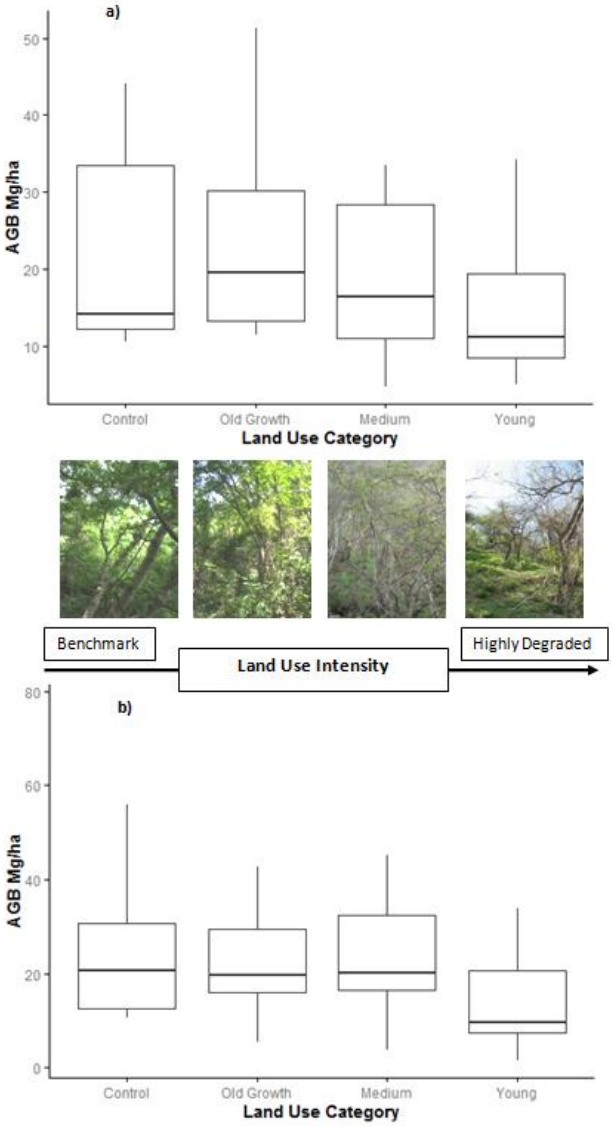

Figure 2.2 Aboveground biomass for tropical dry forests grouped in four land use categories according to altitude:

a) 1200-1700 (*n*=47) b) 900-1200 (*n*=54) for the Junta Intermunicipal de la cuenca del Rio Ayuquila, Jalisco, Mexico. Land use categories are defined according to time since last cleareance: Control= no clearance (Benchmark), Old Growth= more 40 years (D1), Medium= 10-20 years (D2), Young= less than 6 years (D3-highly degraded). The error bars showed the maximum and minimum value for each category and the box corresponds to first and third quartile, the centerline is the median value.

Finally, as more information becomes available, benchmarks can be compared and refined and historical baselines could, in the long run, be developed using them. Simple characteristics can be used by projects as guidelines for classifying areas into different

degradation levels, e.g. the percentage of the forest that is under slash-and-burn agriculture. For logged forests, Sasaki *et al.* (2011) have proposed that the number of trees above the minimum diameter at breast height for legal harvesting that are found in an area could be used as an indicator of the state of degradation. Recent evidence has shown how important are large trees (Sist *et al.*, 2014)

2.6. Conclusions

There are a number of reasons why defining forest degradation in a consistent and operational manner is complex. As a consequence, the result of any assessment of degradation is likely to be very dependent on the scale to which the definition applies. Given the multiple temporal scales of natural change in forest condition, the absence of adequate historical data with which to define the range of conditions that may exist in the non-degraded counter-factual is a particular constraint. The efficacy of a definition will depend on the consistent reliability of the indicators that can be applied to it, but there has been a serious lack of research to test this. Thus, all the definitions present challenges and stakeholders in the international policy development process and the voluntary carbon markets will have to deal with the intrinsic level of uncertainty associated with the process of forest degradation and continuously seek improvements in the operational definition. In the absence of a perfect system, practical solutions need to be developed that will enable countries such as Mexico at least to get started with the process of national scale REDD+ monitoring. To assist with this, the primary goal of this paper was to propose an operational definition and system of measurement, contextualized for the case of Mexico.

Assessment of degradation (as well as deforestation) for REDD+ requires a definition of forest in terms of thresholds, and we suggest that the minimum threshold for tree canopy cover should be 30% because this encompasses the types of degraded forest which have the most chance of increased carbon stocks with improved management. Although there is undoubtedly a need in Mexico for habitat protection and restoration of some areas with a lower level of tree canopy cover, we believe that this could be better achieved by other conservation instruments and policies. Mexico´s forest law is clear that agricultural plantations do not count as "forests", but it is not yet clear whether trees introduced as a result of the promotion of sustainable agroforestry practices will be eligible for crediting under a national REDD+ programme.

When it comes to identifying areas that are degraded, and change in these areas over time (i.e. "degradation activity data"), we suggest that it is not possible at present to construct a baseline or reference emission level, relevant to most types of degradation in Mexico, based

solely on remotely sensed data. This is primarily because the available high resolution images, although they are useful in identifying areas which appear to be degraded now, and have good potential to track changes in these in the future, are too recent to provide sufficient historical coverage. In addition, data from the national forest inventory are also of too recent to be used to determine past degradation levels. Meanwhile, low- and mid-resolution remotely sensed images, which have been available for longer, are far too coarse in resolution to allow sufficiently accurate identification of areas that are degrading. As degradation frequently occurs as a cyclic phenomenon over a management unit (e.g. over forest areas used by a community of small farmers for slash-and-burn agriculture or for repeated commercial unsustainable timber harvesting) it needs to be assessed in an aggregated way at the management unit level or over the whole landscape. In Mexico appropriate units could be an ejido, community or small private property, or perhaps a landscape unit that captures a relatively homogeneous pattern of local forest uses across multiple ejidos.

Current available remote sensing data and methodological approaches do not permit accurate quantification of the rate of loss of biomass within degrading forests (which would form the basis for the estimate of emission factors), as they only observe canopy cover. Historical optical satellite data can only estimate activity (area) data, not tree biomass stock per hectare. Biomass stocks can be estimated with lidar and intense field sampling, but as there are no historical lidar images available it is not yet possible to construct a baseline against which to compare future measurements to assess loss and gain of forest biomass. The Mexican national forest inventory, which does provide data on biomass stocks, has records going back only to 2004 or 2007 with only one re-measurement in most cases. Currently, this is not sufficient for construction of a baseline for degradation emissions data (for which data from more than 10 years would be needed). Moreover, the inventory plots are so widely spaced that they cannot be used to assess stock change at the forest management unit level. At this scale the best future solution may be inventories made by landowners or communities themselves, as an integral component of their REDD+ management activities.

At present it will be very difficult for Mexico to make claims for reduction in emissions from degradation. This will have to wait until sufficient data are available to construct an appropriate baseline or reference emission level. However, to the extent that technology permits assessment of increases in forest biomass over the coming decade (e.g. evidence at national level from the national forest inventory, and possibly lidar data from particular sites of REDD+ interventions), these could be expressed in terms of tonnes of carbon and credited as forest enhancement, that does not fundamentally require a baseline.

We propose that, in the meantime, a local level, bottom-up approach will be needed, not only to assess forest degradation emissions effectively, but more importantly to assess the effectiveness of different REDD+ interventions which aim to reduce degradation. For this, the setting up of benchmarks, which reflect local conditions over relatively homogeneous areas, would be invaluable. The use of benchmarks needs to be well informed by an understanding of the dynamic processes that are occurring in each forest assessed in order to prevent the unjustified assumption that if the degradation agent is removed forest will follow a determined successional path. Under current capabilities the use of benchmarks is likely to offer the only realistic option for evaluation of the impacts of REDD+ activities on forest degradation.

Chapter 3. Identification and quantification of drivers of forest degradation in tropical dry forests: a case study in Western Mexico

This chapter is based on: Morales-Barquero L, Borrego A, Skustch M, Kleinn C, Healey J Identification and quantification of drivers of forest degradation in tropical dry forests: a case study in Western Mexico *Land Use Policy* 49:296–309.

Abstract

The intensity of forest degradation is linked to landowners´ decisions on management of their shifting cultivation systems. Understanding the processes involved in this land use type is therefore essential for the design of sustainable forest management practices. However, knowledge of the processes and patterns of forest transition that result from this practice is extremely limited. In this study we used spatially-explicit binary logistic regression to study the proximate factors that relate to forest degradation by combining biophysical and socio-economic variables. Our study region is within the Ayuquila Basin, in Western Mexico, a typical fragmented tropical dry forest landscape dominated by shifting cultivation. Through a survey and semi-structured interviews with community leaders we obtained data on the forest resources and on the uses that people make of them. Detailed forest cover maps for 2004 and 2010 were produced from high-resolution SPOT 5 data, and ancillary geographical data were used to extract spatial variables. The degree of social marginalization of each community and the ratio of forest area to population size were the main factors positively correlated with the probability of the occurrence of forest degradation. Livestock management and use of fence posts by the communities were also positively associated with forest degradation. Among biophysical factors, forest degradation is more likely to occur in flatter areas. We conclude that local drivers of forest degradation include both socioeconomic and physical variables and that both of these factors need to be addressed at the landscape level while developing measures for activities related to REDD+.

Keywords: forest degradation, drivers, shifting cultivation, logistic regression, *ejido*, tropical dry forests, REDD+, forest cover change

3.1. Introduction

Determining the proximate and underlying causes of deforestation and forest degradation of tropical forests is a key prerequisite for the development of activities for REDD+ (Reducing Emissions from Deforestation and Forest Degradation) (Salvini *et al.*, 2014). Developing countries participating in REDD+ are encouraged to report on human-induced activities that are linked to greenhouse gas (GHG) emissions from forest land (UNFCCC, 2010; Hosonuma *et al.*, 2012). The identification of these activities and locating them in a spatially explicit manner may be of utmost importance for effective REDD+ interventions (Kissinger *et al.*, 2012). While there is considerable understanding of the processes causing

deforestation (Geist & Lambin, 2002), knowledge of drivers that cause changes in forest carbon stocks in forests that remain forests (i.e. degradation) is quite limited, especially for tropical dry forests (TDFs) (Murdiyarso *et al.*, 2008a).

Tropical dry forests have not received as much attention as humid forests in the context of REDD+, mainly because they have lower carbon stocks and increments per area (Blackie *et al.*, 2014). Nonetheless, TDFs cover extensive areas (approx. 42% of the tropics and subtropics worldwide (Murphy & Lugo, 1986; Miles *et al.*, 2006), and may potentially play an important role in climate change mitigation. They are notably important ecosystem in the Neotropics, where they cover an area of approx. 520,000 km^2 (Portillo-Quintero & Sánchez-Azofeifa, 2010), that corresponds to more than half of the global total extent of TDFs (Miles *et al.*, 2006). Moreover, TDFs provide a variety of ecosystem services (Maass *et al.*, 2005) and although holding lower values of species richness than rainforests, they have particularly high levels of endemism and beta biodiversity (Gentry, 1995).

Despite their importance in providing ecosystem services, TDFs are among the most threatened ecosystems in the Neotropics (Miles *et al.*, 2006). They have suffered high conversion rates and the remaining areas are heavily degraded and fragmented (Trejo & Dirzo, 2000; Sánchez-Azofeifa *et al.*, 2005). This is because TDFs often support high human population densities, with many people depending on forest land and forest resources (hereafter forest resources) for their livelihoods (Sunderlin *et al.*, 2008); particularly through shifting cultivation (Saikia, 2014), but also to provide fuelwood, charcoal, house-building materials, fence posts and non-timber forest products (NTFP) (Maass *et al.*, 2005). In addition, commercial logging and cattle grazing frequently affect the structure and composition of TDFs (Sanchez-Azofeifa & Portillo-Quintero, 2011).

This paper presents an analytical framework to identify drivers of forest degradation in TDFs and other variables that are correlated with it. Satellite imagery that provides data at a scale fine enough to detect forest degradation due to shifting cultivation is used together with on-the-ground data on the local use of forest resources. It is important to stress that, in our analysis, shifting cultivation (here meaning slash-and-burn agriculture, subsistence farming and swidden cultivation, following the terminology of Mertz (2009) is considered to cause forest degradation rather than deforestation because its cycle of operation involves clearance followed by regrowth of forest that creates a landscape with lower biomass density that still qualifies as forests, in contrast to deforestation that implies a permanent conversion of land cover from forest to non-forest (Houghton, 2012). As a result, landscapes where shifting cultivation is practiced are complex mosaics made up of patches that are losing or gaining forest carbon stocks (Mertz *et al.*, 2012). However, although there can be carbon gains at the landscape level during particular periods of time, in their early development stages the

resulting secondary forests on average usually hold lower carbon stocks than mature forests (Read & Lawrence, 2003; Lawrence *et al.*, 2005; Becknell *et al.*, 2012). Furthermore, lower capacity to store carbon and modified species composition have been observed in secondary forests as an area is subject to more cycles of clearance and recovery (Lawrence *et al.*, 2010). Therefore, they must be considered as degraded forests in the REDD+ context, both in terms of carbon stocks and regarding their ecological characteristics. However, since most of the discussion on forest degradation has been on selective logging (Putz & Redford, 2010); the inclusion of shifting cultivation as a driver of forest degradation within REDD+ is unclear, and this has significant consequences on countries carbon stock estimations (Pelletier *et al.*, 2011). The core questions relies on whether fallows are classified or not as forest land; while the IPCC (IPCC, 2003) considered fallows as land under predominantly agricultural use, in reality it is a stage of forest re-growth. Most importantly, the methods used by most countries do not distinguish secondary growth due to shifting cultivation from other types of secondary forest (Houghton 2012). Consequently, we argue that these stage of secondary re-growth should be considered degraded forest, because it is not a permanent loss of forest cover to be classified as deforestation and it holds less carbon density.

In order to capture the pattern of forest clearance and subsequent regrowth of forests carbon stocks, observations and analysis at suitably fine spatial and temporal scales are required. Previous studies which analysed multiple dates are limited by coarse and medium spatial resolution (Pelletier *et al.*, 2012a; Li *et al.*, 2014) and may not be adequate to detect patches of small-area agriculture ($\pm$2 ha) with short cycles of forest clearance and regrowth (3-6 years). Many studies have used spatial scales that are too coarse to detect degradation related to shifting cultivation, e.g. Bonilla-Moheno *et al.,* (2013) used data from MODIS with a pixel size of around 250 m. Multi-date medium resolution Landsat data (30 m) have been used in combination with detailed field inventories to detect shifting cultivation in rainforests where clearings are on average 2 ha (Pelletier *et al.*, 2012a). Clearings and fallows were classified using spectral unmixing analysis, a technique that has been successfully applied to the detection of selective logging mostly in moist and wet tropical forests (Asner *et al.*, 2005; Souza *et al.*, 2005). However, in TDF coarser spatial and temporal resolution limits the capacity to differentiate between natural open forest areas that have never been cleared and degraded forest or forest recovering after clearance via secondary regrowth, because of overlapping spectral signatures. So far, to the best of our knowledge, only one study Hurni *et al* (2013) has managed to delineate landscape units in which shifting cultivation prevails, by using higher spatial resolution (10 m pixel) satellite data. Nonetheless, this analysis was only done for a single date, i.e. it does not examine change over time.

The scale of analysis is also extremely important in evaluating the human factors that could potentially influence the observed patterns of forest degradation defined by cycles of regrowth and clearance. Typically, proximate causes of forest cover change are hypothesized and tested from national census datasets or data that are aggregated at regional or municipal level because they are readily available. As a result, these analyses may be of limited utility in evaluating local processes in dynamic socio-ecological systems such as shifting cultivation landscapes (Geoghegan *et al.*, 2004). Only a few studies (e.g. Roy Chowdhury, 2006; Getahun *et al.*, 2013) have integrated community-level information or analysed it across scales from household to regional (e.g. Overmars and Verburg 2005). Likewise, regional studies that evaluate factors that affect forest degradation at a landscape level are rare (Saikia, 2014).

This situation is not desirable in the context of REDD+ because on-the-ground projects are implemented at a landscape level, and activities are undertaken by individuals and communities on their own parcels of land. To tackle efficiently the causes and consequences of forest degradation, analysis at a scale compatible with the degradation processes is needed. For example, in Mexico, where some studies have claimed that as much as 80% of the forest area is on communal land managed by rural agrarian communities (Bray *et al.*, 2006), data at the community level is required (Skutsch *et al.*, 2013). These agrarian communities are in any case the target group of most REDD+ programs in Mexico (Corbera & Estrada, 2010) since the policy of the Mexican government is to use REDD+ as a strategy to promote cross-sectoral rural development, as well as to foster the sustainable management of forest ecosystems (SEMARNAT, 2010).

In this paper we use as a case study a landscape in Western Mexico that contains large areas of TDF in which shifting cultivation is the traditional way of growing crops. We address three main questions: 1. Can the patterns of forest cover change in TDF be associated with forest degradation at the landscape scale? 2. Which factors determine forest degradation in a TDF landscape under a shifting cultivation system? 3. Can variation in the use of, or demand for, forest resources and forest land by communities provide an indication of the probability of forest degradation in a TDF socio-ecological landscape? To explore these questions, a detailed forest cover map was produced through an approach that allows land cover changes due to shifting cultivation to be tracked. Next, the information derived from the interpretation of this map was used in a statistical model that allows the identification and quantification of the probability of forest degradation from an integrated set of biophysical and socio-economic variables. Finally, we further explore the relationship between the use of forest resources such as firewood and poles, and forest degradation

associated with shifting cultivation, to explore the utility of using demand for forest resources as an indicator for monitoring forest degradation in the context of REDD+.

3.2. Materials and Methods

3.2.1. Study Site

The study was carried out in the Ayuquila Watershed (~19°25' - 20°10.0"N, 104°3' - 103°3'W), in the state of Jalisco, Mexico. The study area embraces 10 municipalities and has an area of about 4,000 km². The southern boundary of the study area is formed by the Sierra de Manantlán Biological Reserve (Fig. 3.1), which is known for its high biodiversity and which protects a water catchment providing water for more than 400,000 people (Cuevas *et al.*, 1998). Due to its importance for water, biodiversity and other ecosystem services, and because the municipalities are already working together on environmental planning under a *Junta Intermunicipal del Rio Ayuquila* (JIRA), the area was selected as a REDD+ Early Actions Area by the Mexican government (SEMARNAT, 2010).

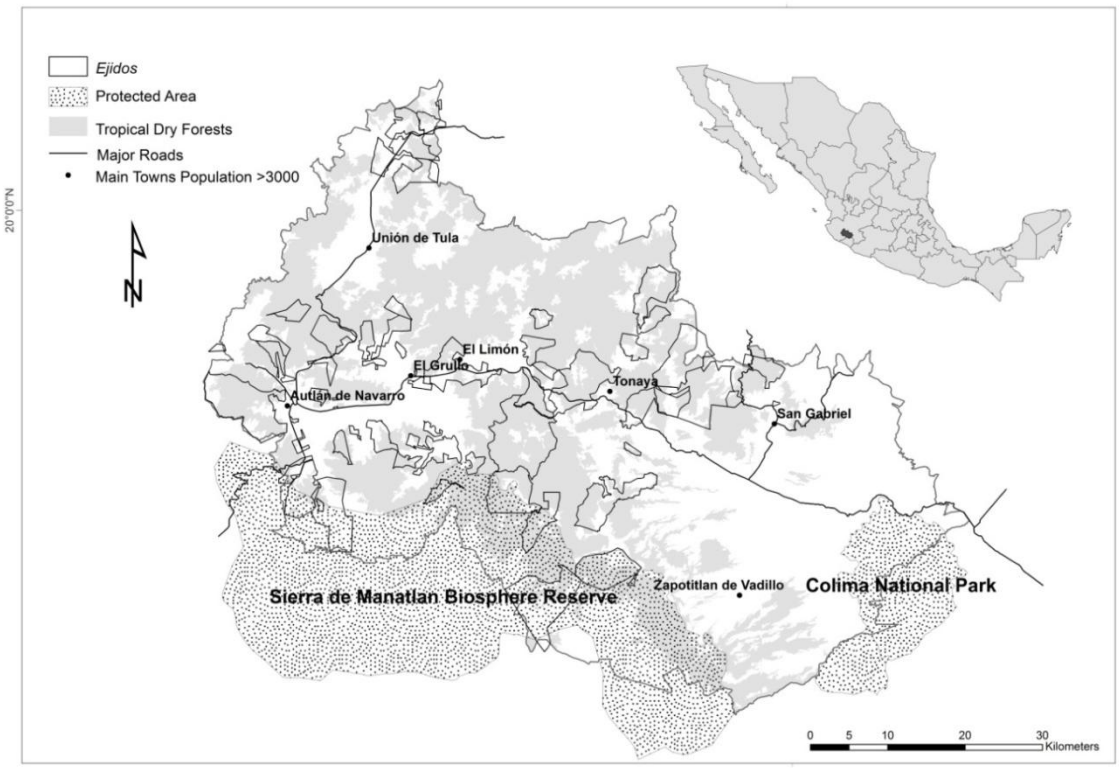

Figure 3.1 Regional map of the study area showing the 29 sampled communities ("*ejidos*") within Ayuquila Watershed, Jalisco, Mexico.

The study area has a complex topography that ranges from 260 m to 2500 m above sea level. The average annual precipitation is 800-1200 mm, and occurs mainly between June and October; and the range of average monthly temperatures is 18-22 °C (Cuevas *et al.*, 1998). The topographical and climatic conditions have created a variety of vegetation formations. High altitude areas are dominated by pine and oak-pine forests. At intermediate elevations, and where appropriately moist conditions are present, small patches of cloud forest are found. Lower elevations are dominated by TDF (*selva baja* (Rzedowski, 1978)). Trees in this vegetation type typically lose their leaves in the long dry season. In the undisturbed state, these deciduous and semi-deciduous forests have a height range of 4-15 m and a high number of endemic plant species (Gentry, 1995). In terms of population dynamics, the XI, and XII Population Censuses of Mexico show that the communities within the study area have not experienced major population changes in the last two decades (INEGI, 2000, 2010a).

3.2.2. Description of the land use system

The landscape is composed of a mosaic of TDF patches within a matrix of agricultural land. Most of the tropical dry forest is found within *ejidos*, which are settlements with a communal land tenure system. *Ejidos* implement a type of decentralized forest management where decisions regarding land use and management of common resources are taken in a General Assembly, which is chaired by the *ejido* leader and is composed of all those people in the community that have rights to the land (*ejidatarios*). Generally, rights to the land are established when the *ejido* is formed and can only be inherited by one person in a family. All the activities are discussed and approved in a General Assembly and, therefore, *ejido* leaders can be seen as key informants with respect to the use of resources in the *ejido*.

Land is, in principle, a communal resource. Within each *ejido*, there is an agreed division of land uses with defined areas for permanent agriculture and for shifting cultivation, as well as areas of forest. Forest is usually managed communally, although in some *ejidos* an informal privatization of this common land has occurred with each *ejidatario* managing several parcels. The main agricultural products in the *ejidos* in the study area is maize (which is either produced in the shifting cultivation system within the forested areas or in areas which have been permanently cleared for agriculture), and to a lesser extent sugar cane, avocado, and agave (all of which are planted exclusively in permanent agricultural lands).

Allocation of land use within the *ejido* is partly related to topography: permanent agriculture takes place in the low and flat areas, while hilly and stony areas are commonly

used for shifting cultivation. The parcels under shifting cultivation, known as *coamiles*, have an average size of 2.5 ha and the majority of the crops are grown for subsistence (i.e. maize production is primarily for consumption within the household). *Coamiles* are typically cultivated for two-three years and then left abandoned for a fallow period that varies from three to eight years (Borrego & Skutsch, 2014). During this fallow period secondary vegetation regenerates naturally, as a mixture of shrubs and trees. When a patch of land is selected again at the start of a cultivation cycle, this secondary vegetation is cleared. Crops are then sown when the rainy season starts (June/July) and harvested six months later. Afterwards, livestock are kept on the land and fed with the crop residues before the land is abandoned to the fallow period. During the wet season, cattle move around the *ejido*, browsing on the regenerating fallows and forest lands. Consequently, there is a relationship between the number of cattle that an *ejidatario* can own and the area of shifting cultivation. In some cases, *ejidos* may only be able to support that quantity of cattle that can be maintained during the dry season fed on the crop residues of shifting cultivation areas. In addition to cattle grazing, regenerating fallows and forest areas are also the source of fence posts and fuelwood (Fig. 3. 2).

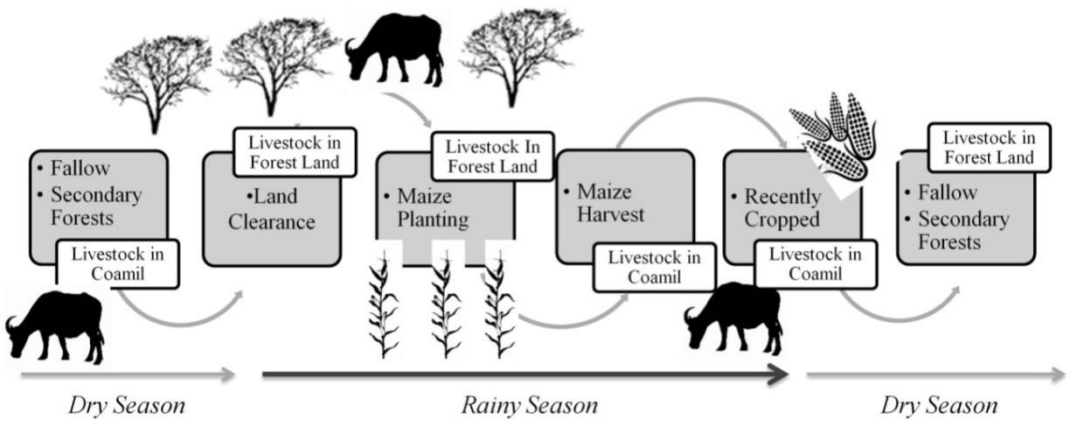

Figure 3.2 Illustration of the shifting cultivation system practiced within tropical dry forests in western Mexico, based on information from field interviews.
The grey boxes show a typical sequence of land cover changes in a parcel found in the area, and the white boxes show the location of the livestock.

3.2.3. Data

To investigate the relationship between different factors involved in forest degradation we conducted a community-level survey (described in section 3.2.3.2 below), together with a parallel analysis of TDF cover change. Our method to assess the probability of forest

degradation uses two sets of data: 1) biophysical variables derived from remote-sensing image analysis; 2) socio-economic variables derived from the community-level survey and ancillary information. The independent variables described in Table 3.1 are hypothesized to be explanatory of forest cover change, which we consider to be a proxy response variable representing forest degradation in shifting cultivation landscapes. The selection of these variables was based on previous participatory mapping exercises done in five of the surveyed *ejidos* and field interviews.

3.2.3.1. Spatial variables

Forest Cover Change map as a proxy of forest degradation

Temporary forest cover change was analysed to provide an indirect measure of forest degradation. We assumed that having excluded permanent agriculture, this map reflected the temporary forest cover changes in TDF that are indicative of a shifting cultivation system with clearance and regrowth, and that this regime as a whole can represents a form of forest degradation.

This forest cover map was based on SPOT 5 imagery for the years 2004 and 2010. The study area was covered by four scenes corresponding to the dry season (Table S 3.1), when there is the best discriminatory capacity for change detection in dry forests (Kalacska *et al.*, 2008). The images were atmospherically and geometrically corrected to facilitate detection of change over time. Atmospheric correction was performed using FLAASH as implemented in Envi 4.7 (Envi 2006). The geometric correction achieved an accuracy of less than one pixel (10 x 10 m) and images were re-sampled using the nearest neighbour method. Images were mosaicked and co-registered to obtain a pixel-to-pixel correspondence between the two dates (Table S 3.1).

The classification of tropical dry forests and shifting cultivation landscapes is a difficult task, because of the overlapping spectral signature that these land covers have as well as the temporal dimension. Therefore, a previous step was to mask out land cover types not of interest for this study, mainly permanent agriculture and vegetation types different from TDF. This mask was created by segmenting the 2010 image (criteria minimum region size of 1500 pixels, using the mean shift segmentation algorithm). Firstly, segments that match what was classified as permanent crop, urban, bare, permanent pasture, or pine and oak forest land according to maps produced by the National Institute for Geography and Statistics (1:250,000) (INEGI, 2010b) were excluded. This allowed us to remove the bulk of the permanent agricultural areas. Then, any segments found above 1500 m.a.s.l. were removed, because they are outside the distribution range of TDF in the study area. To further refine the

mask, we used image visual interpretation in combination with random field GPS points and ancillary data. Segments were checked against Google Earth historical images (2000-2012), and if the segment had no visible vegetation over that period it was excluded. Segments were differentiated based on their spatial context: permanent agriculture usually covers large continuous areas of flat land (<10° slope) that is usually planted with agave, sugar cane or maize; whereas shifting cultivation is carried out on hilly areas and on smaller parcels that are embedded in forest vegetation. The visual interpretation of the images was ground-truthed during one year of fieldwork in 2011-12.

The final mask was applied to the 2004 and 2010 images. Masked images were classified using the Random Forests algorithm (Liaw & Wiener, 2002; Horning, 2012), because of its outstanding performance (Rodriguez-Galiano *et al.*, 2012; Mellor *et al.*, 2013). For the image classification, the following vegetation and textural indices were calculated: a) Homogeneity index of band 2 and 3 using a 3 X 3 pixel moving window; b) Normalized Vegetation Index (NDVI), c) Canopy Index (CI) and d) Soil Modified Adjusted Index (SAVI) (Table S 3.2). The final images used as input for the Random Forests model consisted of the four SPOT5 bands, three spectral indices (NDVI, CI, SAVI) and the homogeneity index for band 2 and band 3. The selected spectral indices, mainly NDVI and SAVI, are widely used to enhance the contrast between soil and vegetation, while CI which includes the short wave infrared band (SWIR) has been shown to be suitable for estimating vegetation biophysical characteristics especially above-ground biomass (Eckert & Engesser, 2013). The use of the homogeneity index based on the Red and Near Infrared Band has proved useful for estimating successional stages in TDF (Gallardo-Cruz *et al.*, 2012), and was therefore used in our analysis. Each image was classified into three classes: tropical dry forests (>10% crown cover); shifting cultivation (<10% crown cover), i.e. land that was actively being used for the cultivation phase; and others (shadows and clouds). Training samples were selected on each of the classes based on 243 random GPS field points acquired during field work during 2011-2012.The classified images from 2010 were validated with 94 randomly selected field points. All the image classification and validation procedures were carried out using a combination of Qgis 2.2 (QGIS Development Team, 2013) and R 3.0.0 (R Core Team, 2013).

Finally, the area of regrowth and clearance of TDF was estimated for the whole landscape and for each community. The information derived from this map was used to extract the response variable used in the statistical model.

Other biophysical variables

Other potential explanatory variables were derived from ancillary data, namely altitude, slope, distance to the closest major town (population > 3000) and distance to the nearest road. These variables were selected because they have been used in the identification of factors associated with vegetation changes in previous studies (Crk *et al.*, 2009). Both altitude and slope were derived from a 30 X 30 m resolution digital elevation model (CEM 2.0 from INEGI) and slope percentage was mapped using a 3 X 3 pixel moving window. The distance to the nearest main town was calculated for each point using the tool Hubdistance, available in Qgis 2.2 This tool iterates until it finds the shortest ellipsoidal distance to the closest hub (a town in this case) from a defined point (see sampling procedure in the next section). The distance to the nearest road was calculated as the perpendicular distance between a defined sampling point and the road, this was done using the Near Tool in ArcMap10.0.

3.2.3.2. Socio-economic variables

The socio-economic data were acquired through a survey carried out in 2012 in 29 *ejidos* of the Ayuquila basin (Fig. 3.1). The selected *ejidos* were those with ≥ 20% TDF cover as reported in the INEGI IV Vegetation Map (INEGI, 2010b); their mean TDF cover was 43.6% (± S.D. 18%). The boundary of the land area of each *ejido* was obtained from the National Rural Agrarian Registry (RAN).

Socio-economic variables were obtained by household surveys and semi-structured interviews. The survey was informed by previous fieldwork in the area that included participatory mapping in five communities and informal interviews with community leaders. This previous work provided information on how the population of the *ejidos* used their forest land and what resources were obtained from this forest that could potentially be associated with forest degradation. A detailed description of how the survey was designed and applied is provided in Borrego & Skutsch (2014). Over the 29 *ejidos*, the survey of 300 households provided data from which a number variables could be calculated at *ejido* level, namely parcel size cultivated per year, total number of livestock, fuelwood loads and number of fence posts used per year (Table 3.1). The semi-structured interviews with the *ejido* leaders included questions on management practices, main economic activities and the farming system. Information on the population size and marginalization index of each *ejido* was derived from the national Census of Households and Population 2010 (CONAPO, 2012). Marginalization index variables were used as dummy variables (Table 3.1).

Table 3.1 Description of the explanatory variables tested in the statistical model for prediction of forest degradation (bold letters indicate the variables included in the final model).

Variable	Description (Unit)	Mean	S.D.	Spatial Unit
Elevation[1]	Metres above sea level (m.a.s.l)	1163.4	261.5	Pixel
Slope[1]	Slope percentage (%)	35.2	18.0	Pixel
Slope_Elev[1]	Slope*Elevation (interaction variable)	42959.2	27363.1	Pixel
Dist[2]	Topographic distance to nearest main town (km)	10.6	4.9	Pixel
Road[3]	Topographic distance to nearest road (m)	947.8	721.7	Pixel
Livestock[4]	Number of cows	1991.8	1743.7	*Ejido*
Fence[4]	Number of posts harvested per year (a post length is about 1.5 m)	1467.2	1032.1	*Ejido*
Fuel[4]	Average number of fuelwood loads harvested (a load comprises ca. 50-60 small branches)	392.0	408.7	*Ejido*
Parcel_S[4]	Average parcel size cultivated (ha)	6.2	2.9	*Ejido*
Ejidatarios[4]	Number of registered farmers with land rights	107	97.8	*Ejido*
Parcel_T[4]	Number ejidatarios x parcel size (interaction variable, proxy for total cultivated land)	836.9	775.2	*Ejido*
TDF:Pop[5&6]	Ratio between total TDF area and the total population in the ejido	9.6	14.2	*Ejido*
MMI[6]	Medium Marginalization Index: an indicator based on income, education, housing, and population density	9.7	2.1	*Ejido*
HMI[6]	High Marginalization Index: an indicator based on income, education, housing, and population density	6.8	0.4	*Ejido*

Data Sources: 1 = CEM-DEM- Instituto Nacional Estadística y Geografía (INEGI) (30 X 30 m), 2 = Population map from Instituto Nacional Estadística y Geografía (INEGI) (1:50,000); 3= Road Network from INEGI (1:50 000); 4 = Questionnaire survey (this study); 5 = Land Use and Vegetation Map (2010) from INEGI (1:250 000); 6 = Household census (CONAPO 2010).

3.2.4. Sampling procedure for analyses

A total of 2000 random points were established within the 29 selected *ejidos* to derive both dependent and explanatory variables for the statistical model. The number of sampling points selected for each *ejido* was proportional to its estimated TDF area according to the INEGI Vegetation Map (INEGI, 2010b). We used a random sampling procedure (so that the distance between neighboring pairs of points varies) and evaluated spatial autocorrelation of the dependent variable in our statistical model using three tests: Moran *I*, a geographical representation of model residuals and a semi-variogram of model residuals. To test if there was any spatial autocorrelation, these tests were run for both the random grid and for a set of 2000 points selected randomly from a 300 m X 300 m grid. No difference in the value of the three tests was found, therefore the random points data set was used for the remaining analyses. Sampling points that fall in areas with cloud cover were eliminated from the analysis, therefore the model was developed using 1952 points. Sampling points were selected using the Research Analysis Tool available in Qgis 2.2 and spatial autocorrelation was analysed using the ape (Paradis *et al.*, 2004), gstat (Pebesma, 2004) and sp (Pebesma & Bivand, 2005) packages in R 3.0.0.

3.2.5. Data analyses

For each of the 1952 sample points the environmental/socio-economic variables described in Table .3 1 and the response variable were extracted to model the probability of forest degradation in TDF. The probability that a pixel will be degraded depends on choices made by the *ejidatarios* within a decision context (e.g. farmers' preferences, economic returns etc.) so the dependent variable can be considered an unobserved variable y_i^* corresponding to the observed outcomes, in this case TDF cover change per pixel, that do not directly reveal information on farmers' preferences or economic returns. Consequently in this analysis there are two possible outcomes: a) forest degradation (coded as 1), i.e. there has been a change between cover classes from TDF to shifting cultivation (or vice versa) and b) no change in cover class (coded as 0). As was explained in the introduction section above, due to the complex mosaic landscape of the study area we considered any change in a pixel, both TDF cover clearance and regrowth, as an indicator of forest degradation. The outcome is a discrete dependent variable measured on a nominal scale. Statistically, the output corresponds to a binary model in which the unit of observation is a pixel y^* and is assumed to be a linear function of a set of explanatory variables as follows:

$$y_i^* = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_n x_n + \varepsilon \qquad (1)$$

where y_i^* is the probability of a pixel being degraded; β_0 is the intercept capturing features that do not depend on a given pixel's characteristics; $\beta_1, \beta_2, ... \beta_n$ represent coefficients estimated through regression analysis; $x_1, x_2, ... x_n$ are explanatory variables; and ε is the residual error.

If we assume that the residuals have a logistic distribution the probability of forest degradation $\{Y = 1\}$ can be written as:

$$P\{Y = 1\} = \frac{e^{\beta_0 + \beta_1 x_1 + \beta_2 x_2 ... \beta_n x_n}}{1 + e^{\beta_0 + \beta_1 x_1 + \beta_2 x_{2..} + \beta_n x_n}} \qquad (2)$$

and the model can be estimated with the maximum likelihood approach (Menard, 2010).

The use of logistic regression to model probability of land cover changes is a well-established technique (Overmars & Verburg, 2005; Roy Chowdhury, 2006). The magnitude and direction of $\beta_1, \beta_2, ... \beta_n$ indicate the importance and effect of each factor in the probability of forest degradation.

One potential source of error in logistic regression analysis is collinearity of variables. We tested for correlation between independent variables (Table S 3.3), and in cases where correlations > 0.8 were detected between a pair of variables, only the variable with the strongest impact on the model was retained, as recommended by (Menard, 2010).

Models were evaluated by tests of goodness of fit by using log-likelihood, based on deviance residuals of the null and fitted models and the Akaike Information Criteria (AIC) to compare between models and select the final one. Prediction accuracy of the model was evaluated by estimating the area under the receiver's operational curve (AUC-ROC) using an independent dataset (Pontius & Schneider, 2001). The magnitude of the effect of each variable on the probability of forest degradation was estimated using marginal effects based on the mean values of each variable. Finally, we evaluated the relative importance of each of

the variables in the final model by comparing the difference in the values of log-likelihood. All the statistical analyses were performed in R 3.0.0., using the ROCR package for ROC analysis.

Pearson correlation analysis was used to explore how the variation in the use/demand of forest resources by the *ejidos* (i.e. input variables for the model) related to the change in TDF cover. This analysis was done to further evaluate if a higher intensity of demand for forest resources is linked with regrowth or clearance of TDF cover and therefore whether these variables can be used as a practical indicator in this context.

3.3. Results

3.3.1. Patterns of regrowth and clearance for the tropical dry forest cover

Approximately 65% of the study area showed no change in TDF cover between 2004 and 2010, and was therefore presumed not to have been used for shifting cultivation at all. About 35% of the study area (which was made up of 20 936 ha of TDF clearance, 24 090 ha of regrowth, and the areas under shifting cultivation (Table 3.3)) can be considered as degraded TDF. From this, 24% underwent transition (cover clearance or gain) (Fig 3.3 & Table 3.2), indicating that it had been used for shifting cultivation between these dates but was not being cultivated in these particular years and 11% was classified as under the cultivation phase of shifting cultivation in both dates (Table 3.3). The areas classified as shifting cultivation on both dates (i.e 11% of the study area), most probably were cultivated in 2004, then left to rest and started a new cultivation cycle shortly before 2010. As the area of clearance and gain of forest cover is similar (Table 3.3), forest cover in the region may be considered stable in the long run, despite the fact that at least 24% of the area was undergoing cover change. This highly dynamic pattern of TDF cover is replicated in most of the 29 individual *ejido:* with 17 experiencing a transition in TDF cover on more than 20% of their area, a further six on 15-20% of their area, but none experiencing a net loss of TDF cover of more than 15% of their total area, and only four having a net loss between 10 and 15% (Table S 3.4).

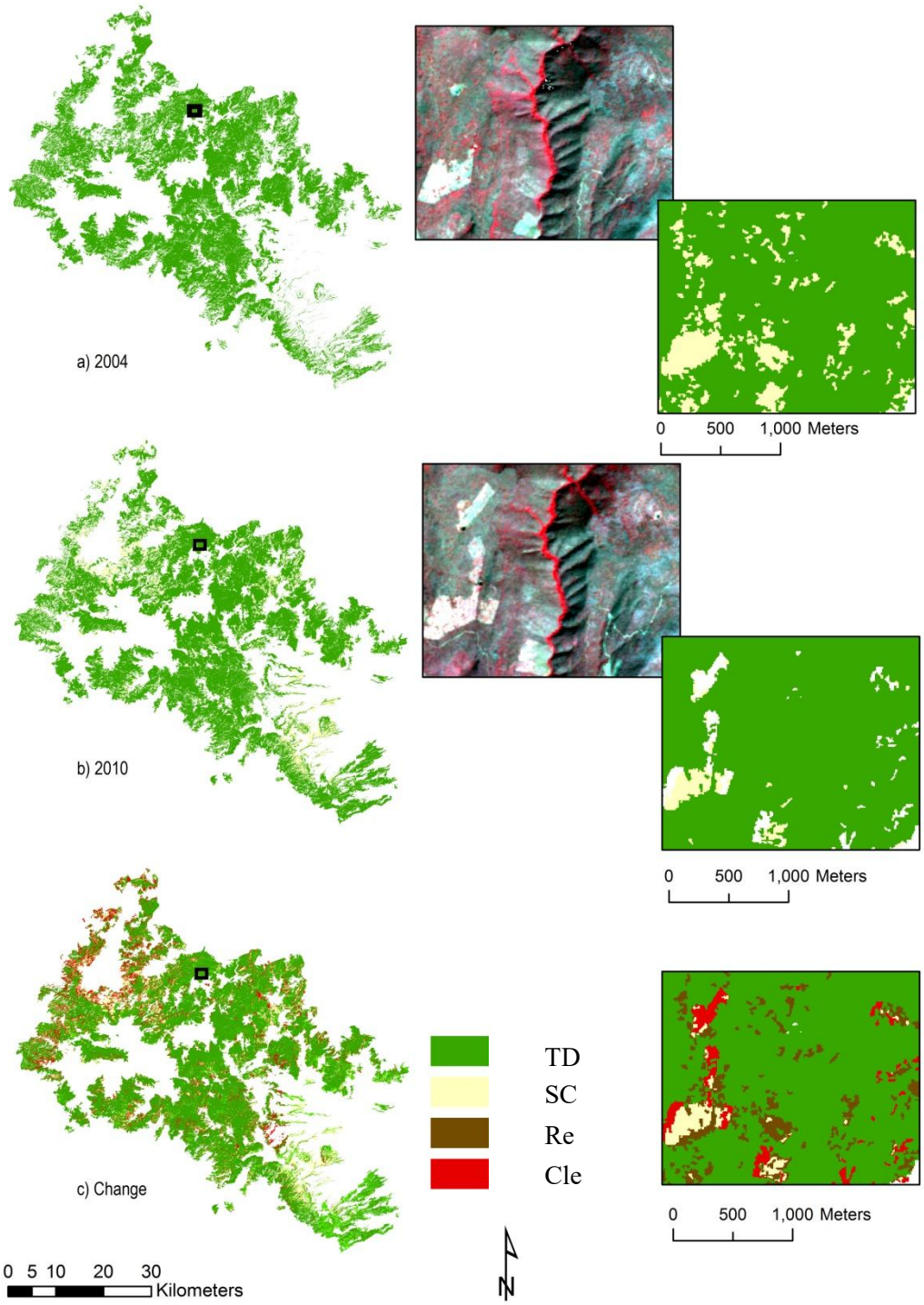

Figure 3.3 Tropical dry forest (TDF) and shifting cultivation (SC) land cover in the Ayuquila Basin, Jalisco, Mexico.

a) TDF and shifting cultivation cover in 2004, b) TDF and shifting cultivation cover in 2010, c) Change in cover between TDF and shifting cultivation 2004-2010. Overall accuracy for 2010 = 98%, kappa coefficient equals 0.973, Minimum mapping Unit (MMU) = 0.9 ha (3 X 3 pixels)

Table 3.2. Estimated areas of tropical dry forest (TDF) and shifting cultivation cover for 2004 and 2010 in the Ayuquila Basin, Jalisco, Mexico.

Land Cover Type	2004 (Ha)	2010 (Ha)
TDF	140 836	143 990
Shifting cultivation	44 583	41 429

Table 3.3. Area estimated for each transition between land cover types in the Ayuquila Basin, Jalisco, Mexico

Transition 2004-2010	Area (Ha)	%
No change, TDF	119 901	64.7
No change, shifting cultivation	20 493	11.1
Change, shifting cultivation to TDF (forest regrowth)	24 090	13.0
Change TDF to shifting cultivation (forest clearance)	20 936	11.3

3.3.2. Factors influencing and related to forest degradation

Alternative models using socioeconomic and biophysical data for the 29 *ejidos* as explanatory variables for the probability of TDF degradation were developed. The variables livestock and fuelwood were highly correlated (r= 0.81, p <0.001) (Table S 3.3), therefore only livestock number was used for model development. We selected the model that had the highest log-likelihood ratio and lowest AIC and residual deviance. The selected model included eight variables, plus an interaction term between slope and elevation (Table 3.4). The evaluation of model residuals showed a slightly positive spatial autocorrelation (Moran's I = 0.015, p <0.001). However, as the model residuals and semi-variogram revealed no spatial structure (Fig. S 3.1 & Fig. S 3.2), no further adjustment of the model was made to account for spatial structure, as the use of spatial autoregressive models is not recommended for logistic regression (Dormann, 2007).

Both biophysical and socioeconomic variables were significantly associated with the probability of TDF degradation (Table 3.4). The model results indicated that for every 1% increase in slope there is a decrease of 0.84% in the probability of forest degradation and that slope is the most important biophysical factor for determining if an area will be used for shifting cultivation. In the case of distance from a parcel of land to nearest main town, for every increase of one kilometer, there is a decrease in the probability of forest degradation of

almost 0.5%. There is interaction between slope and elevation; although probability of forest degradation decreases with slope, it increases at higher elevations with small slopes angles, which may be linked to the use of flat areas on hilltops for shifting cultivation which is common in our study area. Of the socioeconomic variables, the one with the strongest relationship to the probability of forest degradation was found to be "high degree of marginalization" of the community. Comparison of the relative size of the marginalization index variables, showed that both highly marginalized communities and medium marginalized communities have a greater probability of forest degradation (12.3% and 8.4% respectively) than communities with a low index of marginalization. The model showed that a higher ratio of TDF to population size decreased the probability of degradation; this means that the more TDF that is available person, the lower the pressure will be on TDF (Table 3.4). The results also revealed that the number of fence posts used per year and the number of livestock were both positively correlated with the likelihood of forest degradation. The value of the livestock and fence coefficients (0.002% and 0.005%) indicate the marginal impact of one unit change in these variables.

Table 3.4. Model results and estimated probability of occurrence of TDF degradation as a function of a series of potentially explanatory variables in the Ayuquila Basin, Jalisco, Mexico (for variable names see Table 3.1).

Variable Name	Estimated coefficient (*b*)	S.E.	p	Marginal effect
Slope	-0.06121	0.01119	0.0000	-0.8424
Dist	-0.03539	0.0161	0.0281	-0.4870
Road	-0.00036	0.0001	0.0010	-0.0050
TDF:Pop	-0.01778	0.0067	0.0075	-0.2447
Fence	0.00033	0.0001	0.0001	0.0046
Livestock	0.00017	0.0001	0.0032	0.0024
HMI	0.89220	0.2189	0.0000	12.2787
MMI	0.61050	0.2498	0.0145	8.4019
Parcel_T	-0.000415	0.0002	0.0180	-0.0057
Slope_Elev	0.00004	0.00001	0.0000	0.0005

Constant	-1.38800	0.3052	0.0000	-19.1020

n = 1952, S.E. = standard error of estimation of the model, model log likelihood ratio = -763.76 (df = 11); AUC = 66.35; residual deviance = 1527.5; null deviance = 1605.2;AIC = 1549.5

Variables were ranked according to their importance (i.e. their contribution to the log-likelihood value of the model estimation). The relative effect showed that the biophysical variables, which were observed at pixel level, contributed altogether to 39% of the log-likelihood value of TDF degradation, and community-level information explained around 61% (Table 3.5). Among the biophysical variables Slope and Slope_Elev combined explained 34 % of the variance of the model; while among the socio-economic variables, the number of fence posts ranked highest, accounting for 21% of the log-likelihood value, followed by the high marginalization index (17%).

Table 3.5. Contribution of explanatory power for each variable in the statistical model in the Ayuquila Basin, Jalisco, Mexico (for variable names see Table 3.1).

Variables	Change in Log Likelihood (*df*)	% Explained by each Variable	Variable Importance Rank
Intercept	-802.6		
Slope + Slope_Elev	-789.3 (3)	34.1	1
Fence	-768.9 (9)	20.8	2
HMI	-780.8 (6)	17.1	3
Parcel_T	-763.7 (11)	7.6	4
TDF:Pop	-777.0 (8)	7.0	5
Livestock	-766.71 (10)	5.7	6
Dist	-788.0 (4)	3.2	7
MMI	-779.7(7)	2.8	8
Road	-787.47 (5)	1.6	9
Total		100	

The model's goodness of fit (AUC = area under the curve) was 0.66 (Fig. 3.4), which means that it can correctly predict changes from TDF to shifting cultivation and *vice versa* with a probability of 0.66, which is better than that predicted only by chance (AUC =0.5) (Gellrich *et al.*, 2007).

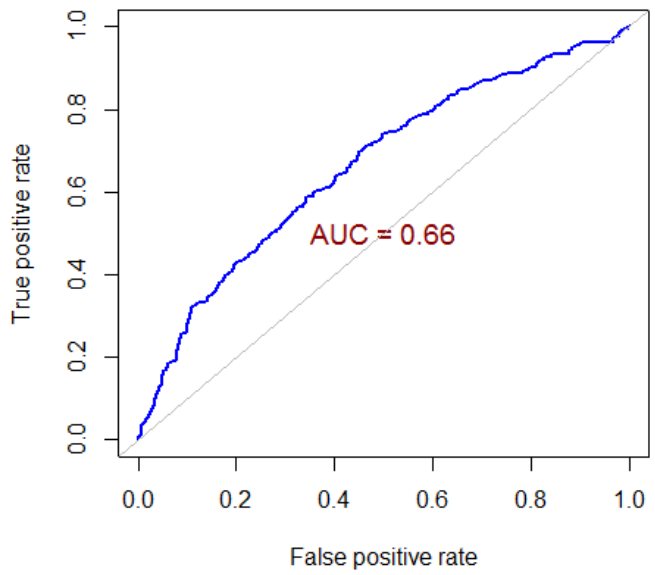

Figure 3.4 Receivers operating characteristic (ROC) curve for the probability of TDF degradation in the Ayuquila Basin, Jalisco, Mexico.
Overall model prediction accuracy evaluated by AUC = 66%.

The number of livestock observed in each *ejido* correlated positively with the amount of TDF regrowth and TDF clearance (Fig 3.5), although its contribution to the log-likelihood value is less important than the number of fence posts (Table 3.4). There are around 6 *ejidos* that have large amounts of TDF change (points that deviate strongly from the regression line), as well as high levels of both livestock and fuelwood loads (Fig. 3.5a & 3.5b), which implies that these communities have a greater demand for forest resources and forest land. The observed positive association between TDF change and livestock suggests that the number of livestock is a good indicator of the intensity of use of the forest resources and might be a proxy that could be used in monitoring forest degradation in this type of socio-ecological landscape.

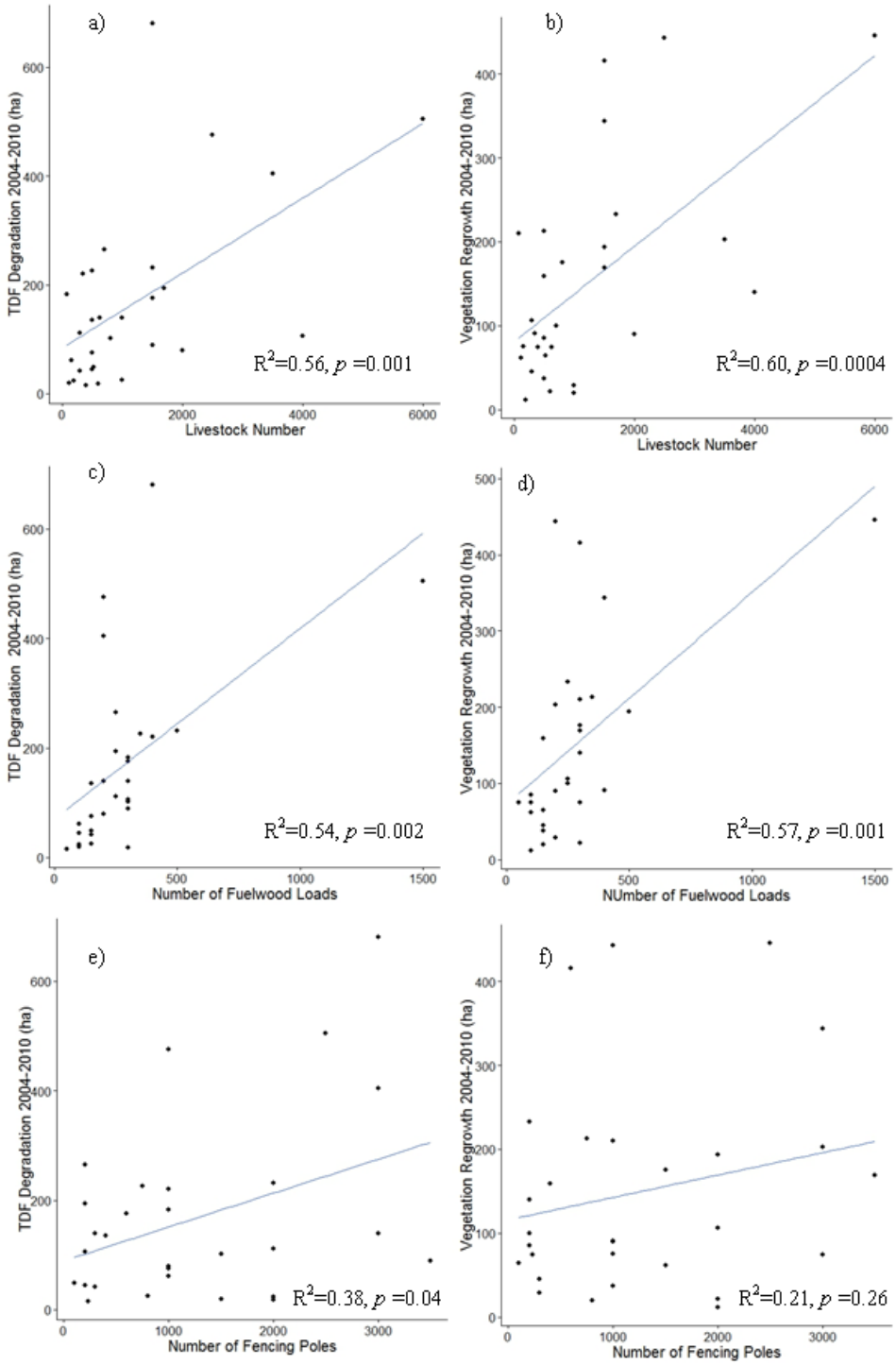

Figure 3.5 Correlations between the resources used and the amount of TDF cover change for 29 *ejidos* in the Ayuquila Basin, Jalisco, Mexico.

a) number of livestock versus forest clearance; b) number of livestock versus forest regrowth; c) number of fuelwood loads extracted per year versus forest clearance; d) number of fuelwood loads harvested per year versus forest regrowth; e) number of fence posts harvested per year versus clearance; f) number of fence posts harvested per year versus regrowth (* $p<0.05$, $df = 27$).

3.4. Discussion

3.4.1. Monitoring and detection of forest degradation in shifting cultivation landscapes

In this study we characterized changes in TDF cover, showing that they can be statistically associated with forest degradation caused by the practice of shifting cultivation. The fact that there were similar amounts of forest regrowth and clearance over a 6-year period, both at the community and landscape levels, suggests that these landscapes under shifting cultivation are essentially sustainable, at least in terms of forest cover area and thus levels of above-ground carbon stock that can be associated with forest cover. However, the total carbon balance of shifting cultivation systems, will depend on many factors, some related to management practices, such as the use of fire for clearing, and other ecological factors like the carbon sequestration capacity of forest regrowth. Several authors have reported rapid accumulation rates of above-ground biomass (AGB) during TDF regrowth after complete clearance (Lawrence *et al.*, 2005; Álvarez-Yépiz *et al.*, 2008; Lebrija-Trejos *et al.*, 2008); and age of land abandonment has been found to explain up to 46% of the variation in AGB for TDF (Becknell & Powers, 2014). Recent studies indicate, furthermore, that shifting cultivation can conserve and even increase carbon stocks in the soil (Salinas-Melgoza *et al.,* 2015). On the other hand, in terms of their structure and composition of species (and also probably functional traits), secondary TDFs formed after clearance are very different from their old-growth counterparts (Chazdon *et al.*, 2007) with a much lower average biomass density (Marín-Spiotta *et al.*, 2008; Kauffman *et al.*, 2009). In this sense they can be considered degraded, although their delivery of ecosystem services and value as habitat for biodiversity is still higher than many other land cover types.

We have provided evidence that shifting cultivation, as practiced within the *ejidos*, contributes to forest degradation but not to a net loss of forest cover. In our study area, shifting cultivation systems represent a form of local equilibrium, with a balance in rates of forest degradation (clearance) and recovery at the landscape scale, and as a result the potential for no net carbon emissions being produced in the long-term (Houghton, 2012). However, this situation could easily change if management practices within the *ejido*, government policies or markets favor an intensification of the agricultural practices, causing a shortening of the fallow periods or the cultivation of cash crops as has occurred in other areas (Dalle *et al.*, 2011; van Vliet *et al.*, 2012).

The methodology of the present study, a combination of high resolution image segmentation and a robust classification method (Rodriguez-Galiano *et al.*, 2012) based on spectral-textural information from the image, was successful in detecting small patches

under shifting cultivation and enabling quantification of both the clearance and regrowth transitions of TDF subject to shifting cultivation management. As such, we suggest it might be a valuable tool for more widespread use to quantify forest degradation. Nevertheless, we recognize that using forest area cover change as a proxy of forest degradation could lead to underestimation, because further reductions in tree density can happen within the forest area, as has been found in arid and semi-arid ecosystems (le Polain de Waroux & Lambin, 2012). To improve the analysis, a classification of the canopy cover density could be integrated with the forest cover change analysis, however this will require even higher resolution data (~1 m) and the development of algorithms that can count tree crowns for TDF, which can be challenging due to seasonal leaf phenology and variability of forest structure (Arroyo-Mora *et al.*, 2005).

The difficulties of detecting forest degradation that occurs under the canopy, such as overgrazing, excessive fuelwood collection and small-scale selective harvesting for timber, with satellite data have been widely acknowledged (GOFC-GOLD, 2013). We tried to overcome this limitation by associating the effect of these factors with the cycles of clearance and regrowth within a shifting cultivation landscape. These activities are possibly occurring in those parts of the TDF that showed no change in forest cover (65%), therefore part of this area could be considered low degradation. It is possible that the estimate of degradation that our method produces is not well correlated with these below-canopy impacts. Ideally, measurements of the amount of biomass actually extracted should be made. Though challenging, further research should be undertaken to investigate on-the-ground data of spatial variation in rates of grazing and wood extraction (ideally at a pixel level) with satellite data, to find out whether the latter detects the impact on forest structure and composition of the former (Romero-Duque *et al.*, 2007; Chaturvedi *et al.*, 2012). This is especially important in the context of REDD+, since avoiding degradation should not prohibit the use of forest resources but rather encourage change towards sustainable use.

The landscape-scale forest cover dynamics observed in the present study might have important implications for national and international forest environmental policy. In Mexico, there is a financial incentive for farmers to continue to clear regenerating forest from previously cultivated land because of the rules of the subsidy Program of Direct Payments to the Countryside (PROCAMPO), which makes payments per hectare of agricultural land. If the fallows are left uncut and advanced secondary forest develops, the government will classify it as abandoned land that is no longer used for agriculture and therefore the *ejidatarios* will lose their subsidies from PROCAMPO. Moreover, according to the modification of the legal Mexican Forest Code, once the land is designated as forest (when it is an advanced regenerated state), any tree harvesting in such areas will require a

management plan (Román-Dañobeytia *et al.*, 2014). However, in addition to that, leaving the fallow to recuperate for long periods is not favored by farmers for logistical/labor reasons. As several farmers mentioned during our field interviews: "We need to clear the area because it grows too fast, in two-three years it is too tall, and then we cannot clear it". However, more detailed socio-economic and policy-oriented research is required to determine the effects of current forest and agricultural policies on the shifting cultivation cycles observed in complex TDF landscapes, such as those of the current study, and how they will affect the sustainability of shifting cultivation systems.

3.4.2. Drivers of forest degradation in tropical dry forest

We examined the importance of different biophysical and socio-economic variables to explain change in forest cover, which itself can be used as a proxy for forest degradation in a mosaic landscapes with shifting cultivation. Amongst the tested biophysical variables, slope was most closely related to forest degradation. Flatter areas had a higher probability of being used for shifting cultivation, but this is slightly influenced by elevation, such that there is a higher probability of degradation in flat areas on hilltops. Several studies have reported greater forest clearance on areas with less steep slopes (e.g. Newton & Echeverria, 2014), which can be attributed to better soil quality and less investment in labor than for steep slopes, where indeed most of the remaining unconverted TDF is found (Becknell *et al.*, 2012). This might have implications for management decisions related to land use planning that aim to enhance carbon stocks and avoid forest degradation in the landscape, because better environmental conditions that might increase net carbon sequestration of the landscape will be found on less steep terrain.

With reference to the tested socio-economic variables, as with all explanatory models, care needs to be taken not to confuse correlation with cause. The modeling results demonstrated that areas with a higher degree of marginalization had a higher probability of forest degradation. The marginalization index, which is a standard tool used to guide social policy in Mexico, is built on eight variables related to economic factors and education level of the entire population living in an *ejido* (CONAPO, 2012). Our findings suggest that *ejidos* characterized by lower incomes and low education levels, as well as less available TDF per person (those with higher population densities), are more dependent on clearing land for shifting cultivation. However, the causal order here needs to be considered carefully. Are communities carrying out shifting cultivation because they are marginalized (poor) and depend on it for subsistence, or are they poor because they are carrying out shifting cultivation? This question cannot be answered from our data but is important for the development of policy. In order for *ejidos* to participate in carbon mitigation projects the

opportunities and constraints of each community should be carefully evaluated, so that poorer communities can also benefit from projects (Tschakert *et al.*, 2006). Furthermore, as discussed by Borrego & Skutsch (2014), there are marked differences within an *ejido* population in the proportion of income obtained from shifting cultivation and benefits derived from the TDF, by larger and by smaller operators.

Individual tests found evidence of significant positive correlation between the number of livestock or of fuelwood loads or (less strongly) fence posts and TDF cover change per *ejido*. Again, the relationship between number of cattle and fence post extraction with area dedicated to shifting cultivation should not necessarily be seen as causal since these could also be by-products (effects) of other processes. Moreover, the model selection procedure for probability of TDF cover change per sample pixel showed that these variables only had a weak relationship (and because of its high correlation with the number of livestock, fuelwood was not included as a separate explaining variable). It is possible that the effect of these variables is confounded with other variables included in the model, especially those related to socio-economic characteristics that distinguish the *ejidos*. In this area, livestock are used as a liquid asset that can be converted in an emergency; owning cattle requires capital and therefore only higher-income *ejidatarios* will be able to own several animals (Borrego & Skutsch, 2014), and the proportion of community members in this group are reflected in the marginalization indexes evaluated.

Statistical models are useful to determine the relative importance and interaction of possible agents of forest degradation, especially because it is feasible to incorporate many context-specific data, in this case information on livestock, harvested forest products, the ratio between TDF area and local population size etc. (Roy Chowdhury, 2006). However, there are many factors that interact and which together have an influence on the socio-ecological systems shaping the use of TDF resources. As with any model, the initial set of factors to be included will determine the outcome. For this reason, it is crucial that the context in which forest degradation is taking place is well understood on the ground (Mon *et al.*, 2012). For Mexico, future assessment of drivers of forest degradation and appropriate interventions to address it should include information on the different types of payment for ecosystem services and on other major market and subsidy incentives influencing decisions by land users, as well as factors influencing rural population density, e.g. through migration, that might be important in certain areas.

In Mexico REDD+ interventions promoting maintenance or enhancement of carbon stocks will probably be directed to *ejido*s, and there will therefore be a need for monitoring protocols that can effectively evaluate local interventions (Danielsen *et al.*, 2011; Mertz *et al.*, 2012) and that do not themselves impose major costs (Morales-Barquero *et al.*, 2014).

The approach of collecting field data through interviews in combination with analysis of remotely sensed data, as tested in the present study, can be used to support the evaluation of REDD+ or other policy interventions. At a regional level keeping records of activities related to agriculture that drive forest degradation, such as the density of livestock, human populations and the size of agricultural parcels, is easier and less costly than obtaining precise estimates of AGB. It is important that if monitoring of land use activities is used instead of, or complementary to, AGB measurements, that such an analysis include both biophysical and socioeconomic data. This is important as these two types of information contributed almost equally to the explanation of spatial variation in the occurrence of forest degradation, in our study.

3.4.3. Shifting cultivation in the context of REDD+

Views on the sustainability of shifting cultivation are contested (Sunderlin *et al.*, 2008; Mertz *et al.*, 2012; Fox *et al.*, 2014) and this debate needs to be revisited in the context of REDD+ and the opportunities for climate change mitigation offered by modification of shifting cultivation practices acknowledged. Traditionally, shifting cultivators have been blamed for deforestation and there is a negative view towards this type of agriculture that argues in favor of land allocation to more intense agricultural systems in order to spare other land for conservation (Chandler *et al.*, 2013). However, secondary forests that derive from fallow systems recover carbon stocks and foster natural regeneration of some commercial TDF species (Valdez-Hernández *et al.*, 2014). Moreover shifting cultivation is the source of livelihoods for many smallholder farmers and represents the primary source of food security for many rural households (Padoch & Pinedo-Vasquez, 2010; Fox *et al.*, 2014). Therefore, in many circumstances prohibiting shifting cultivation and promoting a transition to a combination of intensified permanent agriculture systems and set-aside protected forest land is not socially nor environmental desirable (van Vliet *et al.*, 2012).

To maintain or enhance the sustainability of these systems, REDD+ interventions should target areas with higher potential for carbon sequestration for protection or, where necessary, active restoration (Hardwick *et al.*, 2004). Promoting longer fallow periods may be valuable to avoid the depletion of the carbon sequestration capacity of shifting cultivation systems (Lawrence *et al.*, 2010). The restriction of livestock browsing to certain areas within the shifting cultivation landscape would promote forest regrowth and carbon stock enhancement in other protected areas, though with a high risk of spillover leakage effects to other areas (Hett *et al.*, 2012). Incentives that seek to increase yield from shifting agricultural systems through improve management practices and new technologies without increasing carbon emissions (e.g. climate smart agriculture) should also be part of REDD+ interventions

(Olander *et al.*, 2012), as has been demonstrated in the case of coffee agroforestry systems by Noponen et al.(2013). If, as a result, ejidatarios are able to produce enough maize for their own consumption and to feed their cattle on a smaller area of cultivated land, it is likely that a greater land area within the ejido can be allocated to carbon sequestration and fallow periods will be longer. This change could be incentivized, for example, by credit programs and subsidized fertilizers and seeds, and promoted through agricultural extension programs (Angelsen & Rudel, 2013).

Although there are options by which shifting cultivation can contribute to climate change mitigation, designing REDD+ payments to include shifting cultivation schemes poses multiple challenges. First, the consideration of shifting cultivation as a contributor to forest degradation will depend on the definition of forest that is applied in each country (Houghton, 2012), and on the time period at which the baseline is set. Second, designing payment systems for REDD+ to compensate for avoiding degradation by removing shifting cultivation is likely to run into problems in fulfilling the criterion of equity; unless they are well designed they risk removing the source of food security and livelihood of the most vulnerable community members without adequate compensation, especially in highly marginalized *ejidos*. Third, the impacts on the overall carbon budget of applying alternative agriculture management practices needs to be better understood, as well as the effects of such practices on local livelihoods, because so far there is little empirical evidence of effects of alternative management practices (Palm *et al.*, 2010). Fourth, including shifting cultivation in REDD+ interventions will require cross-sectoral coordination. For instance Mexico already has in place a system that subsidizes agriculture (PROCAMPO) and a payment for ecosystem services program. Both have potential for use in REDD+, but this will mean a joint work plan from institutions involved in the agriculture and the forestry sector. Despite these challenges, shifting cultivation has the potential to provide a good synergy between carbon, biodiversity and food security, if policies are well designed and take into consideration the above mentioned factors among other issues.

3.5. Conclusions

This study illustrates the value of integrating socio-economic and biophysical information to model potential drivers and correlates of forest degradation. Human decisions on how to use forest resources shape TDF landscapes, and form patterns that can be linked to specific activities. The assessment of patterns of forest change with high resolution satellite imagery allowed determination of the dynamics of small-scale agriculture in the area, and revealed that, over the time period studied, clearance and regrowth of TDF was balanced. This implies long-term sustainability and no net carbon emissions, although a large proportion of the

existing TDF is, to a certain extent, degraded and will differ in structure, composition and carbon content from the old-growth forests of the area.

The approach of collecting field data through interviews and combining these with spatial analysis of remotely sensed data at the appropriate scale can be used to develop monitoring protocols aimed at evaluating REDD+ or other policy interventions at a landscape level. By identifying the activities that are linked to forest degradation, easy-to-measure indicators can be developed. Once the appropriate scale of analysis has been identified, this approach can be extended to other areas of TDF with a mosaic landscape structure dominated by cyclical patchy forms of land use (e.g. many African woodlands, (Lambin, 1999)) and similar types of degradation process (e.g. selective logging or fuelwood collection). The integration of socio-economic and biophysical variables, as carried out in the present study, is essential to understand the impact of the use of the land and forest resources of TDF landscapes. Finally, socio-ecological landscapes such as TDF dominated by shifting cultivation are complex to analyse and there are still important knowledge gaps as regard to their dynamics. These interesting socio-ecological systems will continue to be a challenge for carbon mitigation policies for some time.

3.6. Appendices

Table S 3.1. Spot 5 image data used in the study.

Image Reference Name	Row - Path	Date of acquisition	RMSE (pixels)	Number of Ground Control Points
E55773100401311J2A00009	577-310	31.01.2004	0.66	45
E55783100401212J2A09009	578-310	21.01.2004	0.47	14
E55783110401212J2A05007	578-311	04.01.2004	0.42	13
E55793110403282J2A08002	579-311	28.03.2004	0.92	16
E55773101001282J2A06002	577-310	28.01.2010	0.86	13
E55783101002242J2A09017	578-310	24.02.2010	0.23	52
E55783111002242J2A06020	578-311	24.02.2010	0.19	31
E55793111011162J2A00035	579-311	11.16.2010	0.18	25

Table S 3.2 . Vegetation indices used in the study.

Index	Algorithm	Reference
Homogeneity Index *	$\sum_{i,j=0}^{N-1} \frac{Pij}{1+(i-j)^2}$	Haralick *et al.*,(1973)
Canopy Index**	$\mathrm{CI} = \mathrm{SWIR} - \mathrm{G}$	Vescovo & Gianelle (2008)
Normalized Difference Vegetation Index**	$\mathrm{NDVI} = \frac{\mathrm{NIR}-\mathrm{R}}{\mathrm{NIR}+\mathrm{R}}$	Rouse *et al.* (1973)
Soil Adjusted Vegetation Index **	$\mathrm{SAVI} = \frac{\mathrm{NIR}-\mathrm{R}}{\mathrm{NIR}+\mathrm{R}+0.5} * (1+0.5)$	Huete (1988)

* Is calculated based on the grey level co-occurrence matrix (GLCM), each element of the GLCM indicates the relationship between grey levels of pixels in specific directions or distances. *Pij* indicates the probability in that cell of finding the reference value *i* in combination with a neighbour pixel. *j*.

** G = green band (Spot 5 band 1), R = red band (Spot 5 band 2), NIR = near infrared band (Spot 5 band 3) and SWIR = short wave infrared (Spot 5 band 4).

Table S 3.3 Pearson correlation coefficient values (r) for the numeric variables used in the statistical model for estimating probability of forest degradation in Ayuquila Basin, Jalisco, Mexico (Variable explanations and names are provided in Table 1) .

	Elevation	Fuelwood	Fence	Livestock	Dist	Slope	Ejidatarios	Pop:TDF	Parcel_ S	Road
Elevation	1.000	-0.207	-0.299	-0.249	0.119	0.356	-0.145	-0.070	-0.313	0.460
Fuelwood	-0.207	1.000	0.442	0.811	-0.351	-0.171	0.571	-0.231	0.635	-0.143
Fence	-0.299	0.442	1.000	0.399	-0.260	-0.031	0.580	-0.183	0.623	0.011
Livestock	-0.249	0.811	0.399	1.000	-0.309	-0.212	0.581	0.054	0.672	-0.169
Dist	0.119	-0.351	-0.260	-0.309	1.000	0.141	-0.523	0.113	-0.466	0.096
Slope	0.356	-0.171	-0.031	-0.212	0.141	1.000	-0.147	-0.076	-0.196	0.384
Ejidatarios	-0.145	0.571	0.580	0.581	-0.523	-0.14	1.00	-0.286	0.052	-0.135
Pop:TDF	-0.070	-0.231	-0.183	0.054	0.113	-0.076	-.286	1.000	-0.270	-0.099
Parcel _S	-0.313	0.635	0.623	0.672	-0.466	-0.196	0.052	-0.270	1.000	-0.194
Road	0.460	-0.143	0.011	-0.169	0.096	0.384	-0.135	-0.099	-0.194	1.000

Table S 3.4. Area (ha) of tropical dry forest found in each community of the Ayuquila Basin, Jalisco, Mexico.

ID	Name	Area analysed (ha)	*Ejidatarios*	Number of Households	Population	No land cover change (ha)	TDF cover lost (ha)	TDF cover gain (ha)	Net change in TDF cover (2004-2010)
1	Agua Hedionda y Anexos	902	57	50	237	531.3	220.4	91.1	-129.2
2	Ahucapan	841	129	271	985	668.5	79.9	89.7	9.8
3	Ayuquila	456	60	230	862	341.6	49.0	64.4	15.4
4	Ayutita	614	40	98	334	390.9	139.7	74.7	-64.9
5	Chiquihuitlan y Agua Salada	3724	148	60	237	2507.4	681.5	343.6	-337.9
6	Coatlancillo	1558	45	159	565	1112.3	226.3	212.7	-13.6
7	El Ahucate	291	23	72	242	245.0	25.0	20.0	-5.0
8	El Chante	1074	240	524	1880	853.5	112.0	105.9	-6.2
9	El Jardin	577	45	40	175	435.8	61.2	75.3	14.1
10	El Limon	1360	450	961	3102	1099.0	89.0	169.0	80.0
11	El Palmar	322	90	15	234	286.5	23.7	11.3	-12.4
12	El Rodeo	1502	32	41	161	1174.7	101.9	175.8	73.9
13	El Temazcal	5403	81	33	116	4469.1	475.5	443.3	-32.1
14	La Laja	1591	50	114	454	1168.9	182.4	210.2	27.8
15	Lagunillas	808	98	242	836	694.4	74.9	37.2	-37.6
16	Las Pilas	456	47	94	387	325.4	45.0	85.0	40.0
17	Los Mezquites	1427	57	72	301	1109.0	135.0	159.0	24.0
18	Mezquitan	500	64	230	885	416.8	19.2	62.1	42.9
19	San Agustin	935	140	102	342	762.7	139.9	28.8	-111.2
20	San Antonio	1650	90	158	669	1211.5	194.4	233.2	38.8
21	San Buenaventura	1267	26	46	158	1178.0	14.7	74.3	59.7
22	San Clemente	1328	212	310	1182	960.2	264.7	99.6	-165.0
23	San Jose de las Burras	2494	150	134	541	1876.8	176.3	415.9	239.6

24	San Juan Jiquilpan	1144	130	455	1789	881.7	106.1	140.1	34.0
25	San Miguel	668	45	132	446	626.7	18.1	21.3	3.2
26	Tecomatlan	802	53	35	129	710.0	41.0	45.0	4.0
27	Tonaya	4826	282	955	3497	3823.4	505.1	446.1	-59.0
28	Tuxcacuesco	2051	165	405	1538	1380.0	404.0	203.0	-201.0
29	Zenzontla	2400	67	60	381	1943.0	231.0	194.0	-37.0
	Total	42971.0	3116	6098	22665	33184.2	4836.6	4331.6	-505.0

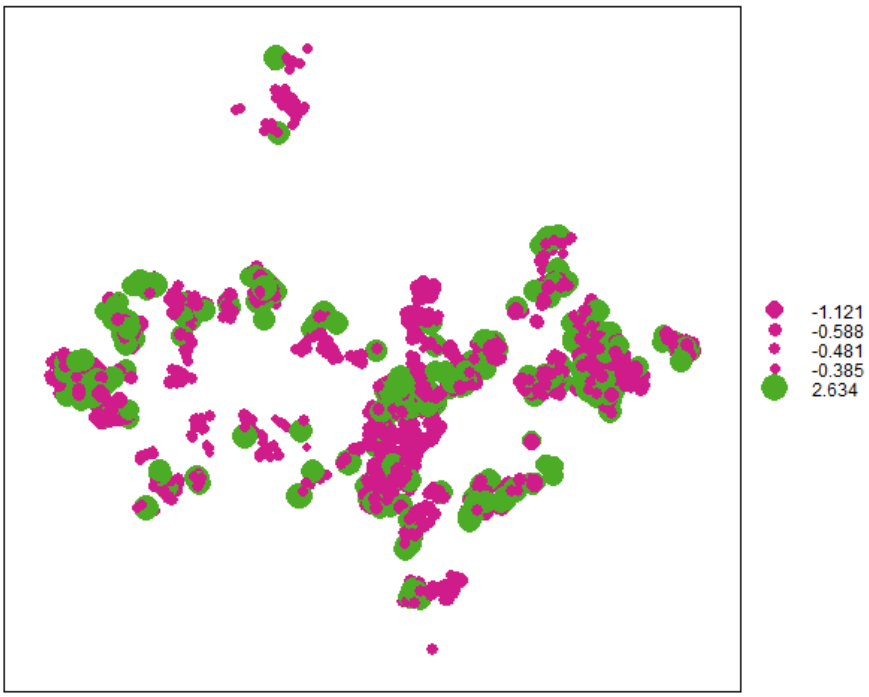

Figure S 3.1. Geographic representation of residuals for the probability model of forest degradation for the Ayuquila Basin, Jalisco, Mexico

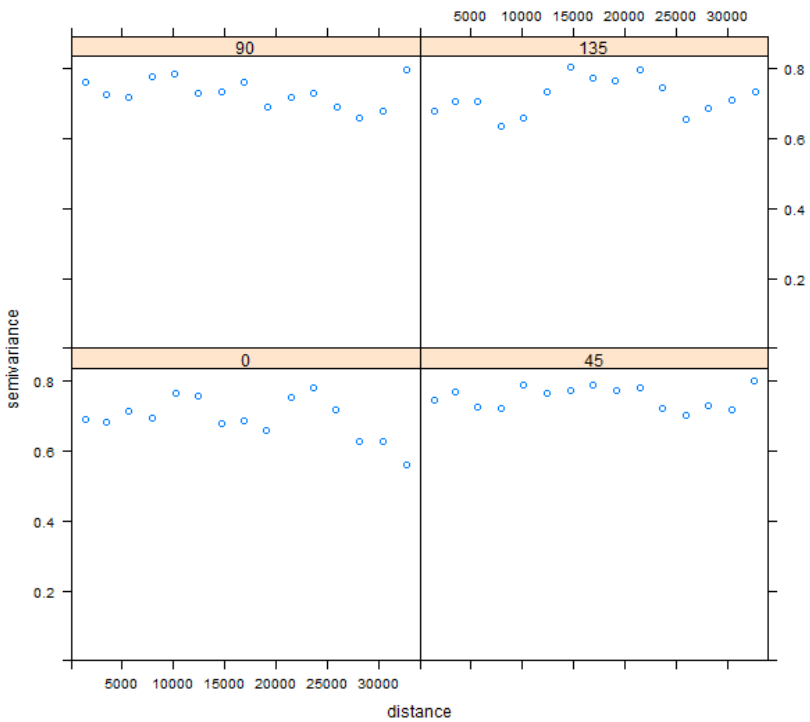

Figure S 3.2. Semivariogram of residuals for the probability model of forest degradation for the Ayuquila Basin, Jalisco, Mexico

Chapter 4. Assessing forest degradation on the ground and from space: developing indicators to evaluate the state of tropical dry forests in Mexico

Abstract

The assessment of forest degradation is a complex task, for which methods are poorly developed, although it is recognized as a key element within forest-related climate change mitigation policy. Forest degradation can be related to capacity of forest to conserve biodiversity and deliver a wide range of ecosystem services; but in the recent context of global climate change policy it has tended to be defined as a state of reduced forest carbon stocks that can be clearly linked to human activities that cause forest disturbance. In Mesoamerica, human-induced disturbance processes that lead to forest degradation in tropical dry forests (TDF) are predominantly related to the use of the forest for cattle grazing, as a source of fuelwood and selective harvesting of fence posts. In this study a disturbance index that can provide an approximate measure of forest degradation based on these processes is proposed. For this, *in situ* variables related to the presence of cattle and removal of trees and branches are quantified in a western Mexican landscape in 106 plots, and the degree of disturbance is then compared with the potential stocking level of above-ground biomass (AGB) that can be expected for the area. The disturbance index is highly correlated with field estimates of AGB ($r = -0.62$, $P < 0.001$), basal area ($r = -0.59$, $P < 0.001$) and to a lesser extent canopy cover ($r = -0.49$, $P < 0.001$), suggesting that it has potential value for monitoring and to inform restoration of this type of forest. To investigate the potential to extend this analysis to assess forest degradation at the landscape level, vegetation and texture indices derived from SPOT 5 and RapidEye data of wet and dry seasons were used as predictor variables of the levels of forest degradation. For this, the disturbance index obtained from the field data was used to generate classification into four, three and two levels of forest degradation. Then, two statistical methods (random forests and linear discriminant analysis), which used the remote sensing data as input variables, were applied to model these three classifications categories of forest degradation levels and the accuracy of each model was evaluated. The remote sensing data had a moderate potential to predict the classification categories of levels of degradation at the landscape level, as show by the different model's accuracy that range between 44 and 72%. Nonetheless, the analysis highlighted the value of including texture indices for the assessment of the state of TDF. This research provides evidence of the utility of *in situ* disturbance indicators as complementary measures that present a clear link between management practices and AGB in TDF, which can be particularly important in the context of carbon emissions mitigation schemes, to advance understanding of how to measure and monitor forest degradation and enhance forest recovery in TDF.

Keywords: disturbance indicators, texture indices, grazing, forest monitoring, forest structure, forest carbon stocks, REDD+

4.1. Introduction

Despite reducing forest degradation being a key part of REDD+ (Reduced Emissions from Deforestation and Forest Degradation) mechanism of the United Nations Framework Convention on Climate Change (UNFCCC) and central to achieve the objectives of the Convention on Biological Diversity (CBD 2010), it remains poorly understood (Murdiyarso *et al.*, 2008b; Guariguata *et al.*, 2009; Sasaki & Putz, 2009) and largely unmeasured. The estimates of carbon emissions attributed to forest degradation vary greatly, but they are thought to be substantial, between 10-40% of the net global carbon emissions (Houghton, 2012) and increasing (Federici *et al.*, 2015). Moreover, understanding where and how forest degradation is occurring is essential for the success of forest restoration, which is generally dependent on achieving a cessation of the activities causing degradation, that could potentially change degraded tropical forest lands into carbon sinks (Grace *et al.*, 2014), and achieve sustainable landscape management (DeFries & Rosenzweig, 2010).

Even though, its importance, the current capacity to identify, measure and monitor the different aspects of forest degradation is still very limited (Herold *et al.*, 2011; Goetz *et al.*, 2015). We argue that in any operational assessment of forest degradation, potential field-based indicators should be tailored to the specific characteristics of that forest's ecosystem, as well as to the type of disturbance that is being evaluated (Ahrends *et al.*, 2010; Chaturvedi *et al.*, 2012; Dons *et al.*, 2015). For instance, a different set of indicators would be needed to define degradation due to logging in a rainforest than for fuelwood collection in a dry forest. Despite these obvious differences, there has been a tendency to define and measure forest degradation only in terms of forest attributes such as above-ground biomass (AGB) or canopy cover (Schoene *et al.*, 2007; Simula, 2009). Where forests are subject to chronic disturbance due to continuous activities (e.g. fuelwood extraction, cattle grazing and harvesting timber for posts), which do not result in such obvious changes in AGB and canopy cover as when a large tree is logged in a rainforest; underpinning the definition and measurement of forest degradation solely on AGB and/or canopy cover is problematic. Above ground biomass, as a simple indicator of forest degradation is of limited utility in that it presents a wide variability range related to environmental factors and land use history (Chazdon, 2003; Becknell & Powers, 2014).Thus, it is also practically difficult to determine true changes in AGB due to human activities between measurements over time with an acceptable degree of certainty, particularly if the changes are small (Chidumayo, 2013). Moreover, in a policy or project context, without a clear link to human activities, changes in

AGB will not provide an equitable basis for any consequent enforcement action or payment for ecosystem services (Skutsch *et al.*, 2013). Furthermore, limiting monitoring of forest degradation only to forest attribute indicators does not provide information on the management of an area, thus it is of limited use for designing intervention actions to avoid forest degradation and promote forest recovery.

Increase or decrease in canopy cover is another commonly used indicator of forest degradation as it can be evaluated through remote sensing analysis and consequently it is used in almost all international definitions on the topic (FAO, 2007). However, this approach has the limitation that, contrary to selective timber extraction, many degradation processes occur below the canopy, without producing immediate changes in canopy cover. These processes cause a more gradual and less noticeable type of forest degradation, that may only alter the canopy cover and forest structure in the long term (De Sy *et al.*, 2012; GOFC-GOLD, 2013; Miettinen *et al.*, 2014). In addition, canopy cover varies significantly throughout the year in deciduous forests, thus techniques developed to monitor the degradation of evergreen forests cannot reliably be extrapolated to such deciduous forest types (Blackie *et al.*, 2014; Hesketh & Sanchez-Azofeifa, 2014). A major contribution to overcoming these problems in assessing forest degradation would be made by new methods that clearly link the state of forest attributes, particularly AGB as well as canopy cover, to the effects of human-induced disturbance processes. Furthermore, monitoring of forest degradation at the landscape level could be improved by methods that indirectly link the effects of human activities to remote sensing variables through the changes in forest structure that are reflected on the satellite data (Joseph *et al.*, 2010; Herold *et al.*, 2011). Assessing these links is of particular importance for improving the management of tropical dry forests (TDF) in developing countries that are subject to high levels of degradation due to high dependency on forests as a source of fuelwood, building materials, grazing and crop lands.

Background

a. Forest degradation processes in tropical dry forests

In comparison with moist and wet tropical forests, the potential to apply carbon emissions mitigation measures has received considerable less attention in TDF (Blackie *et al.*, 2014). This can be attributed to assumptions that TDF hold lower carbon stocks and are a lower priority for global biodiversity conservation (which has often been the underlying motivation for REDD+ and other carbon-linked payment for ecosystem services projects) (Becknell *et al.*, 2012; Portillo-Quintero *et al.*, 2014). Nonetheless, TDF landscapes; are among the most threatened and least studied forest ecosystems (Janzen, 1988; Sánchez-Azofeifa *et al.*, 2005; Miles *et al.*, 2006). Tropical dry forests used to cover extensive areas in Mesoamerica,

however between the 1930's and 1970's most of them were cleared for agricultural cultivation and pasture. The remaining areas, 27% of its original cover in the case of Mexico, are very fragmented and confined mainly to less accessible sites (Miles *et al.*, 2006; Portillo-Quintero & Sánchez-Azofeifa, 2010) that commonly have poor soils and low water availability (Dupuy *et al.*, 2012).

These remaining TDF typically experience a form of "cryptic" forest degradation, due to their use for low intensity grazing and fuelwood and timber harvesting. This form of cryptic forest degradation may not cause immediate detectible loss of canopy cover; but is chronic and spatially pervasive (Guariguata *et al.*, 2009). In addition, TDF are used for shifting cultivation practices, and consequently a high proportion of the remaining area is now secondary forest regrowth (Marín-Spiotta *et al.*, 2008; Dirzo *et al.*, 2011). The common response of TDF to disturbance is marked by a higher rate of coppicing or resprouting, than moist forest types, which affects forest structure. and the temporal trend of AGB recovery (Ewel, 1980; Chazdon *et al.*, 2007). The combination of all these degradation and recovery processes has lead to a simplification of forest structure and loss of ecological functions in a substantial part of TDFs (Griscom & Ashton, 2011), which results in lower AGB values and differences in structure and composition compared with those expected for old growth TDF under similar environmental conditions (Larkin *et al.*, 2012).

The effect of disturbance in TDF has been studied most commonly by using chronosequences. This approach has provided valuable information on the dynamics of secondary succession but it also has several limitations (Chazdon *et al.*, 2007). Firstly, it is based on the assumption that the observed differences in structure and composition are explained by the stand age and that the forest will follow a determined recovery path (i.e. succession curve) (Johnson & Miyanishi, 2008; Quesada *et al.*, 2009). Although this assumption might hold in some cases, recovery processes are highly dependent on site biophysical characteristics and land use history (Chazdon, 2003) and, therefore, there is important variability in AGB, structure and composition within successional stages (Fig. 2.2). Secondly, the majority of chronosequence studies in TDF were carried out using plots located within protected areas, e.g. Chamela-Cuixmala, in Mexico and Santa Rosa in Costa Rica (Sanchez-Azofeifa *et al.*, 2014a), thus they are usually not further subjected to any major human disturbance. Consequently, there remains an important gap in knowledge of the most appropriate methods to study disturbance processes in TDF socio-ecological systems.

b. Analysis of forest structure in tropical dry forests with remote sensing

Another commonly used approach to study changes in TDF structure and composition due to disturbances processes is combining chronosequences with remote sensing and

additional ground based data (Dupuy *et al.*, 2012; Gallardo-Cruz *et al.*, 2012; Hernández-Stefanoni *et al.*, 2012; Martinuzzi *et al.*, 2013; Hesketh & Sanchez-Azofeifa, 2014). Vegetation and texture indices derived from images obtained from satellite medium (30 x 30 m) and high resolution sensors (< 10 x 10 m) have been used to characterize and map the extent of secondary succession stages. As vegetation indices provide information on the quality of green vegetation, and texture indices take also into account the spatial configuration of the vegetation, they are often combine in vegetation monitoring assessments (Jones & Vaughan, 2010). For example, Arroyo Mora *et al.* (2005) found that it was possible to distinguish early stages from mid-late stages of succession in TDF by using vegetation indices derived from satellite images, demonstrating that forest structural characteristics, e.g. basal area (BA) and canopy cover, can be linked with medium- and high-resolution spatial remote sensing data. Using a combination of the Normalized Difference Vegetation Index (NDVI) with texture indices calculated from Landsat data, Hartter *et al.* (2008) obtained an accurate separation of succession stages that were identified based only on BA, i.e. early (BA < 15 m^2) and mid-late succession (BA 15-30 m^2). Further research has demonstrated the correlation between texture indices and forest stand attributes in different successional stages (Gallardo-Cruz *et al.*, 2012). As these previous studies provide evidence that spatial variation caused by disturbances can be linked to remote sensing, its potential for assessments of degradation in TDF should be further explored.

So far, most research on the degradation of TDF has focused on acute disturbance events such as fires and on the dynamics of secondary succession; and only a few studies have dealt with forest degradation processes that are less conspicuous (Griscom & Ashton, 2011). The effects of processes that lead to cryptic forest degradation (namely fuelwood collection, grazing and selective logging) need better characterization, particularly if remote sensing techniques are used to identify their incidence and severity. The long-term effect of these processes might be reflected in the canopy cover and, with the availability of new algorithms and data sources that provide greater spatial and spectral details, new insights for evaluating cryptic forms of forest degradation might be gained. In order to achieve this, remote sensing data need to be referenced with field-based data that provide clear evidence of human-induced disturbance processes and its effects on forest structure.

Aim:

In the present study we used locally relevant indicators that are clearly linked to human activities causing forest degradation and that are easy to measure in the field, to explore the relation between forest attributes, forest degradation and remote sensing data. Therefore, the first objective is to test whether an index of locally relevant disturbance measures (such as the presence of cattle dung, evidence of cut of stems, bare soil and a low proportion of large

stems) are associated with other conventional forest attributes that are more commonly used to assess forest degradation (AGB, basal area, canopy cover and species richness), but that are not directly linked with management and hence are of limited utility to assess forest degradation. The second objective is to test whether remote sensing can discriminate between areas that are classified by this index along a scale of increasing disturbance. The aim was to access the potential use of remote sensing in modelling forest degradation at the landscape level for the purpose of monitoring, by means of classifying the landscape into different degradation levels.

4.2. Methods

4.2.1. Study site description

The research was conducted in the Ayuquila Watershed (~19°25' - 20°10.0"N, 104°3' - 103°3'W), an area of approximately 4000 km^2 located in Jalisco, Mexico. It is limited to the south by the Sierra de Manantlán Biological Reserve (Fig. 4.1), recognized as a UNESCO Biosphere Reserve. The watershed is part of the early REDD+ actions selected by the Mexican government to tackle forest degradation (SEMARNAT, 2010).

The average annual precipitation varies between 800 and 1200 mm, with a distinct dry season from November to May, and the average temperature ranges between 18 and 22 °C (Cuevas *et al.*, 1998). The elevation range is 260-2500 m above sea level. The complex topographic and climatic conditions have created a variety of vegetation formations. High altitude areas are dominated by oak-pine forests and small patches of evergreen cloud forest. In the lowland areas, where the research was focused, tropical deciduous and semi-deciduous dry forests, a form of known in Mexico as *selva baja*, are found (Rzedowski, 1978). In their mature-undisturbed state these TDFs have closed canopies during the wet season, with the top of the canopy ranging between 4 and 15 m height, and a dense understory layer dominated by shrubs , and a poor developed herbaceous cover. For the TDFs of the Pacific coast of Mexico it has been estimated that 75% of tree species shed their leaves during the dry period (Lott *et al.*, 1987). When, undisturbed, these Mexican Pacific coast TDFs have very high levels of plant endemism and beta biodiversity (Balvanera *et al.*, 2002; Linares-Palomino *et al.*, 2011); with an estimated average of 94 species per 0.1 ha plot (Lott *et al.*, 1987; Gillespie *et al.*, 2000).

As in many other TDFs in the neotropics, in the study area cattle grazing is a common use of the forest during the rainy season, as well as extraction of fuelwood and fence posts. Natural fires are considered to be rare in the study area, thus conforming to the general condition of TDF (Murphy & Lugo, 1986; Janzen, 1988; Vieira *et al.*, 2006; Hughes *et al.*,

2013; Dexter *et al.*, 2015), but burning an area to use it for shifting cultivation is a common practice (Maass, 1995). Some of these areas are converted to permanent pasturelands for cattle after several shifting cultivation cycles (Sanchez-Azofeifa & Portillo-Quintero, 2011; Borrego & Skutsch, 2014).

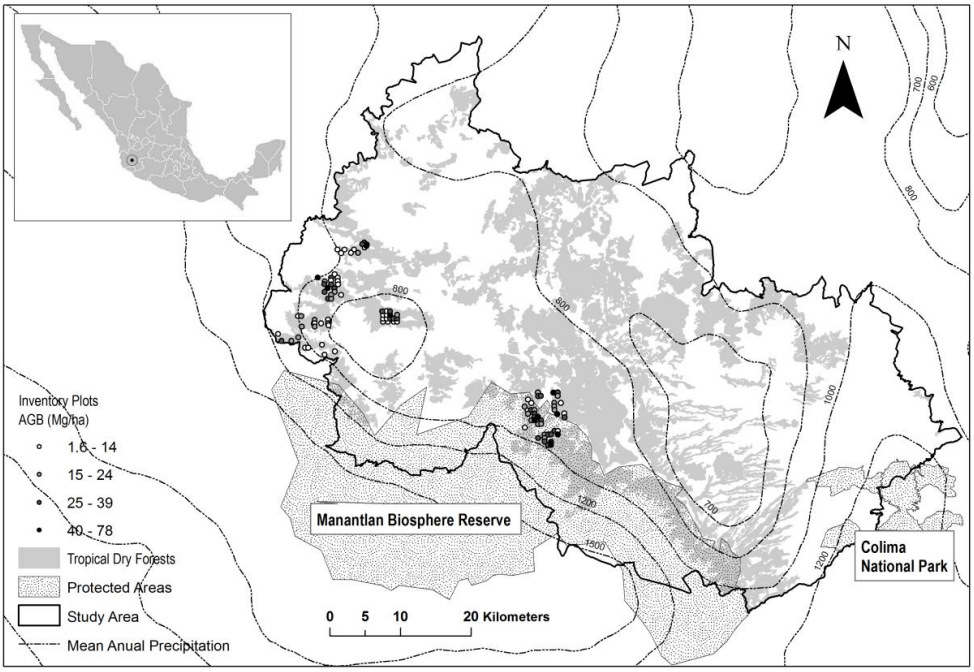

Figure 4.1 Location of the study area and field plots

4.2.2. Field data collection

A total of 106 field plots were sampled in areas of TDF, within the land of four communities, during May-August 2012. A systematic random sampling design was used, were sample points were randomly selected from a 500 X 500 m grid. They covered areas with different land use intensities, from low-disturbance areas to those that are more intensively used by communities. Although our approach was not focused on understanding the relationship between forest attributes and land use history, this is an important factor in prediction of forest structure in TDF (Dupuy *et al.*, 2012; Becknell & Powers, 2014), and therefore, information on stand age was incorporated into the analysis. The stand age was defined as the time since abandonment from agricultural land use, as determined by interviews and participatory mapping with local residents who have been living in the community for more than 50 years. Four stand age classes were determined: young (<10 years), medium (10–20 years), old-growth (>40 years) and control (areas that have never been cleared). It was not possible to obtain age information for five plots.

At each of the 106 sample points a circular concentric plot with 2 subplots was established. In the 500 m^2 (radius = 12.62 m) subplot tree stems with a DBH > 5 cm and in the 100 m^2 (radius = 5.65 m) subplot tree stems with a DBH > 2.5 and $\leq$ 5 cm were measured. Tree height and species was determined for each tree and DBH was measured for each tree stem. If identification to species or genus level was not possible in the field, a sample was taken to be identified by J.A. Solis, of the herbarium of the Department of Ecology and Natural Resources at the University of Guadalajara. Number of tree stumps (i.e dead trees (>10 cm DBH) that were harvested presumably for fence posts), as well as the number of stems of living trees that were observed to have stems cut by machete, (hereafter number of machete cuts), which is the usual method for fuelwood collection, were recorded in the 500 m^2 subplot.

In addition, at each sample point two perpendicular 10 m line-intercept transects were established and the length (cm) covered by the following variables were recorded: (a) cow trails, (b) cow, horse or goat dung (hereafter manure), (c) bare soil, (d) herbaceous plants other than pasture grasses (hereafter herbaceous), (e) shrubs and (f) pasture grasses (hereafter pasture) (Fig. 4.2). Transect lines were also used to estimate tree canopy cover per plot by recording the presence or absence of canopy cover every 0.5 m with a vertical densitometer (Geographic Resource Solutions (Stumpf, 1993)The AGB per tree was obtained using the allometric model of Martínez-Yrizar *et al.* (1992), which was developed using data on the TDF of the Chamela-Cuixmala region. The AGB per tree was summed to obtain the total AGB for each plot.

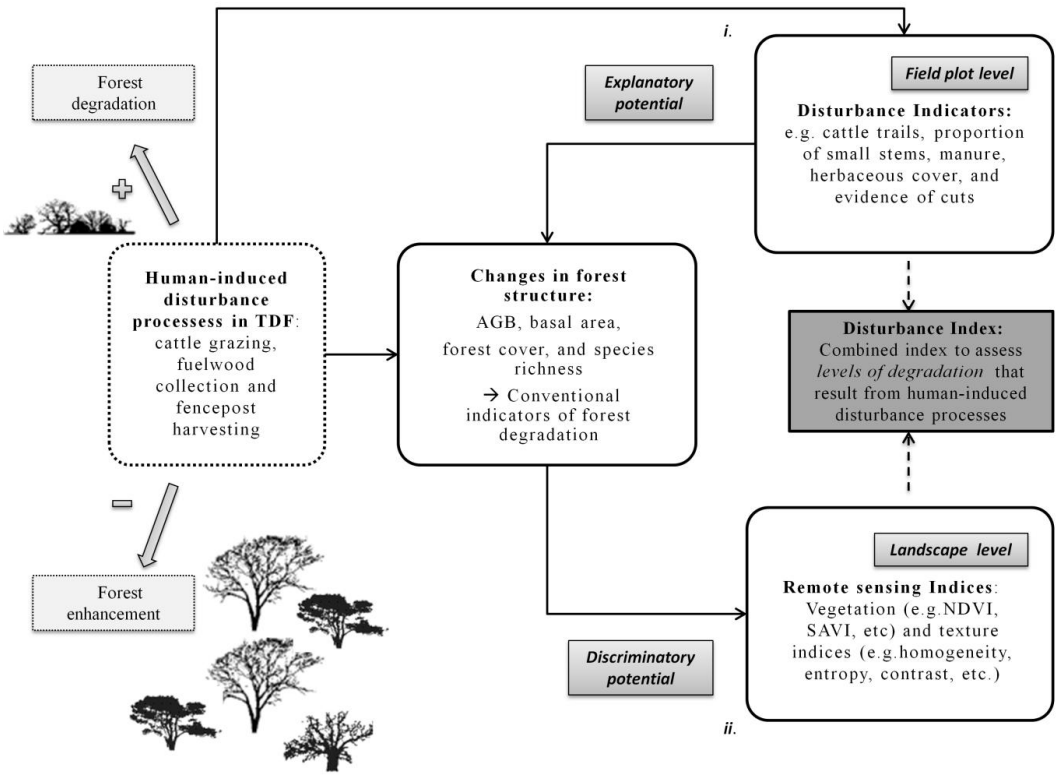

Figure 4.2 The analytical approach used in this study to link disturbance processes with forest structure in order to assess forest degradation through the development of a disturbance index.

Variables selected as disturbance indicators that were directly measured in the field and those obtained from remote sensing data are defined in the text and here presented in white boxes with a black solid boundary, while the disturbance index that was derived from the field variables is shown in the dark grey box. The variables recorded in the field at the plot level provide evidence of the link between changes in forest structure (which are the conventional indicators of forest degradation) and disturbance processes (i.). These changes in forest structure due to disturbance processes are reflected in the remote sensing indices that could potentially be used to discriminate between the degradation levels at the landscape scale (ii.).

4.2.3. Calculation of disturbance index

To assess the extent of disturbance we developed a disturbance index (Fig.4. 2) that enables comparison of the forest condition amongst the plots, and groups them into disturbance levels (for subsequent comparison with a remote sensing index – see next section). Ten equally weighted disturbance indicator variables were combined to obtain the overall disturbance index. The variables used were selected based on the following three criteria: (i) the knowledge about the activities that communities carry out in the forest from

previous participatory mapping exercises and field interviews, complemented by relevant information about the impact of these activities in the literature. For instance, previous studies have found that grazing and/or selective harvesting of posts in TDF commonly results in an increase in the number of small stems (DBH < 10 cm) (Vieira & Scariot, 2006); (ii) an increase or decrease in the values of the variables should be clearly an outcome from human activities, e.g. standing dead trees and rock cover were excluded because they could also result from natural causes; (iii) the variables should not be an input for AGB calculation, so tree DBH, height and wood specific gravity were excluded; (iv) variables should be easy to understand and to measure in the field. The following disturbance indicator variables were therefore used to generate the index: cow trails, manure, bare soil cover, herbaceous cover, shrub cover, pasture cover; number of machete cuts, number of tree stumps, percentage of all stems that were small (DBH 5-10 cm) and percentage of all stems that were large (DBH > 20 cm). All these variables were summed except those that are characteristic of undisturbed tropical dry forest, namely percentage of large stems and shrub cover, which were subtracted, to obtain the overall disturbance index. As this set of variables is associated with the effects of fuelwood collection, cattle grazing and/or extraction of forests resources (mainly fence posts), they serve as proxy measures of disturbance. Thus, the values of the disturbance index will be higher in plots that are more intensively used as grazing areas and/or sources of fuelwood, while values will be lower in less disturbed areas characterised by larger stems and greater shrub cover.

After the disturbance index values was calculated, we divided its range (18.6 - 104.9) into two, three and four degradation levels, as to represent classification categories of forest degradation. The classification categories were as follows: a) a two level category, low (18.6-61.8) versus high (61.9-104.9); b) a three level category, low (18.6-47.4) vs medium (47.4-76.2) vs high (76.3-104.9); c) a four level category, low (18.6-40.2), medium (40.3-61.8), high (61.9-83.3), very high (83.4-104.9). For each of these three classification categories each plot was then assigned to one of the forest degradation levels to be used in the analysis that are explained in the following sections.

4.2.4. Calculation of the remote sensing indices

Two types of satellite image data were used for the analysis: SPOT 5 and RapidEye. Although RapidEye records in five spectral bands and SPOT 5 in four bands, they have three bands in common: Green (G), Red (R) and Near Infrared (NIR). Two SPOT 5 (level 2A, 10 x 10 m spatial resolution) scenes acquired in the dry season of 2010 were used to create a mosaic of the entire study area. With the RapidEye images (ortho product 3A, 5 X 5 m spatial resolution), two mosaics were created for the study area, one for the wet season

(April-October) and a second for the dry season (November-May) of 2011/2012, using a total of five scenes to cover the area for each season (Table 4.1). For RapidEye data, preference was given to images acquired in 2012, because they were contemporary with the plot inventory; if no suitable image was found in this year, it was replaced by one from 2011.

All the images were atmospherically corrected using the FLAASH module in Envi 4.7 (ENVI, 2006). In addition, the SPOT 5 data were ortho-rectified using ground control points (Table S 3.1). For each mosaic, vegetation and texture indices were calculated (Table 4.1). Co-occurrence textural indices were used because they can be related to the spatial distribution of the vegetation as they evaluate statistically the relationship between the grey tones of neighbouring pixels. In other words, these indices provide a measurement of the heterogeneity or similarity amongst pixels found within a defined area, which is an indicator of the spatial structure of the vegetation (Jones & Vaughan, 2010; Beckschäfer *et al.*, 2014). Moving windows of 3 X 3 and 7 X 7 pixels were used to calculate textural indices at two different spatial scales for the R and NIR bands of both sensors. With RapidEye images, texture indices were also calculated using the RedEdge (ED) band.

For both image types a similar set of vegetation indices was derived (Table 4.2), with two exceptions: a) for the RapidEye data, two extra spectral indices, based on the ED band were included (NDVI_ED, SR_ED), and b) the Canopy Index (CI) that uses the short wave infrared was included for the SPOT 5 data. In addition, for both data sets, a principal components analysis was performed and the first two components were included in the analysis; as well as data from 30 X 30 DEM (Digital Elevation Model for Mexico v.2). All the vegetation indices and band images were aggregated to 20 m, to account for misregistration effects between images and field data. The calculation of the indices was performed in OTB (Inglada & Christophe, 2009) and Envi 4.7 (ENVI, 2006). A detailed description of the indices used is provided in Table S 4.1.

Table 4.1 Acquisition date of the RapidEye and Spot 5 data

Satellite	Date	Tile_ID
SPOT 5	28.01.2010	577-310
SPOT 5	24.02.2010	578-311
RapidEye-1	04.02.2012	1348217
RapidEye-4	15.11.2012	1348217
RapidEye-3	28.01.2012	1348218
RapidEye-4	16.10.2011	1348218
RapidEye-3	28.01.2012	1348117
RapidEye-4	20.08.2011	1348117
RapidEye-3	31.01.2011	1348118
RapidEye-2	12.11.2011	1348118

RapidEye-2	08.01.2012	1348119
RapidEye-4	08.09.2011	1348119

4.2.5. Data Analysis

a. Analysis of the disturbance index and its relationship to forest attributes

Regression analysis was used to test if the degree of forest degradation, as measured by the disturbance index, effectively explained the response of forest attributes. The forest attributes that were analysed included: a) AGB, b) BA, c) forest cover (defined as the percentage of canopy cover/plot), and d) woody plant species richness (defined as the rarefied number of woody plant species/plot) e) species density (number of woody plant species/plot). The rarefied woody plant species richness, that represents an area independent estimate of species richness, was calculated using the Vegan package in R, based on a sample of 4398 individuals across 106 plots. Pearson's correlation coefficient was used to evaluate the relationship between the forest attributes and disturbance index. To determine which disturbance variables have greater importance for assessing the forest attributes, a stepwise regression using backward elimination was carried out. One-way ANOVA and *post hoc* Tukey HSD tests were used to examine the possible differences in forest attributes between the category of four levels of degradation obtained from the index. This analysis was also done to provide an indication of the usefulness of this index in separating the data into levels of disturbance.

To approximate the effects that disturbance intensity has on AGB, the difference between observed and potential AGB stocking levels was evaluated. A simple regression analysis was done between the disturbance index and the arithmetic difference between the potential and observed AGB. The potential AGB values (for undisturbed conditions) were obtained by averaging values determined for old-growth forests of the Chamela-Cuixmala region in two previous studies (Martinez-Yrizar *et al.*, 1992; Jaramillo *et al.*, 2003). The AGB values reported in each study were averaged and used to obtain a potential AGB value. The Chamela Cuixmala region area is located approximately 150 km west of the site of the present study. It was selected because it is a Biosphere Reserve with large areas of undisturbed TDF that have been well documented by four decades of monitoring (carry out by the Autonomous Mexico National University) to have low levels of human disturbance impact, and it has similar soil and rainfall characteristics to the study site (Quesada *et al.*, 2009). Because of its long history of agriculture and human settlement, such undisturbed TDF sites are extremely rare in Mesoamerica (Portillo-Quintero & Sánchez-Azofeifa, 2010). The Chamela-Cuixmala Reserve is the only site in Mexico where large areas of old-growth TDF occur (Murphy & Lugo, 1986; Sanchez-Azofeifa *et al.*, 2014a). Even though it is 150

km distant from the study site, Chamela-Cuixmala provides a good representation of the structure and composition of western Mexican TDF in the absence of human disturbance processes.

Table 4.2 Remote sensing data and indices used in the analysis to classify forest degradation levels. Abbreviations used for variable names are given in parenthesis

	SPOT 5	RapidEye
Spatial Resolution	10 m	5 m
Spectral Bands	Green (**G**), Red (**R**), Near Infrared (**NIR**), Short wave Infrared (**SWIR**)	Blue (**B**), Green (**G**), Red (**R**), Red Edge (**ED**), Near Infrared (**NIR**)
PCA	1st Principal Component (**PC1**), 2nd Principal Component (**PC2**)	1st Principal Component (**PC1**), 2nd Principal Component (**PC2**)
Vegetation Indices	Canopy Index (**CI**), Enhanced Vegetation Index 2 (**EVI2**), Green Normalized Difference Vegetation Index (**GNDVI**), Modified Soil Adjusted Vegetation Index 2 (**MSAVI2**), Normalized Difference Vegetation Index (**NDVI**), Optimized Soil-Adjusted Vegetation Index (**OSAVI**), Soil Adjusted Vegetation Index (**SAVI**), Simple Ratio (**SR**) and Transformed Normalized Difference Vegetation Index (**TNDVI**)	Enhanced Vegetation Index 2 (**EVI2**), Green Normalized Difference Vegetation Index (**GNDVI**), Modified Soil Adjusted Vegetation Index 2 (**MSAVI2**), Normalized Difference Vegetation Index (**NDVI**), NDVI Red Edge (**NDVI_ED**), Optimized Soil-Adjusted Vegetation Index (**OSAVI**), Soil Adjusted Vegetation Index (**SAVI**), Simple Ratio (**SR**), Simple Ratio Red Edge (**SR_ED**) and Transformed Normalized Difference Vegetation Index (**TNDVI**)
Texture Indices	Co-Occurrence Measures calculated with the R and NIR bands: Mean (**MEAN**), Variance (**VAR**), Homogeneity (**HOMO**), Contrast **(CON)**, Dissimilarity (**DISS**), Second Angular Movement (**SEC**), Correlation (**CORR**), and Entropy (**ENT**)	Co-Occurrence Measures calculated with the R, ED and NIR bands: Mean (**MEAN**), Variance (**VAR**), Homogeneity (**HOMO**), Contrast (**CON**), Dissimilarity (**DISS**), Second Angular Movement (**SEC**), Correlation (**CORR**), and Entropy (**ENT**)

b. Predictability of disturbance levels using remote sensing indices: linking ground assessment of forest degradation with remote sensing indices

To test if it was possible to predict the level of disturbance at the landscape scale, the relationship between forest degradation levels (obtained from categorising the continuous disturbance index into groups each covering an equal proportion of its range) and satellite image data (Table 4.2) was evaluated using two statistical methods, linear discriminant analysis (LDA) and random forests (RF). These two methods were chosen because, while they are both classification methods, they differ in the approach that they use to discriminate between predictor variables and thus how the greatest separation between groups or classes is achieved. Linear discriminant analysis is a multivariate statistical method that assumes that all the variables are normally distributed within the groups and its applicability is limited where there are complex dependent interactions between explanatory variables (Zuur *et al.*, 2007). In contrast, RF is a non-parametric method that can handle collinearity between variables (Breiman & Cutler, 2004), which inherently occurs in remote sensing analysis, since all indices are derived from a limited number of image bands. Moreover, RF is relatively robust to noise and outliers, and it handles large data sets efficiently (Rodriguez-Galiano *et al.*, 2012). Random Forests is an ensemble of many classification trees; to build each tree 2/3 of the data and a set of predictor variables to test in each node of the tree are randomly selected. The trees are then aggregated and a majority vote rule is applied to decide on the final classification. The rest of the data that were not used in each tree (1/3) is used to provide an internal accuracy measure known as out-of-the-bag error (OOB) (Breiman & Cutler, 2004). The decrease in OOB that results from the predictor variable permutation is used to provide a measure of the importance of the variables called mean decrease in accuracy (Rodriguez-Galiano *et al.*, 2012; Grinand *et al.*, 2013)

To evaluate the discriminatory capacity of remote sensing indices (Fig 4.2) to separate degradation levels, we grouped the disturbance index based on the field data into two, three and four classification categories of degradation levels. The degradation levels were obtained, as described in section 4.2.3 above. Then, LDA and RF were used independently to test how well remote sensing indices used as predictor variables, could separate the degradation levels within the three categories of classifications. Each RF and LDA statistical model was developed using three types of image datasets (RapidEye data for the dry and for the wet season, and SPOT5 data only for the dry season), thus a total of 18 models were produced.

For both the RF and LDA methods 80% of the data were used to train the model and 20% were left as independent validation data. The validation data was used to provide a measure of the accuracy achieved by each model in the prediction of the degradation levels in each

classification category In the case of RF, each of the models had two accuracy measures: the out-of-the-bag error (OOB) and the model accuracy (ACC) based on the independent data set. Model development was carried out in two steps. First, for the RF models once the parameters were optimized (using the tuneRF function implemented in randomForests (Liaw & Wiener, 2002)), twenty classification models were developed for the two, three and four categories of levels of forest degradation using a different starting point for each run. For LDA, the models were developed using a different set of training and validation data sets in each run (i.e. cross-validation). This allowed evaluation of consistency in the accuracy that resulted from both methods. In a second step, for each of the three classification categories, the model that achieved the highest accuracy in the first step (the "best fit" model) was selected as the final model and its accuracy was evaluated using a 10-fold cross-validation of the test data. To show which bands and indices of the satellite data were the most important predictor variables in each classification category, the mean decrease in accuracy was extracted for the first six most important predictor variables. The analysis was done using the MASS package (Venables & Ripley, 2002) and randomForest package (Liaw & Wiener, 2002) as implemented in R (R Core Team, 2013).

4.3. Results

4.3.1. Characterization of forest structure and composition

The mean (± SD) plot AGB value was 21.9 (±13.2) Mg ha^{-1} and, although it was smaller for plots with a stand age < 10 years, there was no clear distinction between groups based on stand age (Table 4.3, $F_{(4,101)} = 1.34$, $P = 0.25$). Likewise, no differences were found between the groups defined by stand age, for BA ($F_{(4,101)} = 1.34$, $P = 0.26$), height ($F_{(4,101)} = 1.44$, $P = 0.22$), woody plant species richness ($F_{(4,101)} = 0.75$, $P = 0.52$), tree density ($F_{(4,101)} = 1.23$, $P = 0.30$) and canopy cover ($F_{(4,101)} = 1.09$, $P = 0.36$). The lack of differences suggest that factors other than previous land use (i.e. time since abandonment) might explain the variability in forest attributes amongst the plots.

Table 4.3 Mean (± SD) values of forest structure and composition by stand age for 106 field plots sampled in the tropical dry forest of Ayuquila Watershed, Jalisco, Mexico.

Attributes	Overall Mean *n*=106	Young (< 10 years) *n*= 13	Medium (10-20 years) *n*=29	Old-growth (< 40 years) *n*=22	Control *n*=37
Mean AGB (Mg ha^{-1})	21.9 (±13.2)	14.7 (±11.2)	21.0 (±11.1)	23.1 (±12.4)	22.8 (±14.9)
Mean BA (m^2 ha^{-1})	9.8 (±5.2)	6.8 (±5.6)	9.1 (±4.5)	8.5 (±5.0)	10.2 (±5.6)
Mean height (m)	9.0 (± 2.9)	7.9 (±2.1)	8.7 (±3.0)	10.6 (±3.3)	8.8 (±2.7)
Woody plant species richness (> 2.5 cm DBH)	5.2 (±1.1)	4.9 (±1.0)	5.2 (±1.0)	5.5 (±1.3)	5.3 (±1.1)
Woody plant species density (number of species > 2.5 cm DBH in 0.05 ha plot)	8.8 (±2.8)	7.0 (±2.3)	8.8 (±2.6)	9.14 (±3.1)	9.2 (±2.6)
Density (number of trees ha^{-1})	1302.8 (±598.8)	1170.8 (±608.1)	1226.2 (±546.7)	1258.1 (±531.6)	1471.3 (±666.7)
Canopy cover (%)	70.1 (±19.5)	59.9 (±25.6)	71.1 (±20.1)	71.2 (±18.8)	71.4 (±17.1)

4.3.2. Relationship between disturbance index and forest attributes

Strong negative correlations were found between the disturbance index and the forest attributes AGB, BA and forest cover (Table 4.4), suggesting that the variables from which the disturbance index was derived can be effectively used as proxy measures of forest degradation in TDF that are undergoing similar disturbance processes to those found in our study area. The percentage of small stems was negatively correlated with all four forest attributes and was the variable that consistently had the largest correlation coefficient (Table 4.5); it was also selected in all the final multiple regression models (Table 4.4), except for the species richness model, where the percentage of large stems was the most important variable. Other variables that were important in the models of AGB and BA were bare soil, herbaceous and shrub cover. While the relationship was not so strong, plant species density was significantly negatively correlated with the disturbance index.

Further analysis of the relationships between the individual disturbance indicator variables and the forest attributes confirmed that, as expected, the cover of bare soil increased with the abundance of cattle (Table 4.5), while shrubs and herbaceous cover

decreased. The negative association with the percentage of small stems was stronger for BA and AGB than for forest cover and plant species richness. The density of tree stumps and the number of machete cuts were only weakly associated with the forest attributes, suggesting that they are of lesser value as disturbance indicators in TDF. A strong negative relation (r=-0.58)was found between the percentage of large stems and small stems (Table 4.5)

The tested forest attributes were found to decrease significantly with increasing levels of forest degradation of the plots (Fig 4.3). For AGB ($F_{(3,102)} = 24.25$, $P < 0.001$), the difference was especially significant between the very high disturbance index plots and those that were low or medium (Tukey HSD; $P < 0.001$); but not between the low and medium plots (*post hoc* Tukey HSD; $P = 0.77$) (Fig. 4.3). The same pattern is observed for BA ($F_{(3,102)} = 21.13$, $P < 0.001$). For forest cover ($F_{(3,102)} = 10.03$, $P < 0.001$), differences between both the low and medium degradation level plots (*post hoc* Tukey HSD; $P = 0.54$), and medium and high level plots (*post hoc* Tukey HSD; $P = 0.61$) were not significant. Species richness of woody plants (> 2.5 cm DBH) calculated based on a sample of 4398 individuals across 106 plots, showed no significant reduction with higher levels of forest degradation ($F_{(3,102)} = 0.68$, $P = 0.57$) (Fig 4.3); or correlation with the disturbance index (Table 4.4). However, species richness had a strong positive correlation with the proportion of large stems and a negative one with the proportion of small stems (Table 4.5).

Table 4.4 Correlation coefficients for the relationships between forest attributes and disturbance index values for 106 field plots sampled in the tropical dry forest of Ayuquila Watershed, Jalisco, Mexico, and multiple regression models for forest attributes and individual disturbance variables.

Forest attribute response variable	Correlation with disturbance index	Multiple regression model with individual disturbance indicator variables			
	r [§]	**Model disturbance variables**	**Estimate (± Std. Error)**	r^2	**RMSE**[†]
AGB	-0.62***			0.48***	9.38
		Intercept	54.51 (± 4.07)		
		bare soil cover	-0.97 (± 0.22)		
		small stems	-0.40 (± 0.06)		
Basal area	-0.59***	Intercept	23.48 (± 1.73)	0.49***	3.62
		bare soil cover	-0.38 (± 0.09)		
		herbaceous cover	-0.17 (± 0.06)		
		shrub cover	0.21 (± 0.13)		
		small stems	-0.17 (± 0.02)		
Forest cover	-0.49***	Intercept	83.70 (± 7.78)	0.27***	16.35
		herbaceous cover	0.91 (± 0.27)		
		shrub cover	1.44 (± 0.54)		
		small stems	-0.34 (± 0.09)		
Woody plant species richness	-0.10	Intercept	4.70(±0.16)	0.16***	1.00
		bare soil cover	0.06 (±0.02)		
		large stems	0.07(+0.02)		
Woody plant species density	-0.36***			0.20***	2.43
		Intercept	15.50 (± 1.39)		
		manure	-1.24 (± 0.58)		
		small stems	-0.08 (± 0.02)		
		large stems	0.09 (± 0.04)		

[§] Pearson correlation coefficients for the relationship between individual forest attributes and the disturbance index for each plot. Disturbance indicator variables = cow trails + manure cover + bare soil cover + herbaceous cover + shrub cover + pasture cover + number tree stumps + number of machete cuts + small stems + large stems

*** all linear relationships are significant at $P < 0.001$

[†] Root-mean-square error

Table 4.5 Pearson correlation coefficient matrix of forest attribute and disturbance indicator variables. Shades of grey show the absolute strength of the correlations

	AGB	BA	Forest cover	Plant species richness	Cow trail cover	Manure cover	Bare soil cover	Herbaceous cover	Shrub cover	Pasture cover	Stumps	Machete cuts	Small Stems	Large Stems
AGB	1													
BA	0.93	1												
Forest cover	0.62	0.56	1											
Plant species richness	0.10	0.12	0.19	1										
Cow trail cover	-0.14	-0.22	-0.01	0.19	1									
Manure cover	-0.34	-0.32	-0.29	0.06	0.21	1								
Bare soil cover	-0.51	-0.5	-0.36	0.17	0.22	0.65	1							
Herbaceous cover	0.14	0.05	0.41	-0.04	0.19	-0.32	-0.35	1						
Shrub cover	0.10	0.13	0.27	-0.05	-0.26	-0.42	-0.31	0.22	1					
Pasture cover	0.22	0.21	0.10	0.04	-0.08	0.03	-0.21	0.07	-0.21	1				
Stumps	0.19	0.14	0.14	0.11	0.22	-0.11	-0.06	0.06	0.05	0.18	1			
Machete cuts	-0.07	-0.13	0.03	-0.06	0.21	0.22	0.13	0.22	-0.2	-0.07	0.10	1		
Small stems	-0.63	-0.61	-0.34	-0.22	0.04	0.14	0.36	-0.22	0.1	-0.32	-0.14	0	1	
Large stems	0.33	0.27	0.15	0.34	0.09	-0.07	-0.19	0.27	-0.1	0.24	0.07	0.11	-0.58	1

1-0.8 0.8-0.6 0.6-0.4 0.4-0.2 0.2-0

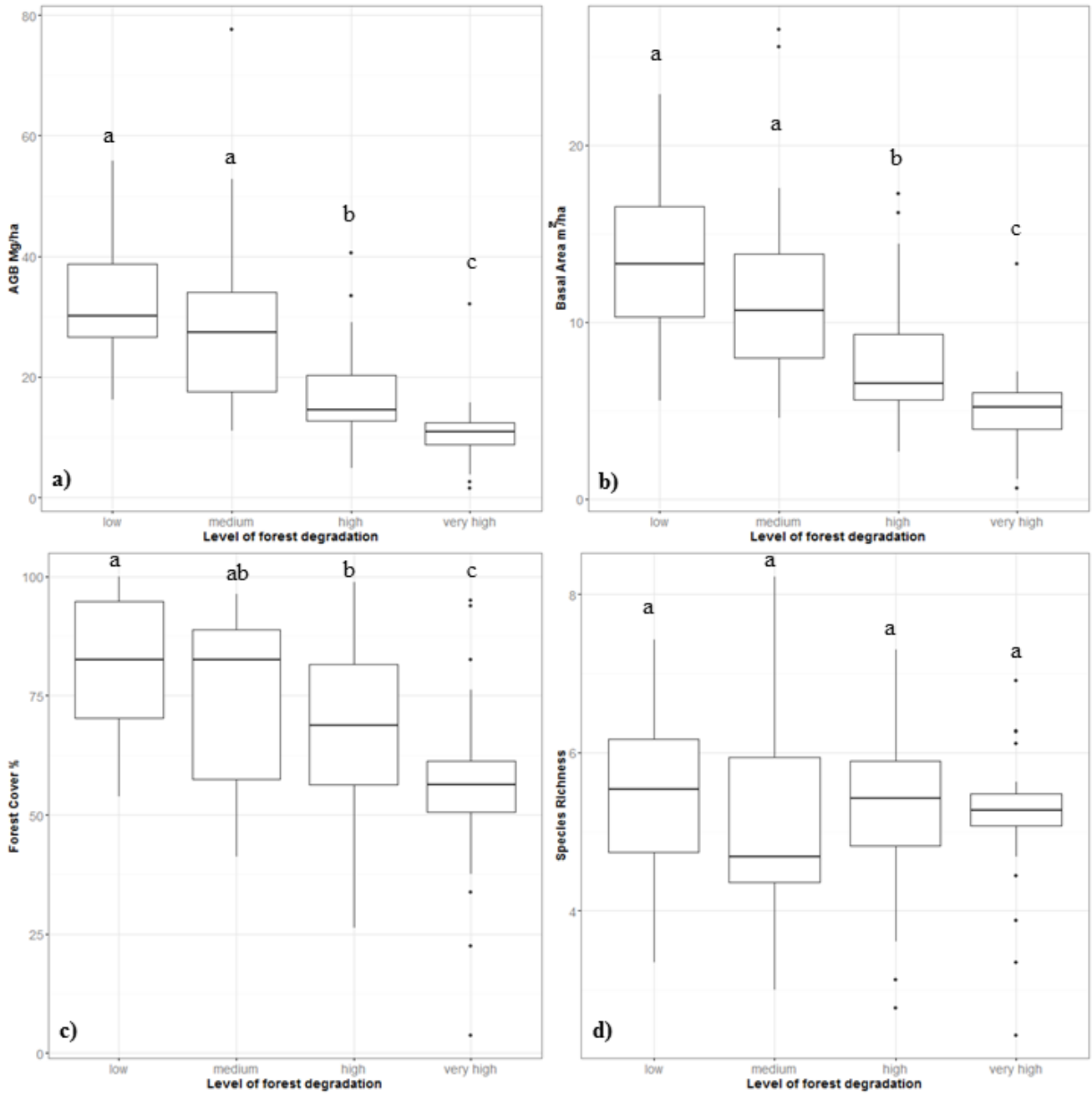

Figure 4.3 Box plots of the values of forest attributes of 106 field plots classified into four levels of forest degradation: a) Total AGB, b) BA, c) Forest cover, d) Plant species richness.
The boundaries of each box show the first and third quartile and the central line corresponds to the median value. The length of the whiskers corresponds to 1.5 times the interquartile range (IQR) and the outliers are plotted as black points outside the box. Bars tagged with different letters are significantly different within each panel ($P < 0.05$).

4.3.3. Difference between potential and current above-ground biomass stocking levels as an indicator of forest degradation

Higher values of the disturbance index were positively associated with a larger difference between the potential and current AGB stocking levels (linear regression model $r^2 = 0.38$, $P < 0.05$, Fig. 4.4). The majority of plots had an AGB 20-40% lower than the potential value. Only four plots, which are located near the Biosphere Reserve, had AGB values greater than the potential values (those reported from the reference site of undisturbed mature TDF). At high levels of forest degradation (disturbance index > 61.8), there is less scatter of points from the linear regression line. This might indicate that higher levels of disturbance reduce the natural spatial variability of AGB in heterogeneous TDF landscapes.

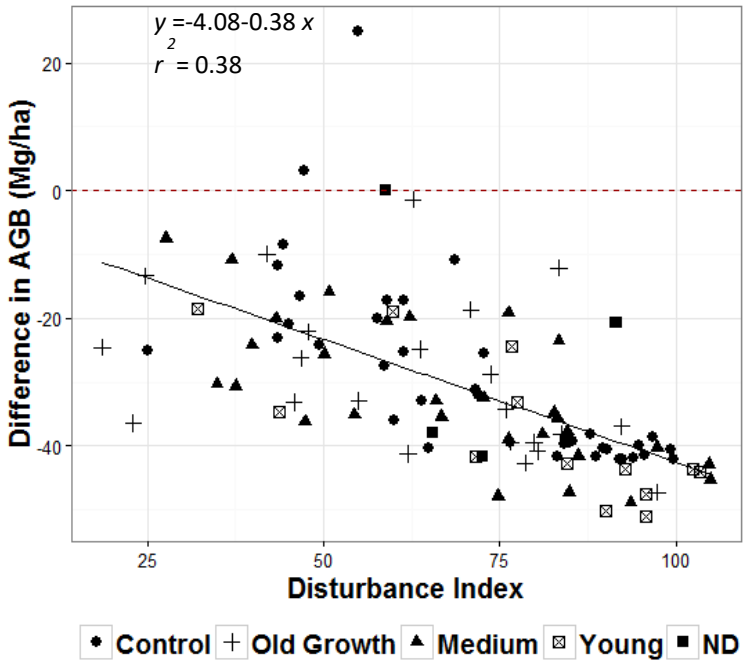

Figure 4.4 Relationship of the difference between potential and current above-ground biomass stocking levels with disturbance index value for 106 field plots. The horizontal dashed line represent zero difference between the current and maximum potential AGB value (75.3 Mg ha^{-1}). The plots are classified into five groups (shown by different symbols) according to their recent land use history: control is areas of forest that have never been cleared, old-growth is forest that were last cleared more than 40 years ago, medium 10-20 years ago, young less than 10 years ago, and ND indicates that for five plots it was not possible to obtain age information.

4.3.4. Relationship between ground assessment of forest degradation and remote sensing (spectral and texture) indices

The potential to classify disturbance by remote sensing was evaluated using RapidEye data for wet and dry seasons and SPOT 5 data for only the dry season. For each image data set, models were constructed using RF and LDA for each classification category of forest degradation levels based on the field data. The discriminatory power of these models to predict the classification of different levels of forest degradation in TDF varied between methods (Fig. 4.5). The accuracy of the RF models was consistently higher than the LDA models, except for those developed based on SPOT 5 data where it was similar, based on the out-of-the bag error (OOB). In the tests for all three remote sensing data sets, higher accuracy in predicting the classification categories of degradation levels was always achieved for the independent test data (ACC) with the RF models than for the LDA models, while OOB showed lower accuracy than ACC for the RF models (Fig. 4.5).

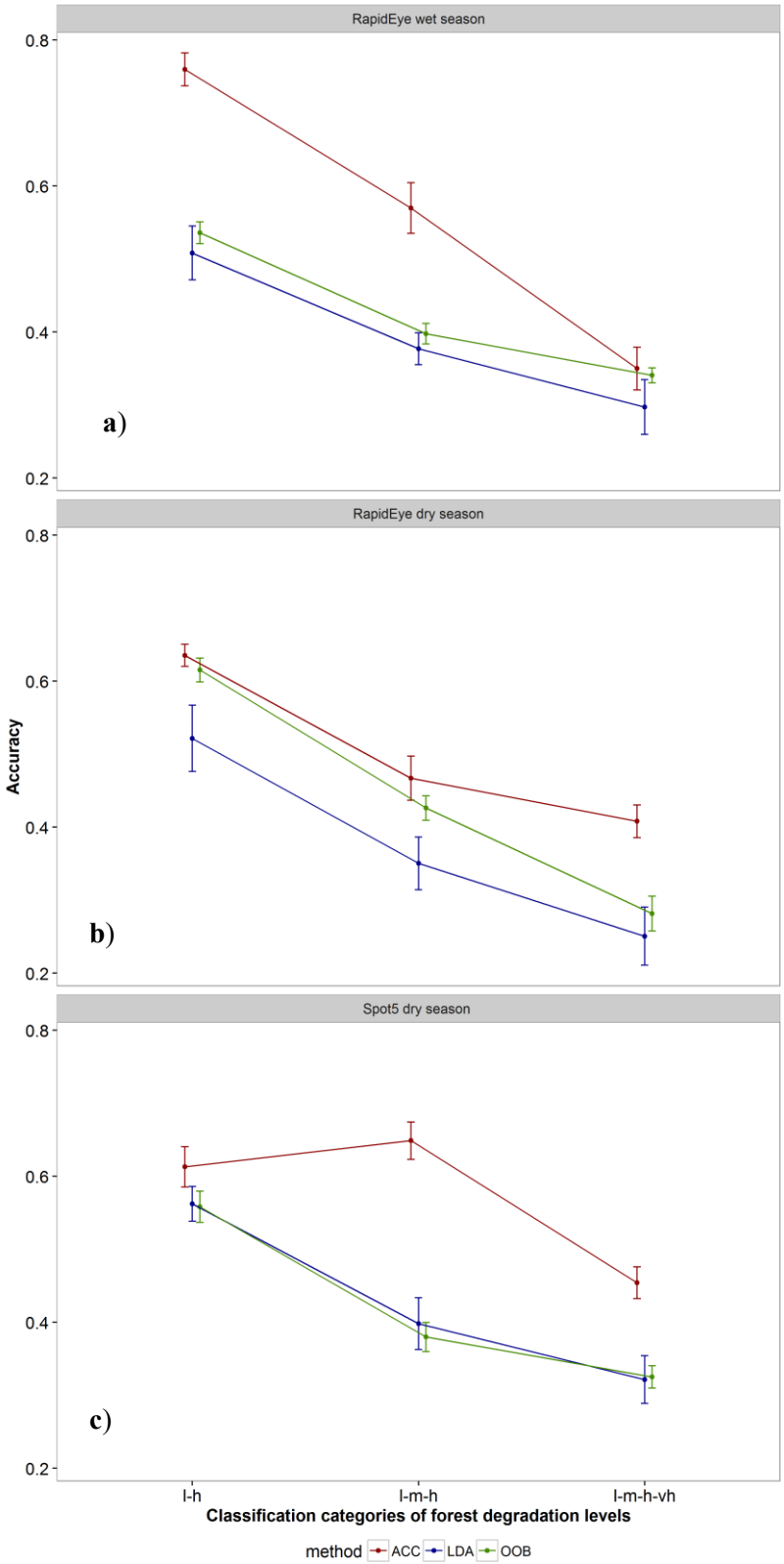

Figure. 4.5 Mean accuracy (+/- SD) of RF and LDA models based on three types of remote sensing dataset (a) RapidEye for the wet season, b) RapidEye for the dry season, c) SPOT 5 for the dry season); obtained in the classification of 106 field plots

into two, three and four categories of forest degradation levels.
The x-axis shows the three classification categories of forest degradation levels based on the disturbance index derived from field data: l-m-h-vh is a four-way category between low, medium, high and very high; l-m-h is a three-way category between low, medium and high; l-h is a two-way category between low and high. Accuracy of the RF classification model was measured using an independent validation data set (ACC) of 20% of the data and out-of-the-bag error (OOB). For the LDA models, accuracy was calculated using a 10-fold cross validation as the test data set. The error bars represent 95% confidence intervals.

The four-way classification category of degradation levels showed low accuracy for both classification methods and all three data sets. For the three-way classification of the field data, the best result was obtained using the dry season SPOT 5 data and the RF model (65% ± 3.5%) (Fig. 4.5c). The highest accuracy for the two-way classification category was achieved with wet season RapidEye data using the RF model (76 % ± 3.1%, Fig. 4.5a). However, models developed with dry season data had slightly less variability within each classification type (Fig. 4.5 b & c). As RF performed better than LDA, the RF models with the highest accuracy for each classification category were selected for further analysis.

Further evaluation of the selected models, using a 10-fold cross-validation, showed marginally better results than the accuracy expected for a completely random classification (Fig. 4.6). The much greater accuracy obtained in predicting the three-way classification category with either dry season SPOT 5 data (72 % ± 2%), dry season RapidEye (44% ± 2%) or wet season RapidEye data (57% ± 4%), compared with the accuracy of the random classification of only 33%, suggests that the best potential of modelling of the levels of forest degradation based on remote sensing data is found in a three-way classification system. The two-way classification performed well, with all three data sets producing accuracies far greater than the random classification (average 20% greater). However, the prediction of the four-way classification category was unsuccessful, achieving accuracies for the three data sets on average only 12% better than the random classification.

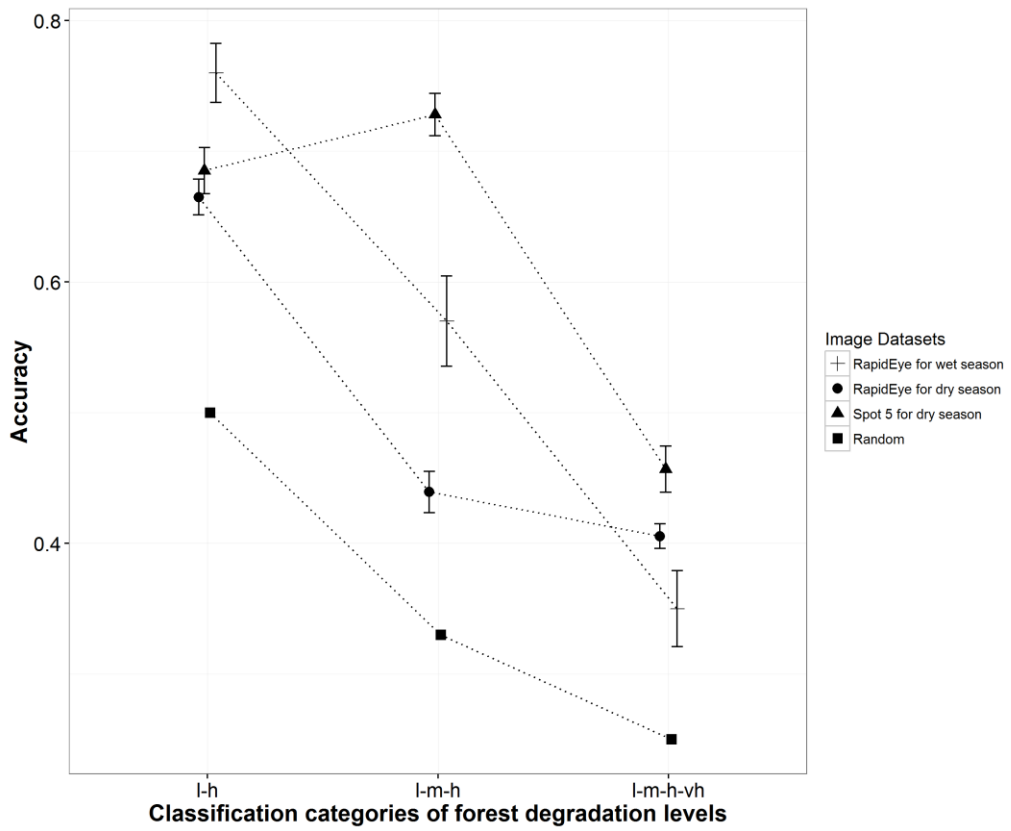

Figure 4.6 Comparison between the accuracy of the RF models based on three types of remote sensing datasets and the expected accuracy from a random classification (as a control).

The accuracy of each model was based on a 10-fold cross validation and is shown as mean (+/- SD). The x-axis shows the three categories of classification of forest degradation based on the field data of 106 field plots. In the x-axis l=low, m=medium, h=high, and vh=very high.

No consistent pattern was observed among the remote-sensing image derived predictor variables across the RF models (Fig. 4.7). However, in all the models, texture indices were ranked amongst the six most important predictor variables. The exception to this pattern was the prediction of the two-way classification based on RapidEye wet season data, which is noteworthy as this was the one that achieved the highest accuracy using the independent validation data set. In this case, vegetation indices, mainly GNDVI and NDVI_RE, were the most important predictor variables and only one textural variable was included (ENT_ED) (Fig. 4.7a).

It is also noteworthy that for the prediction of the three-way classification category by the model based on dry season SPOT 5 data (which achieved the greatest improvement in accuracy over the random classification), principal component 1 (PC1) and the red band

(RED) were ranked second and third amongst the variables contributing to the classification model. These two variables were only important for the model based on SPOT 5 data. For the two- and four-way classification categories with both dry season data sets (in contrast to the wet season Rapid Eye data), texture indices derived from the NIR band appear to be more important than the ones from the RED or ED bands. Amongst the texture indices two variables stand out as most important in the prediction of the classifications, namely correlation (CORR, both R & NIR) and entropy (ENT, mainly NIR) which ranked high in 7 and 6 of the 9 models respectively (Fig. 4.7).

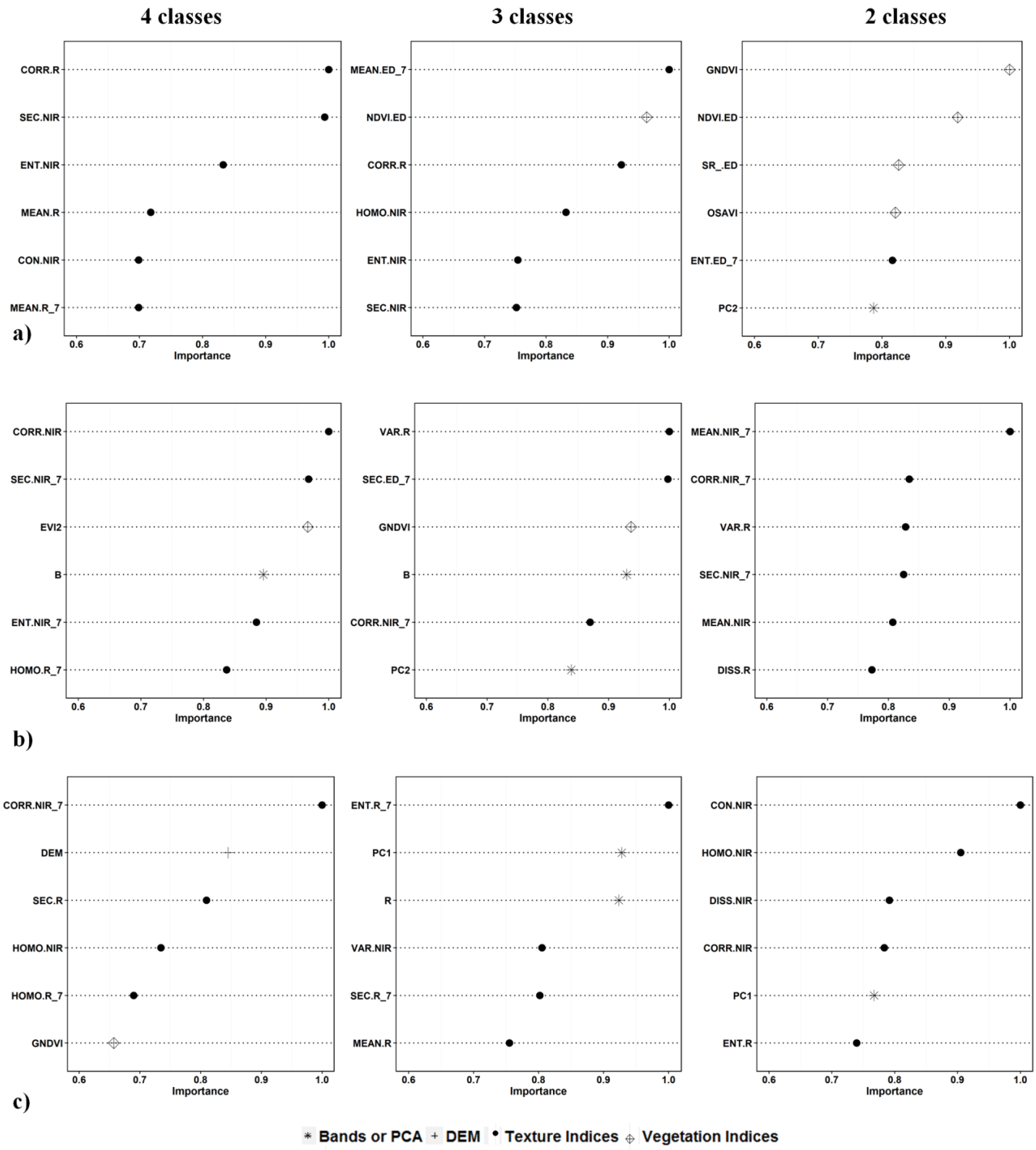

Figure 4.7 Relative contribution of the predictor variables derived from three types of remote sensing data (a) wet season Rapid Eye, b) dry season Rapid Eye and c) dry season SPOT5) to the accuracy of each RF model developed in the classification of 106 field plots into two, three and four classification categories of forest degradation levels.

The units of importance are the percentage reduction, in accuracy of predicting the classification, that would result from removing a given predictor variable. The definition of the remote sensing indices shown in the y-axis labels are given in Table 4.2. The symbols used for these indices distinguish those that are spectral bands or principal components analysis axis scores, a digital elevation model (not derived from remote sensing data, see section 4.2.4), texture indices and vegetation indices).Variables with a 7 at the end of the name indicate texture measures derived on a 7x7 pixel window; if no number is given texture measures refer to a 3x3 pixel window.

4.4. Discussion

4.4.1. Evaluating levels of forest degradation based on the relationship between indicators of human disturbance and forest attributes

This study confirmed that there was a strong significant relationship between measured indicators that were used to calculate a disturbance index and the AGB (relative to the potential stocking level) of TDF plots in the Mexican study site (Table 4.4, Fig. 4.4). This showed that the variation in current plot AGB is not only a consequence of stand age, or environmental factors, but that it is also clearly correlated with the ongoing human disturbance regime. Stand age is commonly cited as the main factor explaining the variability in AGB in TDF (Martinez-Yrizar, 1995; Becknell & Powers, 2014), however that finding is based mostly on studies of secondary forests that are recovering in protected areas, and are thus experience minimal further human disturbance. Our study provide a slightly different picture, as it is focus on unprotected TDF that is subject to on-going use by people, as is the case for the majority of TDF in Mesoamerica (Chazdon *et al.*, 2009a). It is likely that, although accumulation of AGB is occurring as the forests age, ongoing human-induced disturbances impede recovery. This lack of recovery is supported by the low absolute measured values of AGB and BA, in combination with the evidence of multiple human-induced disturbances found in most plots.

A limitation of our study was the use of a non-local reference value of potential AGB, however the land use dynamics of the study area mean that there are no large patches of comparable undisturbed forest where cattle have not been present in the long term. Although the data that we used from Chamela-Cuixmala provided a fair reference of estimated potential AGB for a first comparison, further work should focus on refining this by assessing the less disturbed forests of the region outside protected areas that span a wider range of environmental conditions. Regardless of the reference value used, previous work has suggested that, in contrast to wet forests, TDF can recover more rapidly from disturbance as they have a relatively simple structure at maturity (Ewel, 1980; Murphy & Lugo, 1986; Vieira & Scariot, 2006). The relatively high rates of AGB productivity have been reported for TDF, 6-16 Mg $ha^{-1}y^{-1}$ (Murphy & Lugo, 1986; Martinez-Yrizar, 1995; Jaramillo *et al.*, 2011; Becknell *et al.*, 2012); imply that our study area, and Mexican western Pacific TDF in general, have the potential for relatively fast accumulation of AGB, if human-induced disturbance was limited.

This study provides statistical evidence of the relationship between an increase in human activities that cause forest degradation in TDF and the changes in forest attributes such as basal area, AGB and forest cover. This is important for the objectives of the study because it

shows that *in situ* indicators of human activities can be used to evaluate the causes of forest degradation signified by a reduction in the values of these attributes. Testing with the resulting index, that is based on the indicators of human disturbance activities that are characteristic of TDF, showed statistically that disturbed TDF landscapes can be classified into three levels of forest degradation (Fig.4.3). There was no clear distinction between areas classified as having low and medium disturbance levels for all the forest attributes studied, which showed a very high variability amongst plots (potentially reflecting high natural variability linked to the environmental heterogeneity characteristic of TDF (Balvanera *et al.*, 2002)). Furthermore, areas with high levels and those with very high levels of human disturbance were both much less variable in their forest attributes (potentially linked to the structural simplification that occurs in high disturbance regimes (Chazdon *et al.*, 2007; Griscom *et al.*, 2011), and the three classes of low/medium, high and very highly disturbed areas were clearly distinct. Even though indices and classification systems have limitations, they are of high value for modelling using remote sensing data, which greatly increases the potential to extend from plot to landscape scales. Our study suggests that these tools have applicability for a monitoring method based on site indicators, which are measurable and transparent, that can bridge between the level of disturbance, management practices and AGB, and thus have great potential for evaluating interventions designed to reduce carbon emissions from forest degradation.

The strong correlation obtained between the disturbance indicators and AGB, BA and, to a lesser degree, canopy cover (Table 4.4) suggests that the variables selected for use in the disturbance index are useful proxy measures for estimating the level of forest degradation in areas of TDF associated with shifting cultivation and cattle grazing regimes. From the variables included in this study to assess forest degradation, the percentage of small stems (5-10 cm DBH), along with bare soil cover, had the highest explanatory power to predict forest AGB and the other forest attributes (Table 4.4). The proportion of small stems has been suggested as a major structural factor explaining variation in TDF AGB (Martinez-Yrizar, 1995). The mean proportion of small stems (< 5 cm DBH) in the undisturbed Chamela-Cuixmala forests used as a one of the references for the present study is only 23% while its mean AGB is 84 Mg ha^{-1} (Martinez-Yrizar *et al.*, 1992), while in the Guarnica forest in Puerto Rico, the proportion of small stems is 85% and the biomass is only 49 Mg ha^{-1} (Murphy & Lugo, 1986). In our study site, that also had a low mean AGB value (21.9 Mg ha^{-1}), the average proportion of small stems was 71%. Hence, the high proportion of small stems (≤ 10 cm DBH) in TDF, suggest that monitoring AGB measuring only large trees, as has being suggested for moist forests (Slik *et al.*, 2013; Sist *et al.*, 2014), although

practical might not adequately estimate the changes in AGB during the forest degradation-recovery cycle in TDF.

The value of the proportion of small stems as a disturbance indicator in TDF can be attributed to the strong capacity for re-sprouting after disturbance that is a distinctive feature of TDF (Ewel, 1980; Kennard, 2002; Vieira *et al.*, 2006; McDonald *et al.*, 2010; Lévesque *et al.*, 2011), which has been interpreted as an evolutionary response to disturbance in water-limited environments, where there is a high rate of mortality of seedlings and saplings (Vieira & Scariot, 2006; Griscom *et al.*, 2011). Álvarez-Yépiz *et al.* (2008) found that the proportion of small stems in TDF increases under higher grazing intensities, Kennard (2002) reported 90% resprouting of individuals < 2.5 m tall after moderate fire and plant removal treatment in Bolivia, while McLaren and McDonald (2003) showed that 81% of species in a Jamaican TDF will resprout after cutting treatments. Then McDonald et al. (2010) concluded that resprouting decreases with time since disturbance. All of this evidence points to the value of the abundance of small stems as an indicator of forest degradation in TDF that are subject to a range of impacts including grazing, tree cutting fuelwood collection and clearing.

The indicator value of bare soil cover is illustrated by its strong positive correlation with manure cover and negative correlation with AGB (Table 4.5). Thus, higher grazing intensity is linked to a greater cover of bare soil, which is linked to lower AGB. In fact, many of the plots with low AGB are located to the west of the study area (Fig. 4.1), where higher densities of cattle have been reported at the community level (Chapter 3). In contrast, in the central area, near the boundary of the Manantlan Biosphere Reserve, the four plots with the highest AGB have levels similar to the potential values of the mature undisturbed forest at the reference site. In field interviews, local community leaders indicated that in the area close to the Manantlan Biosphere Reserve efforts have been made, as part of a payment for ecosystem services project, to eliminate cattle grazing, mainly by constructing fences around some sections of forest.

The use of TDF for livestock grazing has not been extensively studied in comparison with other types of disturbance (mainly shifting cultivation or tree harvesting) and little is known about the effect that it has on forest structure in combination with other forms of disturbance (Cantarello *et al.*, 2011). Lower AGB and BA have been reported in TDF areas under high grazing intensity in comparison with moderate grazing intensity (Sagar & Singh, 2006; Álvarez-Yépiz *et al.*, 2008). Other studies have found that grazing significantly changes forest structure in TDF, mainly because it removes non-woody vegetation promoting greater abundance of less palatable shrubs that may inhibit the establishment of new trees leading, in the long term, to a reduction in tree canopy cover (Stern *et al.*, 2002; Chaturvedi *et al.*, 2012;

Larkin *et al.*, 2012). As the forest canopy becomes more open after prolonged intensive grazing, there is a reduction in the benefit of canopy shade in retaining higher moisture levels, which reduces the rate of tree seed germination and seedlings survival, especially in drier TDF sites (Stern *et al.*, 2002; Vieira & Scariot, 2006; Derroire *et al.*, 2016a).

There is a complexity of factors influencing the species richness, density, and floristic composition of TDF, including environmental factors, and past disturbances and specific site (plot)-level factors (Chazdon *et al.*, 2007; Powers *et al.*, 2009; Norden *et al.*, 2015), thus establishing the value of disturbance indicators to assess forest degradation in relationship with biodiversity species is challenging. In the present study, the relationship of species richness of woody plants ($\geq$ 2.5 cm DBH) with the disturbance index was lower, while for species density its relationship was stronger with the disturbance index. Our results showed a positive correlation of woody plant species richness with the proportion of large stems and a negative one with the proportion of small stems. These findings suggest that a the subset of woody plant species that are most likely to competitively exclude other species in these TDF are the ones that dominate the small stem size class, e.g. through a high capacity for re-sprouting. Moreover, grazing promotes the establishment of a few shrubby species, which may competitively exclude (at least in the short-term) the regeneration of tree species capable of growing to larger stem sizes that are characteristic of mature TDF (Gillespie *et al.*, 2000; Stern *et al.*, 2002; Romero-Duque *et al.*, 2007; Lebrija-Trejos *et al.*, 2008; Rojas-Sandoval *et al.*, 2014), thus increasing the proportion of small stems. In fact, visual inspection of the woody species composition of our plots showed that a high abundance of shrub species (particularly of *Lysiloma microphyllum*) occurs in the plots with high and very high degradation levels.

Another issue to consider is that across our study plots woody plant species richness showed a slight trend to increase with forest stand age, in accordance with the findings of (Derroire *et al.*, 2016b). This finding suggests that in addition to the effects of grazing, the legacy of clearing on species richness and density is stronger than for attributes related to forest structure (Chazdon *et al.*, 2007; Martin *et al.*, 2013; Poorter *et al.*, 2016). All these findings indicates that future work should focus more on the ecological characteristics of the species composition and abundance (including whether they are characteristic of mature forests, their growth form, their drought and fire tolerance and the capacity to regenerate after disturbance), rather than the simply abstract measure of species richness. Such a functional characterisation of the species is likely to generate more insight into the combine effects of disturbance due to grazing, fuelwood collection and shifting cultivation, which are the dominant activities that occur in the majority of TDF left in Mesoamerica (De Clerck *et al.*, 2010; Dirzo *et al.*, 2011).

While we have not found good evidence that species richness can be strongly linked to indicators of disturbance, it remains a characteristic of forests' natural capital of high value to many stakeholders and indeed for REDD+ programmes and other payment for ecosystem services schemes. Nonetheless, we recommend that the relative importance of species density (per area) and area-independent estimates of total species richness should be considered carefully. From the perspective of TDF conservation, we consider our result that woody plant species density was negatively correlated with the disturbance index developed in the study to be a finding of potential importance. However, in terms of cost-effectiveness, plant identification is complex, so it might not be a practical aspect to include it in routine monitoring of forest degradation unless local project requirements placed a high emphasis on biodiversity.

The moderately strong (and highly significant) correlations found between the disturbance index and AGB, BA and forest cover (Table 4.4) provide evidence that the selected variables can be used in the monitoring of forest degradation within sub-national level projects designed to reduce TDF degradation. Assessment that links levels of forest degradation to its underlying causes is of particular importance for the successful adaptive management and external evaluation of such projects, e.g. for carbon-based payment schemes that seek to link actions to results (Salvini *et al.*, 2014). Such assessment of forest degradation is a complex task, because it requires monitoring schemes that are at least precise enough to determine if AGB loss (due to human disturbance activities) exceeds AGB growth (Clark & Kellner, 2012). Conventional approaches to monitor changes in AGB are usually based on the repeated detailed measurement of permanent sample plots, which is costly and time-consuming, e.g. Chidumayo (2013). However, because of the high variability in AGB (Read & Lawrence, 2003; Balvanera & Aguirre, 2006; Urquiza-Haas *et al.*, 2007), it is difficult to determine true changes in carbon stocks across a forest over time, and conventional monitoring methods provide no basis to attribute these changes to natural- or human-induced disturbance.

By using indicators that are problem-oriented, because they focus on human-caused change, direct evidence is provided about the effect of the management of a forest area (Lindenmayer *et al.*, 2011a). This is essential for the monitoring component that is central to adaptive management, informing what changes are needed to overcome shortcomings in the management of an area (Lindenmayer *et al.*, 2011b). In addition, if indicators are selected that are relatively inexpensive to measure, are easy to understand, and can be complementary to more formal forest inventory efforts, they could be incorporated successfully into monitoring schemes carried out by members of the community (Danielsen *et al.*, 2011; Pratihast *et al.*, 2013). The clarity of the link that they provide to the community's

management decisions should help to motivate this (Garcia & Lescuyer, 2008). Community-based adaptive management informed by this monitoring would result in changes to forest management practices, such as exclusion of cattle and prohibition of tree cutting in certain areas. The subsequent monitoring would inform the community whether this has produced the anticipated change in both the selected indicator variables and consequently the priority forest attributes (e.g. AGB linked to carbon stocks).

In addition, further research should investigate the linkage between the approaches to monitor forest degradation using the disturbance indicator level approach developed in the present study, to the stock-difference method of monitoring carbon stocks based on the average changes in carbon stocks per unit area between the start and end of each accounting period, that is one of the standard approach used in international forest carbon stock change assessment (GOFC-GOLD, 2013).

4.4.2. Potential of remote sensing data for classification of forest degradation

The potential of remote sensing data analysis to detect levels of forest degradation was evaluated using two statistical modelling methods with high spatial resolution images from the dry and wet seasons. The accuracy of both methods was limited, but the non-parametric method, RF, outperformed the traditional LDA statistical model. The superior performance of RF provides a good basis for improving methods to relate changes in forest structure detectable by remote sensing indices to the effects of on-going disturbance processes in TDF. These offer the potential to extrapolate from local-scale field assessment of forest degradation processes to landscape-scale monitoring. However, the encouraging findings of the present study are just preliminary and these relationships still need to be verified using larger and more balanced training and validation datasets from a wider range of sites.

Specific limitations of the present study were that the training data sites for the low disturbance level were fewer in number than for the other three classes. Magdon *et al*. (2014) pointed out that with RF models a limited number of training samples for a class could result in a reduced predictive capacity for that class, affecting overall model performance. However, the nature of our study area, that included communities that rely heavily on tree harvesting and grazing in forest areas, meant that patches of undisturbed forest were overall less frequent. This situation was reflected in the use of a random systematic sampling, which meant that at the end the model tend to over fit towards classes with more training data, in this case areas of higher disturbance. As a result of the lower number of training data for low disturbance classes, plots with low disturbance levels were commonly misclassified using the remote sensing data in all of the models. The effect of the number of training data for each class probably had less impact on the three-way classification, because it assigned

lower values in the medium class to the low class and a better differentiation was achieved. This is in accordance with the ground data, for which three disturbance levels were also clearly differentiated based on AGB and BA (Fig. 4.3a & b).

Particular attention should be given to the result that texture indices have such an influential role as predictor variables in seven out of nine models, because it indicates the link between disturbance and spatial distribution of the vegetation. Our result is in accordance with other empirical studies that have found good correlations of AGB, basal area and, to a less extent, canopy cover with texture indices based on red and NIR bands (Barbier *et al.*, 2010; Gallardo-Cruz *et al.*, 2012; Ploton *et al.*, 2012). The importance of texture indices as predictor variables might be related to disturbance processes creating more open canopies, causing a higher proportion of soil- versus tree-cover pixels, which have very different reflectance values. Consequently, these areas appear more heterogeneous than a closed canopy, which has neighbouring pixels with more similar values. Second order texture indices, including ENT, CON and CORR, evaluate the spatial relationship between pixels, as they are based on the probability of neighbouring pixels in the four directions having a similar grey level (Haralick *et al.*, 1973). In the present study the texture indices correlation (CORR, both R & NIR), entropy (ENT, mainly NIR) and its counterfactual second-angle movement (SEC), that stand out as dominant variables in most of the models, are all measures of the degree of spatial orderliness (Jones & Vaughan, 2010). In other words, they measure how homogeneous the neighborhood of a pixels is. Forest stands dominated by trees with small canopies generally have higher values for these texture indices, indicating that such areas are less homogeneous (Ozdemir & Karnieli, 2011). The RF models provide evidence of the potential of texture indices for linking TDF structure with remote sensing, which could provide the basis for mapping the state of forest degradation in a landscape. However, further work should focus on using higher resolution imagery and/or multi-date images to further explore how the magnitude of the variance in texture indices is related to forest structural characteristics and spatial configuration of TDF.

Vegetation indices were of greater importance in the models using remote sensing data acquired during the wet season than those based on dry season data. The model that classified wet season RapidEye data into two classes, which achieved high accuracy with the independent test data, was based mostly on vegetation indices, including the red edge bands (Fig. 4.7a). A tangible explanation of this seasonal effect is that the information provided by vegetation indices gives a better indication of the tree canopy cover (and thus, in disturbed TDF, AGB) when there are leaves on the crowns of deciduous trees rather than just bare branches (Beckschäfer *et al.*, 2014). As pointed out by Gallardo-Cruz *et al.* (2012), the calculation of vegetation indices actually reduces the internal variability of the image data, in

contrast to texture indices that provide information on the spatial arrangement of pixels. Thus, texture indices can be crucial for differentiation of the amount of vegetation during the dry season for TDF, which is important because during dry season in tropical areas cloud cover is low and therefore higher image quality is available.

In our study all the field plots were located in TDF, therefore the spectral variability was less than would be the case over a wider range of land cover types (i.e. from bare land or recently burned areas to old-growth forests), as is usually analysed in this type of study (e.g. Arroyo-Mora *et al.*, 2005). A consequence of reduced variability in reflectance values is that the models are not dominated by extreme values, which tends to enhance the model fit. It is possible that the models developed in the present study could achieve a better fit if, for instance, bare land was included as another level of extreme disturbance. However, this does not resolve the main issue that within forests there is significant variability in disturbance levels on the ground that is not properly accounted for with remote sensing data. In this study, other types of analysis that could take advantage of the reduced spectral variability by incorporating indicators of disturbance from ground survey were explored and showed only limited potential. Further development of this approach could be achieved by changing the scale of analysis to even finer-scale resolution, and by increasing the amount of sample data from intact or well conserved forest that is made available for training. Also, as argued by Clark & Kellner (2012), remote sensing models will never be accurate until plot-level estimates of AGB are used, and the proper scale to link ground and remote sensing measures is used. Further work is needed to advance the evaluation of forest degradation with remote sensing, but the present study has demonstrated the importance of future studies incorporating available ecological and social information on disturbance processes.

4.5. Conclusions

Assessing forest degradation is widely acknowledged to be a complex task. In general, indicators of forest degradation will be useful if they are capable of assessing natural capital (e.g. biodiversity), ecosystem function (e.g. carbon storage) and even delivery of ecosystem services, over time. For this, locally relevant indicators, that produce repeatable results and are easy to measure in the field, are needed. The information provided by such indicators, combined with reference to the potential AGB stocking levels found in mature undisturbed forests, provides a more complete picture and better understanding of the degradation processes in TDF.

In this study we tested an empirical method to evaluate forest degradation due to the most common drivers of disturbance in TDF in Mesoamerica, mainly cattle grazing, fuelwood

collection, and selective tree harvesting, using indicators that are directly linked to these activities. We found that the level of these indicators in a plot correlated well with the forest attributes that are commonly associated with forest degradation, mainly AGB, BA and, to a lesser extent, canopy cover. Even if it is broadly recognized that these human activities causing disturbance to TDF have detectible effects on forest structure, these effects are seldom evaluated using remote sensing, because they are difficult to detect. In this study we have built upon the association between forest structure and remote sensing, which had been demonstrated by previous research that evaluated the detectability of different successional stages of secondary forests, therefore areas with different forest structure, to test the extent to which new analytical methods with higher resolution data can provide evidence of the level of forest degradation. Our results indicated that the use of the RF classification algorithm applied to texture indices has potential to stratify TDF landscapes into at least two levels of forest degradation, which could enable the mapping of degraded forests and support the monitoring of changes in forest carbon stocks linked to forest degradation.

Although the results obtained have only a limited power of these methods, it showed the potential through further research to link analysis of remote sensing data to assessment of the levels of degradation of TDF attributable to its management. This would enable improvement of the cost-effective planning and monitoring of forest restoration; and management linked to policy processes such as payment for ecosystem services and REDD+.

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4.6. Appendices

Table S 4.1Vegetation indices used in the study. For variable names refer to Table 4.2.

Index	Algorithm	Reference
Canopy Index	$\mathrm{CI} = \mathrm{SWIR} - \mathrm{G}$	(Vescovo & Gianelle, 2008)
Enhanced Vegetation Index 2	$\mathrm{EVI2} = \frac{\mathrm{NIR} - \mathrm{R}}{\mathrm{NIR} + 2.4 * \mathrm{R} + 1} * 2.5$	(Jiang *et al.*, 2008)
Green Normalized Difference Vegetation Index	$\mathrm{GNDVI} = \frac{\mathrm{NIR} - \mathrm{G}}{\mathrm{NIR} + \mathrm{G}}$	(Gitelson *et al.*, 1996)
Modified Soil Adjusted Vegetation Index 2	$\mathrm{MSAVI2} = \frac{2\mathrm{NIR} + 1 - \sqrt{(2\mathrm{NIR} + 1)^2 - 8(\mathrm{NIR} - \mathrm{R})}}{2}$	(Qi *et al.*, 1994)
Normalized Difference Vegetation Index	$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{R}}{\mathrm{NIR} + \mathrm{R}}$	(Rouse *et al.*, 1973)
NDVI Red Edge	$\mathrm{NDVI_ED} = \frac{\mathrm{ED} - \mathrm{R}}{\mathrm{ED} + \mathrm{R}}$	(Gitelson & Merzlyak, 1997)
Optimized Soil Adjusted Vegetation Index	$\mathrm{OSAVI} = \frac{\mathrm{NIR} - \mathrm{R}}{(\mathrm{NIR} + \mathrm{R} + 0.16)} * 1 + 0.16$	(Rondeaux *et al.*, 1996)
Soil Adjusted Vegetation Index	$\mathrm{SAVI} = \frac{\mathrm{NIR} - \mathrm{R}}{\mathrm{NIR} + \mathrm{R} + 0.5} * (1 + 0.5)$	(Huete, 1988)
Simple Ratio	$\mathrm{SR} = \frac{\mathrm{NIR}}{\mathrm{R}}$	(Birth & McVey, 1968)
Transformed Normalized Difference Vegetation Index	$\mathrm{TNDVI} = \frac{\mathrm{NIR} - \mathrm{R}}{\sqrt{(\mathrm{NIR}^2} + \mathrm{R} + 0.5\ )} * 1.5$	(Bannari *et al.*, 2002)

Chapter 5. Forest Degradation and Deforestation dynamics in a tropical moist forest over 40 years: a case study of the Osa Peninsula, Costa Rica

Abstract

Although Costa Rica has high forest cover, the quality of its forests varies greatly across the country. Two past disturbance processes that have affected current forest condition are logging and forest clearance for agriculture. Further understanding is needed of these processes and how to quantify and monitor them in order to implement policies to reduce forest degradation, and promote forest restoration and improved forest management. This study aims to present a new method to quantify the change in cover between undisturbed and degraded forests, comprising logged areas and secondary regrowth forests, by analyzing a long time series (1975-2014) of medium-resolution satellite data in combination with historical data on logging concessions in the Osa Peninsula. A new approach to map disturbed forest is presented based on comparing the ratio of endmembers (the reference materials into which each pixel of a satellite image can be decomposed) between logged and undisturbed forests. The analysis showed that at the beginning of the study period the Osa Peninsula was 80% covered by forests that were largely undisturbed. Total forest cover declined to 71% by 2000 and recovered to 76% by 2014. The majority of loss and gain of forest cover occurred at low elevations (100-200 m asl) and on flat terrain with slopes less than 5°. About half of the 7419 ha of forest cover recovered by 2014 comprised areas that had been classified as secondary regrowth in 2000. Through the analysis of endmembers it was estimated that logging affected about 18% of forest area. In total, secondary growth and logged areas comprise 38 160 ha of degraded forest that represented 30% of the forest cover in 2014. These results and the method presented can potentially inform decision-making process for forest management, as they incorporate the legacy of past disturbances to assess forest quality. Understanding how the landscape is transformed from old growth to degraded forests is important within the REDD+ context to improve spatial planning and forest monitoring. This will be important to ensure that future disturbances, such as any resumption of selective logging in the area, will be made compatible with biodiversity conservation, carbon storage and improvements to the livelihoods of local communities.

Keywords: degraded forests, secondary growth, Landsat, selective logging, endmember, linear unmixing analysis.

5.1. Introduction

In tropical landscapes undisturbed, primary forests play a very important role in the provision of ecosystem services, especially carbon retention, biodiversity conservation, and the maintenance of ecosystem processes (Gibson *et al.*, 2011; Thompson *et al.*, 2012). However, most forests within the tropics considered to be "old-growth" and "primary" have in fact been disturbed by human activities and are to some extent degraded (Defries *et al.*, 2002; Achard *et al.*, 2007; Asner *et al.*, 2009). The contribution of forest degradation to global emissions of greenhouse gases (GHGs) is highly uncertain and depends on how it is defined (Houghton, 2012, 2013). However, it has recently been estimated that in countries with low deforestation rates, GHG emissions from forest degradation due only to logging represent more than half of those produced by deforestation (Pearson *et al.*, 2014) and that timber harvesting has affected at least 20% of the humid tropical forest biome between 2000 and 2005 (Asner *et al.*, 2009). Thus, improving the quantification and monitoring of forest degradation in tropical regions is crucial for the implementation of international agreements on climate change mitigation such as REDD+, as well as for achieving biodiversity conservation goals such as the Aichi targets (Gardner *et al.*, 2012).

While definitions of forest degradation vary, international policy generally includes within the category of "degraded forests" both the secondary forests that regrow after the abandonment of agricultural land and old-growth forests that have been used for selective timber exploitation without adequate management to ensure forest recovery (ITTO, 2002). Taking both carbon stocks and biodiversity into account, degraded forests are likely to have a reduced capacity to provide most ecosystem services compared with old-growth forests, which is how forest degradation is, at least in policy terms, commonly defined (ITTO, 2002; Simula, 2009; FAO, 2011). However, because such a definition is difficult to quantify/apply, we argue that an approximation to mapping degraded forest over a landscape can be achieved by studying the recent disturbances that have transformed previously old-growth forests into secondary and logged forests.

For the above mentioned reason, in this study we use a broad definition of degraded forest, and define it as those forest areas that have undergone disturbance processes of clearance and poorly managed selective timber exploitation in the recent past (<40 years). Such forests have had their structure and composition altered by human-induced disturbance, hence we assumed that their carbon stocks and biodiversity are different from their original undisturbed state. We think this is a valid assumption, as it has been estimated that secondary forests take on average 66 years to recover 90% of the original above-ground biomass after clearance (Poorter *et al.*, 2016), and more than 100 years to reach a similar plant species composition (Chazdon *et al.*, 2009b; Gibson *et al.*, 2011; Martin *et al.*, 2013). Regarding

logged forests, recovery time of carbon stocks and biodiversity will depend on the logging intensity. For example, it has been estimated that removing 25-50% of above-ground carbon stocks will require between 40 and 75 years to recover to pre-logging values (Rutishauser *et al.*, 2015); furthermore, Putz *et al.* (2012) stated that a decrease in timber volumes after the first logging cycle is inevitable. Impacts on biodiversity may take longer to recover due to their effects on key ecosystem functions and processes, which may reduce forest resilience (Ewers *et al.*, 2015; Chaudhary *et al.*, 2016).

It should be acknowledged that a more appropriate term for such areas would probably be "human-induced disturbed forests areas" or "natural forest areas subject to human intervention", since "degraded forests" implies a judgment about the quality of the forest, that varies depending on the beholder. Using the term forest degradation does not imply that such areas should be regarded as lacking conservation value (Berry *et al.*, 2010; Edwards *et al.*, 2011) or that they are in a permanent static state of degradation, as clearly tropical forest has a strong capacity to recover from disturbance given sufficient time and provided that its resilient capacity is not affected (Ghazoul *et al.*, 2015). However, as has been done in other mapping studies (e.g. Souza, 2003; Shearman *et al.*, 2009; Matricardi *et al.*, 2010; Franke *et al.*, 2012; Margono *et al.*, 2012; Bryan *et al.*, 2013; Souza *et al.*, 2013; Zhuravleva *et al.*, 2013), and because the aim of the present study is to spatially analyze the extent of alteration that is found in a tropical forest landscape, we use the term degraded forests.

In this chapter we will focus on devising an efficient and effective way of mapping changes in forest indicative of forest degradation over a long time period, by coupling remotely-sensed satellite images and field (historical) data analysis. In the following subsections, we provide background information important to further understand why we are doing this. We first provide an overview of remote sensing approaches for quantifying and monitoring forest degradation, and a justification for using the method we chose. Finally, we present background information on logging in our case study region, Osa, Costa Rica.

Background

a. The use of remote sensing to map degraded forest areas in the tropics

Despite the importance of monitoring forest degradation, countries have focused their monitoring processes mostly on the extent of deforestation, thus overlooking the condition of tropical forest when assessing their forest resources (Peres *et al.*, 2006; GOFC-GOLD, 2013). This is probably because of the technical difficulties that are still associated with measuring forest degradation, despite the emergence of techniques such as advanced remote sensing analysis (FAO, 2007; Petrokofsky *et al.*, 2012). The differences in spectral information between logged and undisturbed forests are very subtle, in comparison with the

clear signal that is usually produced when an area is deforested (GOFC-GOLD, 2013; GFOI, 2014). Nonetheless, with the publically-available Landsat Archive spanning more than 30 years and the continuous acquisition of new satellite data with Landsat 8 and Sentinel 2, unprecedented opportunities are becoming available to explore effective and efficient ways to monitor forest dynamics, and particularly advance the study of forest degradation (Turner *et al.*, 2015).

Remote sensing-based methods that use multi-year Landsat data have been developed to map tropical forest degradation mainly due to selective logging. They have improved detailed understanding of forest cover dynamics and associated changes in forest carbon stocks. Recent studies have applied visual interpretation of Landsat images to: a) map logging roads, b) detect the extent of logged forest in combination with coarse resolution canopy cover data, and c) estimate the extent of forest degradation when combined with ancillary data on infrastructure (Margono *et al.*, 2012; Zhuravleva *et al.*, 2013; Gaveau *et al.*, 2014; Kleinschroth *et al.*, 2015). Other studies have used sub-pixel analysis, that decomposes the pixel into a series of reference materials, known as endmembers to trace canopy damage due to selective logging in the Amazon (Asner *et al.*, 2005, 2010; Souza *et al.*, 2005; Matricardi *et al.*, 2010). Such studies are based on the principle that areas where logging has occurred will have higher cover of certain reference materials, such as soil, and lower values of others, such as green vegetation. Although limited by the fast regrowth of tropical forests that affects the detection of degradation, the combination of these analyses with field data and historical sources has in some case studies enabled the tracking of areas that have undergone selective logging. These methodologies have been developed and applied in the Brazilian Amazon (Souza *et al.*, 2013), Congo Basin (Laporte *et al.*, 2007) and Borneo (Gaveau *et al.*, 2014); studies of logging based on remote sensing are rare for other regions.

b. Current situation of selective logging in Costa Rica

Costa Rica is aiming to become carbon neutral by 2021 and the government's strategy relies heavily on mitigation from the forest sector by participating in REDD+ (MINAET, 2012). As the forest cover of the country is increasing, incentives are most appropriately focused on reducing the causes of continuing forest degradation (especially of old-growth forest), through implementation of sustainable forest management, and promoting restoration (enhancement of carbon stocks) of previously degraded forest, rather than primarily on avoiding conversion of forest to other land uses (Angelsen & Rudel, 2013).

Selective logging in Costa Rica is regulated by the Forestry Law 7575, approved in 1996. This law established that timber harvesting in natural forests requires a forest management

plan, a technical study that basically describes what will be harvested and where it will be done. This law set the minimum cutting diameter for trees to 60 cm DBH and a maximum harvesting intensity of 60% of trees above this diameter limit that are of species classified as commercial. Another important modification introduced by the new law, is that it permits forest harvesting on untitled land (land that is assumed to be under private ownership but lacks a legally recognised property title). This opened up the possibility for logging companies and landowners to profit from a large stock of highly valuable timber that was previously not accessible.

Logging intensity in Costa Rica varies from 2-3 trees/ha to more than 10 trees/ha in some areas; timber is generally extracted using a skidding system (Quesada *et al.*, 2012; Arroyo-Mora *et al.*, 2014). Consequently, the rate of forest recovery after logging varies greatly across the country. A fifteen years polycyclic cutting cycle was defined in Forestry Law 7575, but this is arguably too short for many forests to recover from the permitted intensity of logging, as multiple studies have indicated longer recovery times for timber stocks (from 30-100 years) for conventionally logged tropical forests (Keller *et al.*, 2007; Huang & Asner, 2010; Hawthorne *et al.*, 2012; Gourlet-Fleury *et al.*, 2013; Osazuwa-Peters *et al.*, 2015; Rutishauser *et al.*, 2015).

Although important efforts have been made in the past to generate information to improve selective logging practice in Costa Rica (e.g. the Boscosa project, Fundecor (Howard, 1993; Donovan, 1994), it still faces multiple challenges (Camacho, 2015). Despite the existence of a legal framework to regulate selective logging which aims to meet international standards of sustainable forest management, experience has shown that its application has being limited (OTS, 2008; Quesada *et al.*, 2010). Country-specific information for decision making is scarce, particularly in relation to timber stocks, spatial distribution and planning of logging, logging intensity, impacts of logging on biodiversity and forest recovery time. In addition, logging has a bad reputation in the country, and is seen as a threat to biodiversity conservation (Sáenz-Faerrón *et al.*, 2010; Camacho, 2015). Recognizing these limitations, as is further explained in the next section, logging in natural forests is banned in many parts of the country. Nonetheless, currently there is pressure to remove these bans, since there is an increasing demand for wood and it is believed that bans foster illegal logging (Chavarria & Castillo, 2011). Thus, Costa Rica now seeks to increase wood production through sustainable forest management (SFM), as part of the country's REDD+ strategy, while continuing its existing forest conservation policies (Sáenz-Faerrón *et al.*, 2010). This creates, among other things, the need for monitoring protocols that can evaluate the state of forest resources by quantifying the extent of old-growth forest, degraded forest and forest re-growth at the landscape scale.

c. History of land use change and logging in the Osa Peninsula

The Osa Peninsula represents the largest lowland rainforest remnant of the Pacific coast in the Neotropics (De Clerck *et al.*, 2010) and hence is considered as a key site to maintain viable populations of many animal species (e.g. jaguar) (Sanchez-Azofeifa *et al.*, 2002). The forests of Osa are unique from a pantropcial perspective, because they contain some of the tallest stature forests in the Neotropics with tree heights of up to 60 m, compared with the Neotropical norm of 35-45 m; in this way they are more similar to African and Southeast Asia tropical rain forests (Taylor *et al.*, 2015). Also, because of its location and geological history, the Osa Peninsula forests are particularly rich in tree species (162 species/ha on average) (Thomsen, 1997), with a species assemblage including elements from both South and North America with about 5% of tree species being endemic to the peninsula (Cornejo *et al.*, 2012).

The Osa Peninsula has a complex history of human colonization that has shaped forest cover dynamics. It is outside the scope of this study to detail this history, so here only the most important events that are relevant to the study, are outlined[9]. During the 1970's, the area formed an unfragmented block of tropical moist forest, with more than 80% of forest cover categorized as intact (Vaughan, 2012), and a very low (about 2.8 persons/km^2) human population density (INEC, 1973; Rosero-Bixby *et al.*, 2002). To protect these natural resources, two national parks and a forest reserve were established during this decade. The establishment of these protected areas that covered most of the Peninsula, led to land use restrictions, particularly through stipulating that land within the Peninsula could not be titled. Despite this, with the increase in accessibility when the main road was opened in 1974, agricultural expansion, mainly for cattle ranching, increased exponentially. In 1983, with the closing of the banana company, which provided a major source of employment in a nearby region, unemployment increased and many people migrated to Osa to search for gold. About 2000 miners became active in the Peninsula, and after mining for gold largely failed, many of these people cleared state-owned forest land to establish new farms.

Forest clearing and migration to the Peninsula continued until slowing down in the late 1990's, when it was replaced by intensive logging as the main impact on the remaining forests. With the approval of Forestry Law 7575, in 1996 logging was permitted in untitled

[9] Readers are referred to Cuello *et al.* (1998) and Vaughan (2012) for a complete overview

land, which represented 80% of the forest area in Osa. Therefore, between 1997 and 1999, 164 logging concessions were approved and extracted all of their allowed timber in one or two years (Barrantes *et al.*, 1999). During this period of logging activity and shortly afterwards, high soil erosion levels were reported (up to 50 tons/month/ha during rainy season) (Lang, 2000).

As in other regions, selective logging created a complex landscape of patches of undisturbed forest, degraded forest and logging roads (Barrantes *et al.*, 1999; Lang, 2000). The large number of logging plans being executed across the landscape, along with reported inconsistencies in the forest management plans and a low capacity of the state to monitor them, led to a period of seriously unregulated forest exploitation, with low adherence to sustainable forest management practices, in the area (Barrantes *et al.*, 1999). Eventually, the obvious negative effects on the region's ecosystems related to this logging activity led to conflicts between the forest management authorities, local communities, loggers and conservation groups. By the end of 1999, the national government, recognizing that the logging activities were a cause of major concern for the conservation value of the area, enacted a logging ban.

Today, the area has a high density of payment for ecosystem service schemes, and although there are multiple conservation initiatives that seek to protect the forest and create sustainable economic activities for local communities, the area continues to be one of the poorest in the country. Oil palm plantations have been expanded significantly, and bush meat hunting and illegal logging continue to be major threats to the forest ecosystems (J J Jimenez, pers. comm.)[10].

Aim:

The aim of this study is to develop methods to quantify and monitor the combined dynamics of deforestation and forest degradation in complex forest landscapes and test their application to improve understanding of the impact of past policy changes on forest condition. In order to do this, we analysed forest cover dynamics in the Osa Peninsula over a 40 year period, focusing on the conversion of old growth to degraded forest by remote sensing analysis of a long time series of data coupled with documentary data on disturbance processes, namely historical forest management plans. We focus specifically on three aspects

[10] Jimenez, Juan Jose, Director of the Golfo Dulce Forest Reserve, Osa Conservation Area.

of forest cover dynamics: i) the conversion from undisturbed forest to other land uses, ii) the spatial modelling of forest degradation, iii) disturbance and the recovery of forest after logging. The implications of the results are discussed in the context of structuring new incentive mechanisms related to forest management within the country's strategy to reduce carbon emissions from forest.

5.2. Methods

5.2.1. Description of the study site

The Osa Peninsula (from now on called Osa) is found on the south Pacific coast of Costa Rica. The study area covers approximately 1730 km^2 located between 83° 43'56" - 83°14' 33" W and 8° 52' 8" - 8° 22' 34" N (Fig. 5.1). The climate is very humid and warm, with a mean annual precipitation of 5500 mm and an average temperature of 25 °C. The topography is complex (Fig. S1), with an average slope of 7.2° ± 8.7° (SD), as calculated from a 30 m spatial resolution Digital Elevation Model, and elevations that range from sea level to 782 m a.s.l. (Kappelle *et al.*, 2002).

The majority of the area (approx. 90%) is categorized as very humid tropical forest, with a much smaller area classified as premontane very humid forest, according to the Holdridge system (Cornejo *et al.*, 2012). This humid rainforest develops on the ultisols found in most of the area, with small patches of inceptisols and entisols. The northern boundary is marked by the biggest wetland area of Costa Rica, the Térraba-Sierpe National Wetland.

The land of Osa is divided into several management categories (Fig. 5.1). Much of the peninsula has been designated as the Osa Biological Corridor, which is a conservation initiative aimed at maintaining connectivity amongst the ecosystems of the area. The species density in Osa is probably one of the highest in the world, as it is estimated that it is home to about 50% of flora and fauna species found in Costa Rica, which is considered to be one of the most biodiverse countries in the world (Kappelle *et al.*, 2002). The area has more than 2 200 native vascular plant species, many of which have a clustered distribution being found only in small patches within the peninsula (Quesada & Castillo, 2010).

The human population of Osa has steadily increased over the last forty years (Rosero-Bixby *et al.*, 2002) and is currently approximately 14,500 people (INEC, 2011). At present, the main economic activity is cultivation of oil palm and to a lesser extent rice. Previously cattle, banana, rice and timber production were the main sources of income for the population. Ecotourism is growing in the area, and there are several initiatives that link conservation and community development (Hunt *et al.*, 2014).

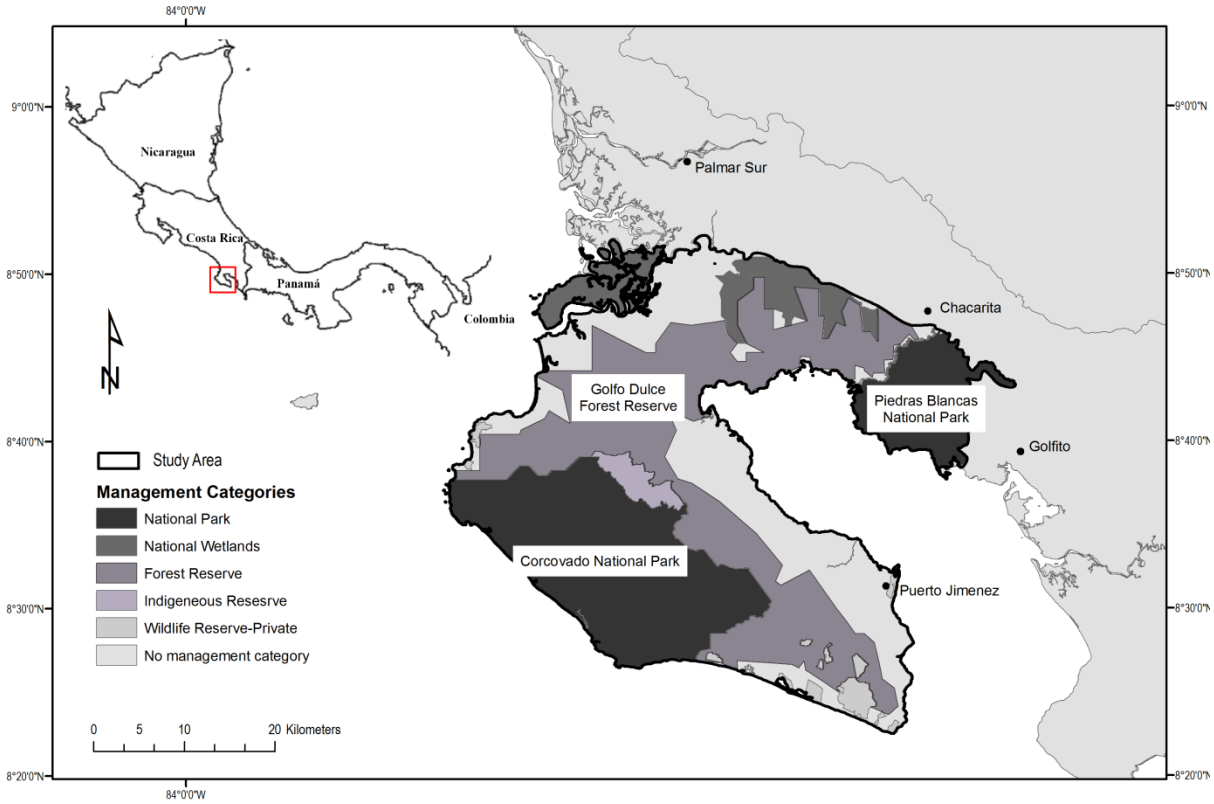

Figure 5.1 Map of the Osa Peninsula study area showing the different land management categories and main protected forest areas.

Boundaries of the management categories are based on Ortiz (2008).

5.2.2. Description of datasets

5.2.2.1. Satellite data

The satellite data used in the study included inputs from four Landsat sensors: Landsat 2 Multispectral Scanner (MSS), Landsat 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+) and Landsat 8 Operational Land Imager (OLI). Images were downloaded via the Glovis platform (http://glovis.usgs.gov/) from the US Geological Survey National Center for Earth Resources Observation Images for four defined years (1975, 1998, 2000 and 2014) (Table 5.1). For each year, the image with the best quality and lowest cloud cover over the study area was used as the main input and another image, separated by ± one year from this main image, was used to fill in the parts with cloud cover. Data on image quality and cloud cover were provided in the image metadata.

Table 5.1 Satellite data used in the study (Landsat Scene Path 54 Row 14).

Year	Day	Description	Landsat sensor	Image Quality§	Cloud % §
1975	79*	Initial state of undisturbed forest.	L2	High	3
1979	22**	Images from before the forest conversion that started after the opening of the main road in 1974	L2	Moderate	0
1997	316**	Initial period of logging concessions	L5	Moderate	0
1998	47*		L5	High	0.4
1999	66**	One year after logging was banned	L5	High	0.4
2000	45*		L7	High	1.1
2013	280**	Current state of forest cover	L8	High	13.6†
2014	043*		L8	High	45.9†

*Main image of each pair, ** image to fill cloud gaps, § as described in the image metadata, cloud cover estimation for the lower left corner that covers the study area, except for years marked with †, where cloud cover estimation is for the whole scene.

5.2.2.2. Data to determine disturbed and undisturbed forest areas

***a. Historical photography*:** Aerial photography taken over the study area between 1975 and 1978 was used as a reference for undisturbed forest cover. These photographs correspond with the period shortly after the opening of the main road. The historical digital photographs were obtained through the National Geographic Institute of Costa Rica (IGN) and included four flight campaigns: a) 1975 (at a scale 1:20,000), b) 1976 (1:40,000), c) 1977 (1:20,000), and d) 1978 (1:35,000); each campaign covered different areas of the Osa. All aerial photographs were georectified.

b. Forest Management Plan (FMP) and land tenure data: Information contained in the forest management plans (FMPs) for logging concessions drawn up between 1997 and 1999 in the Osa Conservation Area (ACOSA) was used as inputs to map disturbed areas. Two sources of information about these FMPs were used: a) the National System of Conservation Area - Forest Geographical Information Systems project (SINAC-FGIS), which is described in detail by Svob *et al*. (2014), and b) the study by Barrantes *et al.* (1999). Both these sources only provide general coordinates of the location of the property area covered by each FMP and no maps of the area planned for forest production. We therefore used the recently completed land tenure database of the Inter-American Development Bank cadastral project (BID-Catastro, 2012) to locate property boundaries and link them with the FMPs using the landowner information. Hereafter, the term FMP refers to one property, for which a logging concession was planned and registered in the Osa Conservation Area between 1997 and 1999. Despite the limitations of the geographical information available, it

was possible by combining the data of Barrantes *et al.* (1999) and that of SINAC FGIS to associate with certainty 85 FMPs to a property defined in the land tenure database. This represents about 51% of the FMPs that, according to Barrantes *et al.* (1999), were registered for the area during 1997-1999. They are distributed across the study area and are mostly located within the forest reserve (Fig. S 5.2).

Guidelines on the information that should be provided in a FMP, as well as any procedures related to logging of natural forests, are described in the Costa Rica Forest Law 7575 (OTS, 2008). This standardized protocol established that a FMP should include a pre-logging inventory and a tree survey, which should be completed by a certified forester. Pre-logging inventories are done using 3000 m^2 (30 m X 100 m) plots distributed over the whole forest area of a property, in which all trees with a diameter at breast height (DBH) ≥ 30 cm are recorded. The area sampled in the pre-logging inventory should produce an error variance not greater than the 20% of the mean basal area (≥30 cm DBH). A separate survey of all trees ≥ 60 cm DBH, classifying them into trees to be harvested and those to be retained, is carried out in the whole area of the property that is classified as productive, from which trees will be extracted for timber. In practice, sometimes the tree survey is not carried out and in such cases trees ≥ 60 cm DBH that were sampled in the pre-logging inventory plots were classified into trees to be harvested or retained. In some other cases only the tree survey was carried out, without the required pre-logging inventory (Svob *et al.*, 2014).

5.2.3. Mapping of forest cover, forest cover change and forest disturbance

5.2.3.1. Methodological approach

To determine changes in forest cover and state throughout the four decades, we first performed a land cover classification of satellite images from four different years (1975, 1998, 2000 and 2014) (Fig. 5.2 section II; methods section 5.2.3.3). Then, the forest area determined for 1998/2000 was further analysed to map disturbance, which was mainly due to logging (Fig. 5.2 section III, methods section 5.2.3.4) by combining image analysis with the FMPs. Together, these two analyses allowed us to evaluate the transformation of the intact forest landscape and assess the extent of degraded forests in the area. The next sections describe the image analysis process used to obtain the forest cover maps and the forest disturbance map, as well as to calculate the change in forest cover (as summarized in Fig. 5.2).

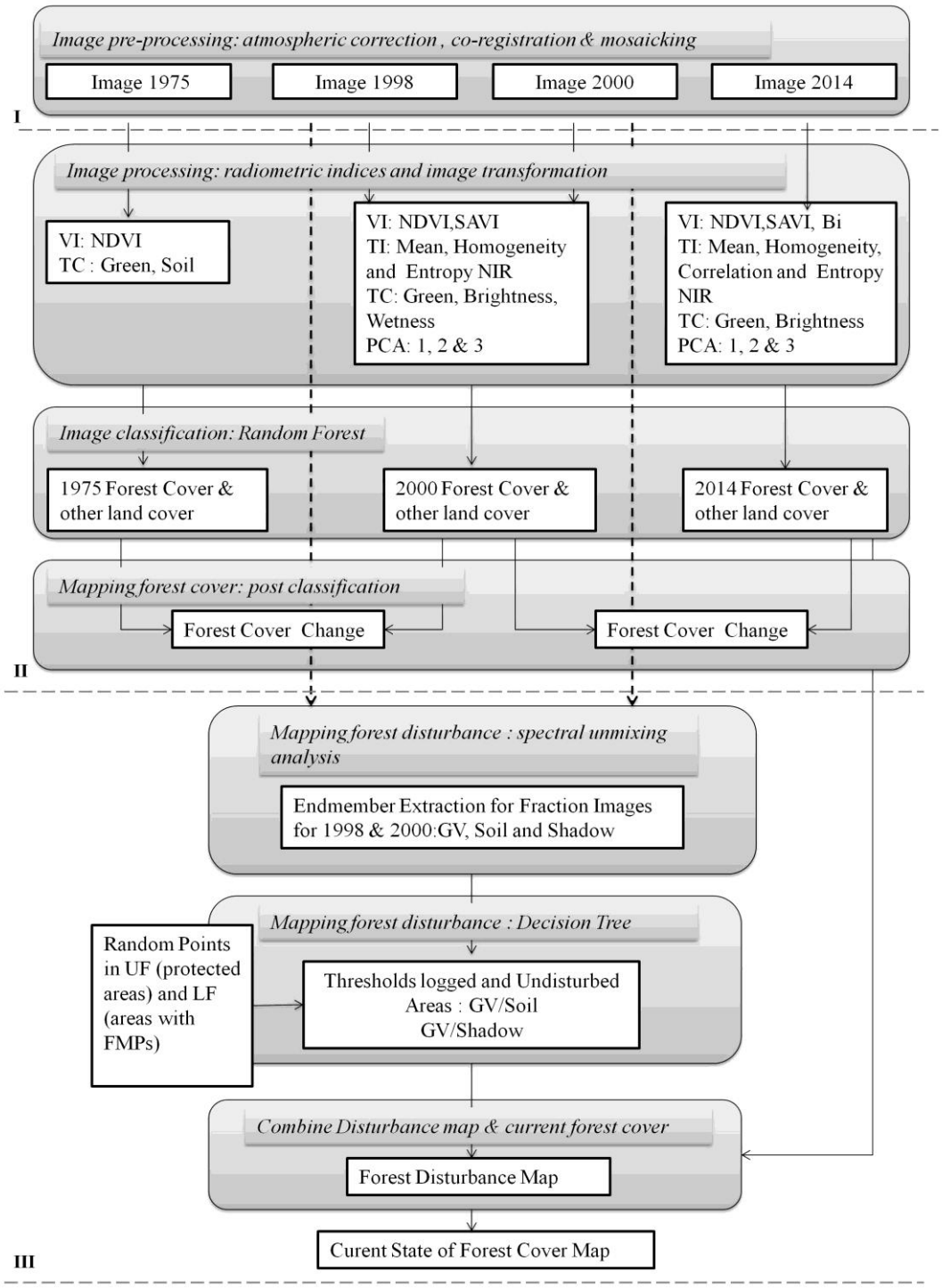

Figure 5.2 Scheme of the methodology used to map forest cover and forest cover change, including undisturbed and degraded forest areas, from 1975 to 2014, based on Landsat images. Grey boxes are used to indicate processes and white boxes represent image data or a product of the analysis. GV = green vegetation, UF = undisturbed forest, LF = logged forest, FMPs = forest management plans; refer to section 5.2.3.2 for the image processing acronyms.

5.2.3.2. Image pre-processing and transformation

To remove the effects of atmospheric contamination and improve the comparison between dates, each Landsat scene was atmospherically corrected using FLAASH as implemented in Envi 4.7 (ENVI, 2006). The 1975 and 1979 scenes were resampled from 60 to 30 m, so that the whole image data set had the same spatial resolution. Using the year 2000 image as a reference, all images were co-registered to obtain a pixel-to-pixel correspondence between dates, obtaining an accuracy of less than one pixel (30 X 30 m). For each year (1975, 1998, 2000 and 2014), images were segmented and the segments that corresponded with cloud cover were removed from that image. To fill the gaps caused by removed areas, images were mosaicked with another scene from the closest available date (Table 5.1), if an area was covered by clouds in both dates, the information from the main image was retained. This procedure resulted in almost cloud free image mosaics, that were used as the input for the rest of the analyses (Fig. 5.2, section I) and they are referred to by using the year of the main image only (i.e. 1975, 1998, 2000 or 2014).

A series of radiometric indices were calculated and image transformations carried out for each image, to enhance the information available to differentiate between land cover categories for the purposes of classification. Not all indices were calculated for all images since the spectral information differs between sensors. Vegetation indices included the Normalized Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI) and Brightness Index (Bi). Two image transformation techniques were applied: principal component analysis (PCA), and tasseled cap transformation (TC) (Crist & Cicone, 1984). Vegetation indices and TC have been widely used to characterize vegetation conditions through time, as they related to the level of greenness of the vegetation (Healey *et al.*, 2005). Texture indices were calculated using the Near Infrared Band (NIR), and they provide information on the spatial distribution of the vegetation, as they evaluate the relation between grey tones of neighbouring pixels. This analysis was done in Envi 4.7 (ENVI, 2006) and OrfeoToolBox (Inglada & Christophe, 2009).

5.2.3.3. Mapping the extent of undisturbed forest (through time)

The extent of undisturbed forest was mapped using the 1975 image as a baseline. The training samples for the classification and validation were guided by historical aerial photographs acquired between 1975 and 1978. The input image used for the supervised classification with the random forests (RF) algorithm consisted of the four image spectral bands, NDVI, TC green band and TC soil band (Fig 5.2, section II). This resulted in a classification of land cover in the 1975 image into the following classes: forest, non-forest, mangrove, palm forest ("*yolillo*"), clouds and shadow. We have assumed that all of the area

classified as forest was subject to very low levels of human-induced disturbance or none at all, as before the opening of the main road into the Osa Peninsula in 1974 there was little human activity in the area (Vaughan, 2012).

To analyse the changes in forest cover through time, forest cover from the 1998, 2000 and 2014 images was mapped. For this, images were individually classified using RF (Breiman & Cutler, 2004) as implemented in R (Horning, 2012; R Core Team, 2013). To increase the information available for the classifier to distinguish between land cover classes, the input data for the 1998 and for the 2000 images included, in addition to the six image bands, several vegetation indices, texture indices, and band transformations: Bi, NDVI, SAVI, Homogeneity, Mean and Entropy indices of the NIR, the first three principal components of the PCA (PC1, PC2 and PC3) and three TC bands (Greenness, Brightness, and Wetness). The input data for the 2014 image included the same bands plus the Correlation Index of NIR and, in this case only, the TC Greenness and TC Brightness were used (Fig. 5.2, section II).

To extract training samples for classification and validation of the 1998 and the 2000 images, we used the ECOMAPAS map (Kappelle *et al*., 2002). This is a detailed map of spatial ecological units produced by the National Institute of Biodiversity (INBio) using aerial photographs taken between 1995 and 1998 with a scale of 1:40,000. In contrast, the training and validation samples for the 2014 forest cover map were based on field data, that we collected in July 2013, complemented by high resolution data available through Google Earth. The classification of the 1998 and the 2000 images included the following land cover classes: forest, non-forest, mangrove, palm forest ("*yolillo*"), forest plantation, secondary regrowth forest ("*matorral*"), clouds and shadow. In addition to these classes, for the 2014 classification, oil palm plantations were added as another class (Table 5.2).

Change in the extent of forest was assessed by comparing the extent of the forest cover class in the classified images (post-classification approach) for the periods 1975-2000 and 2000-2014 (Fig 5.2, section II). The forest cover extent was found to differ little (less than 1.1% of the forest area) between the 1998 and 2000 images, therefore for simplicity forest cover changes were assessed using only the classification result for 2000.

Table 5.2 Description of the land cover and the years that the class was included in the land cover classification.

Class	Description and definition	Years
Forest (Undisturbed Forest)	Natural lowland tropical moist forest. In 1975, the whole forest area was assumed to be undisturbed forest	1975-2014
Non-Forest	Includes urban, bare, pasture and agricultural land	1975-2014
Mangrove	Coastal forest that is located in the intertidal zone	1975-2014
Palm Forest	Inland wetland dominated by *Raphia taedigera (yolillo)*	1975-2014
Cloud/Shadow	Areas covered by clouds and cloud shadows	1975-2014
Secondary Regrowth	Forest regrowth after forest clearance (*matorral*)	2000-2014
Forest Plantation	Areas where teak and gmelina have been planted in monocultures for wood production	2000-2014
Oil Palm	Areas where oil palm has been planted as a monoculture	2014

5.2.3.4. Mapping of forest disturbance

To map disturbed forest areas, a spectral linear unmixing approach was used on the 1998 and 2000 images in combination with the FMPs that could be located using the land tenure database (see 5.2.2.2 b, Fig S 5.2). We analysed images from two dates (1998 and 2000) separately in order to detect the disturbance signal more easily by using the closest date to when the logging might have occurred. Once analysed, the information obtained was combined into a single disturbance map (Fig. 5.2, section III). The details of the mapping procedure are described below.

The linear unmixing approach is based on decomposing each pixel into a series of spectra that correspond with the pure reference materials that are found in each pixel; these spectra are known as endmembers (Jones & Vaughan, 2010). Spectral endmembers were derived from two image subsets (that included different land cover classes) for each image using the Vertex Component Algorithm (Nascimento & Dias, 2005) available in the OrfeoToolBox (Inglada & Christophe, 2009). As proposed by Souza *et al*. (2005) we derived the four endmembers expected for logged forest pixels: Green Vegetation (GV), Non-Photosynthetic Vegetation (NPV), Soil and Shadow. The fraction of each endmember found in each pixel

was mapped using the Hyperspectral Unmixing algorithm in unconstrained mode, which is a type of linear unmixing model (Jones & Vaughan, 2010) implemented in OrfeoTool Box (Inglada & Christophe, 2009). The values of the fraction image provides the amount of each endmember found in each pixel. To calculate image fractions, those areas that were not classified as forest in the 1998 and 2000 images were masked out, so fraction images for each year were calculated only for the forest area.

To establish a threshold value for classifying the potential disturbed forest area, random points were used to extract the values for GV, soil and shadow for undisturbed forests (UF) and forests subject to logging (LF) from the fraction images for 1998 and 2000 separately (Fig. 5.2, section III). The points were extracted from areas defined by the property boundaries of the FMPs for LF and from polygons defined within the two National Parks (Fig. 5.1) for UF. For the UF, it was assumed that in general these areas within the National Parks have experienced no human disturbance (logging, fire or clearance); nonetheless, no polygons were taken from the southern part of the Corcovado National Park, because gold mining activities occurred there in the 1980s. The exact location of these polygons was supported by the author's knowledge of the area and a total of 5600 random points were extracted for UF. In the case of LF, 5300 random points were extracted from the fraction images of 1998, which coincided with FMPs that were registered during 1997-1998 (51 FMPs); and 5700 points were extracted from FMPs that were registered during 1999-2000 (34 FMPs) from the fraction images derived from the 2000 image data.

Since the post-harvesting data available per individual FMP area was in many cases incomplete, the parsimonious assumption, necessary to classify the area for this analysis, was made that all the FMPs were subject to logging, and that logging activity was carried out in the vast majority (if not all) of them. While this creates an associated error, this assumption is supported by the analysis of 136 FMPs carried out by Barrantes *et al.* (1999), that reported 65 054 m^3 harvested between 1997 and 1999. The same authors evaluated in 1999 the correspondence in the field between trees that had been felled and those that had been marked for harvesting in eight randomly selected FMPs. They found evidence of over-harvesting in the FMPs, rather than under-harvesting, as about 16% more trees had been felled than the numbers specified in the FMPs. This observation is in accordance with what I observed during the field work in July 2013, during which the locations of multiple-tree logged areas were observed in all the FMP areas that I visited, and is also supported by my knowledge of the area, since I have worked in the Osa forests since 2005. Taken together this evidence indicates that at least as much volume of timber as specified was harvested in at least a large majority of the FMP areas. Therefore, the use of FMP areas as having been subject to logging for the sampling carried out in the present study is most likely to

correspond to reality in a large majority of cases. Moreover, as the linear unmixing model uses the image data directly, not a classification, the use of FMP areas for the sampling should not result in a major constraint, because if an area was not harvested at all it will just have higher values in the image, as explained in the next paragraph.

As logging will cause openings in the canopy, areas disturbed by logging will have higher values in the soil and shadow endmembers, while undisturbed areas will have higher values in the green vegetation component (GV). Therefore for each random point extracted for UF and LF the ratios of GV:shadow and GV:soil were calculated. The distributions of ratio values for each forest type (UF and LF) were compared using Kolmogorov–Smirnov (K–S) two-sample tests, for each year. The average of the median value determined from these ratios for LF for each year was used as a threshold value to map disturbed forest using a decision tree classifier applied to each year (Fig S 5.3). Using the tree classifier, the areas were classified into UF and LF (Table 5.3). The classifications obtained for 1998 and 2000 were overlaid and combined to obtain one forest disturbance map based on the FMPs (Fig 5.2., section III). This map was then overlaid with the forest cover of 2014, and only areas that were within the forest cover of 2014 were kept, therefore areas that were deforested either 1998-2014 or 2000-2014 were removed. This layer was then combined with the information on forest gains, obtained from the forest cover change analysis (see 5.2.3.6) for the whole 1975-2014 period (also only keeping areas that were within the forest cover of 2014), in order to obtain the current extent of degraded forests (Table 5.3). This combined final map provides an overview of the degradation due to logging and clearance in the study area.

Table 5.3 Description of the classes included in the forest disturbance map and in the current state map.

Class	Description
Degraded Forest	Areas that have experienced disturbance due to logging or forest clearance since 1975. It includes two categories: a. logged forests (LF), areas determined to have been logged based on the threshold analysis of fraction images (see 5.2.3.4); b. forest gain, areas of regrown secondary forest determined from the forest cover change analysis (see 5.2.3.6).
Undisturbed Forest	Areas of continuous forest cover that have not been disturbed by logging or clearance since 1975. This means areas that were classified as forest in 1975, 1998, 2000 and 2014; and were not classified as disturbed areas in 1998 or 2000.

5.2.3.5. Map validation

Map accuracy for the image classification of forest in 1975, 1998, 2000 and 2014 was evaluated using a confusion matrix based on the out-of-the-bag error (OOB) that is provided by the RF classifier. The OOB is an accuracy measure based on the mean square error of the cross validation (Breiman & Cutler, 2004; Rodriguez-Galiano *et al.*, 2012).

For the disturbance map, validation was done using 157 random field points distributed across the whole study area that were collected in December 2012 (B. Yapp *unpublished data*) and between April and July 2013. Secondary and logged forests identified in the field were classified as Degraded Forest, and forests that have not experienced any logging or clearance were classified as Undisturbed Forest, based on the previous land use history determined with the help of local field assistants (Table 5.3).

5.2.3.6. Forest cover change estimation and calculation of rates of forest conversion and forest degradation

The rate of conversion from forest to non-forest land cover, *r*, was calculated using the formula proposed by Dirzo & Garcia (1992):

$$r = 1 - \left(1 - \frac{A_1 - A_2}{A_1}\right)^{1/t}$$

where A_1 is the area (ha) of forest cover at the beginning of the period, A_2 is the area (ha) at the end of the period, and the parameter *t* corresponds to the number of years being evaluated. The same formula was applied to calculate the rate of conversion from undisturbed to degraded forest for the period 1975-2014.

To evaluate if certain elevations or slopes have experienced more forest cover change (either loss or gain) than others, we evaluated if the actual change was proportional to the forest area found in that elevation or slope range at the beginning of the period. Hence, expected change is defined as the change that will be proportional to the forest cover at the beginning of the period analysed in a specific elevation range.

5.2.4. Evaluation of disturbance intensity based on forest management plans

To make an approximate estimate of the logging intensity in the Osa Peninsula and its effects on forest carbon stocks, the information from the prelogging inventories (which correspond to trees ≥ 30 cm DBH) and from the tree surveys (which include only trees ≥ 60

cm DBH) of the FMPs was used. Tree basal area and above-ground biomass values were calculated from the pre-logging forest inventories, which had a mean (± SD) number of plots sampled of 6.3 (± 4.8) per FMP. Using the information from the tree survey, logging intensity was evaluated by estimating the ratio between logged and retained trees, the percentage of the AGB in harvested trees per ha, and the volume and number of trees per ha. To estimate AGB the equation developed by Brown (1997) for tropical forests (with > 4000 mm annual rainfall), which estimates AGB based only on the DBH, was used (Pearson *et al.*, 2005). To further evaluate logging intensity, emissions due to collateral damage were estimated using the equation proposed by Pearson et al. (2014). The impact of logging on the overall AGB carbon stocks was calculated using the FMPs that have both pre-logging inventory and tree survey data (n=47). The study of Barrantes *et al.* (1999) summarised in section 5.2.3.4 above provides independent evidence that the logging intensity that we have calculated with this approach is a reasonable but conservative estimate for this study area.

5.2.5. Evaluation of forest recovery after 14-16 years

To evaluate forest recovery after selective logging, in 2013 two areas (Rancho Quemado and Mogos) were sampled. According to Barrantes *et al*. (1999) these two areas were the focus of intensive logging activities during 1997-1999. The sample plots were located within two FMPs in the Mogos area and four FMPs in the Rancho Quemado area. The undisturbed forests were located in adjacent properties that have had no FMPs (Fig. S 5.2) and have experimented no known human intervention (i.e. logging or forest clearance). A total of 15, 500-m^2 circular plots were sampled in forest logged between 1997 and 1999 (n=11) and in undisturbed forests (n=4).

To locate the sample points, first the coordinates of logged and unlogged areas were identified in the field with the assistance of local guides, who have lived in the area for more than 25 years and some of whom had participated in the logging activities. The points were widely dispersed around each area, with a minimum separation distance of 400 m. Then, to determine the exact location of the sample plot at each of these points, a buffer of 20 m was drawn around the point, and a random location was then established within this buffer using the random point generator available in Qgis 2.6. This random location was used as the centre of the 12.62 m radius (500 m^2) sample plot.

Within each 500 m^2 main sample plot, the DBH of all tree stems ≥10 cm DBH was measured at 1.3 m height using a tape, following the protocols described in Pearson *et al.* (2005) to correctly measure DBH for tropical trees. Tree height was recorded for each tree using a clinometer (Suunto PM5). Trees were identified in the field to genus or, where possible, species levels by two taxonomist P. Juarez and M. Fernandez, PhD. When field

identification was not possible, a specimen was taken to be identified in the National Museum Herbarium of Costa Rica. Other data recorded in the field were: slope, aspect, altitude and canopy cover. Slope was measured with the clinometer from the centre of the plot. Canopy cover was measured from a height of 1.5 m above ground, at every 2 m along two perpendicular transects of 20 m that crossed the plot centre. At every 2 m closed canopy was recorded using a vertical densitometer (GRS) as described by Stumpf (1993). The AGB of each plot was calculated using the allometric equation by Brown (1997) that is based only on DBH for tropical forests (with > 4000 mm annual rainfall) (Pearson *et al.*, 2005). To obtain an indication of the forest's recovery the difference in the values per plot of number of trees (tree density), mean tree DBH, total tree basal area and estimated AGB between the logged and undisturbed forests was tested using a *t*-test.

5.3. Results

5.3.1. Mapping forest cover extent and rate of change

The observed changes in forest cover in the Osa Peninsula revealed a dynamic landscape. In 1975, about 80% of Osa was estimated to be covered by undisturbed forests, the forest extent declined to 71% in 2000 and recovered slightly, to 76%, by 2014 (Table 5.4). The rate of change was not constant during these four decades, the majority of forest was cleared before 2000 (at a rate of -0.41% yr^{-1}). In contrast, after 2000 forest cover increased at a rate of 0.43% yr^{-1}. A significant amount (more than 7000 ha) of this gain in forest cover by 2014 resulted from land that had been classified as "secondary regrowth (*matorral*)" in 2000 (Fig. 5.3, Table 5.4). Other natural ecosystems, mainly mangrove and palm forests, maintained a relatively constant area throughout the time period (about 7%) (Table 5.4). Oil palm plantations have increased in area, and the extent of forest plantations has not changed notably during the time period studied. In terms of map quality, the land cover classification achieved high accuracy, above 92% for the forest, in all the years analysed (Table S 5.1).

Table 5.4 Extent of forest and other land cover types, and area changes in land cover, for the Osa Peninsula between 1975 and 2014 (areas are given in ha).

Land Cover Category*	Year 1975	Change 1975-2000	Year 2000	Change 2000-2014	Year 2014	Total Change over period
Forest	131 676	-12 207	119 469	7419	126 888	-4788
Non-Forest	22 766	-3848	18 919	-1130	17 789	-4978
Mangrove	6604	41	6645	-292	6353	-250
Water	946	245	1191	-284	907	-38
Palm Forest	4387	86	4462	-787	3676	-711
Secondary Regrowth	1110	15 103	16 213	-7393	8821	7710
Plantation	0	591	591	668	1258	1258
Oil Palm	0	0	0	1797	1797	1797
Total Area	167 490		167 490		167 490	

*Class description is given Table 5.2

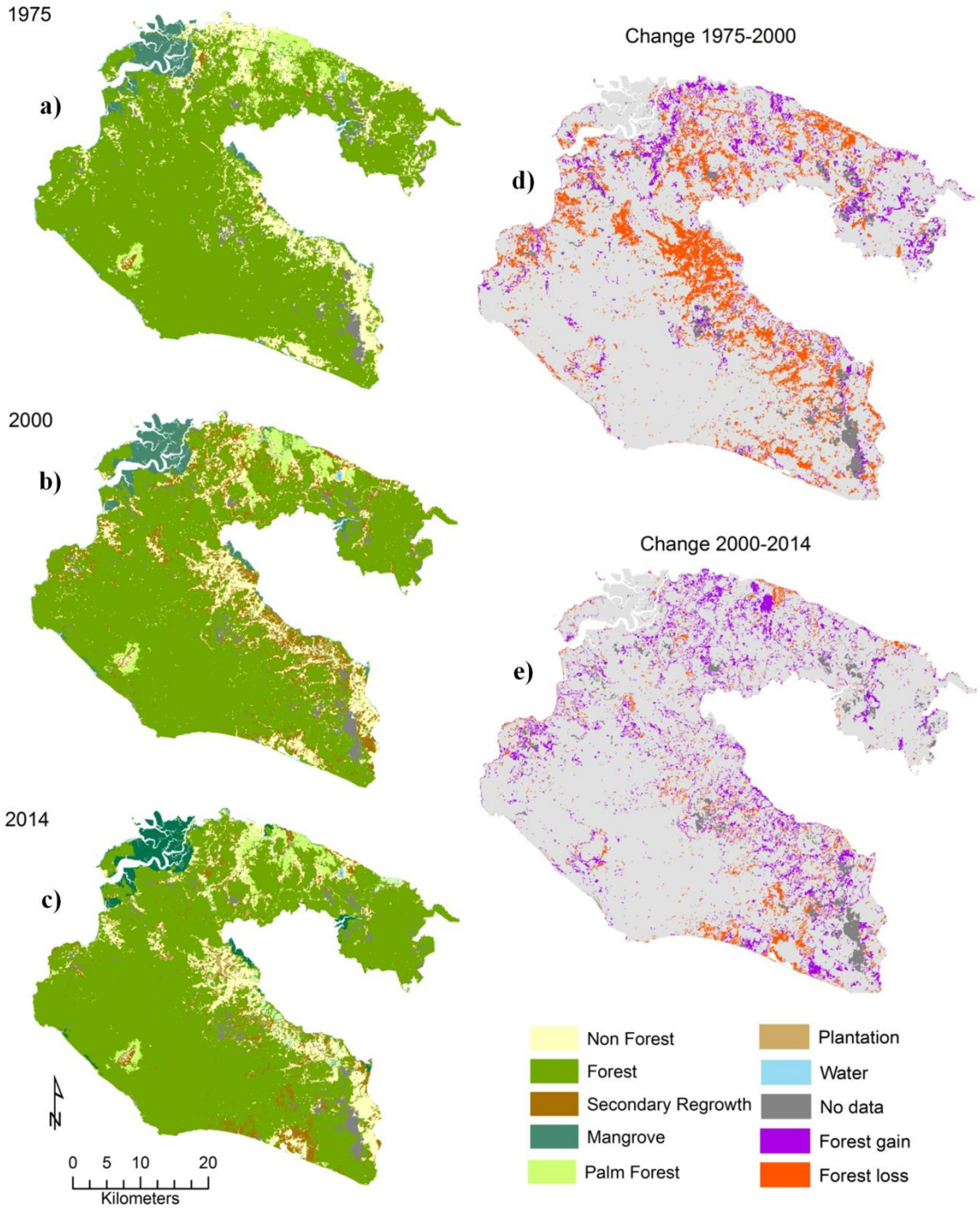

Figure 5.3 Forest cover trajectory over four decades in the Osa Peninsula, Costa Rica. Land cover classification for three years: a) 1975, b) 2000, c) 2014. Land cover change maps for the periods 1975-2000 (d) and 2000-2014 (e); the red colour correspond to areas that have lost forest cover and purple to areas that have gained forest cover during each of the two periods.

Forest cover change, both loss and gain, has occurred primarily in lowland areas (< 200 m a.s.l.) and areas with flat terrain (< 5º slope angle) (Table 5.5, Table S 5.2). Whereas only 55% of the 1975 forest area was on land < 200 m a.s.l. about 86% of the loss in forest cover from 1975 to 2000 and 94% of the gain in forest cover from 2000 to 2014 occurred on this lower altitude land (Table 5.5). Similarly, only 53% and 50% of the 1975 and 2000 forest area (respectively) was on land with slopes < 5º, whereas 80% and 76% of the forest cover change in these periods (respectively) occurred on this land, clearly indicating that these flat terrain areas were far more subjected to forest cover change than land with steeper slopes (Table 5.5).

Table 5.5 Percentage of forest area change during the time periods 1975-2000 and 2000-2014 in sites of different elevation and slope.

	1975-2000		2000-2014	
Elevation Class (m a.s.l.)	**Expected forest cover change (%)***	**Actual forest cover change (%)***	**Expected forest cover change (%)***	**Actual forest cover change (%)***
0-100	7.3	14.1	6.5	16.8
100-200	47.6	71.9	44.7	77.1
200-400	34.3	11.5	36.5	6.0
>400	10.8	2.5	12.2	0.0
Slope (degrees)				
0-5	53.1	80.7	50.3	76.2
5-10	16.9	11	17.5	12.8
10-20	17.8	6.2	18.9	8.9
20-30	8.7	1.7	9.4	1.8
>30	3.5	0.4	3.8	0.3

*Expected change is the change that will be proportional to the forest cover in each elevation class, at the beginning of the period analysed, while actual change is the result from our analysis.

5.3.2. Mapping of degraded forest and its rate of change

The distributions of values for both the GV:Soil and GV:Shadow ratios were statistically different between forest types (LF and UF) (K-S test; P <0.001) (Fig. 5.4). We then used the average median of each ratio for logged forests (LF) as threshold values in subsequent analyses; these were 0.44 for GV:Soil and 0.34 for GV:Shadow. Pixels with values below these thresholds were classified as degraded forest (Fig. S 5.3). The use of these threshold

values to map degraded and undisturbed forests (Fig. 5.5) yielded a mapping accuracy of 77% based on the 157 field points (Table S 5.3). The total area mapped as LF using these threshold values on the 1998 and 2000 image data was 21 548 ha, which represents 18.1% of the area classified as forest in 2000. The sum of the area classified as degraded forest using this method, and the area classified as degraded forest on the basis of it being forest that had regrown during either the 1975-2000 or the 2000-2014 periods, was 38 160 ha. This indicates a coarse estimate of conversion from undisturbed to degraded forests of about 1.1% yr^{-1} between 1975 and 2014 for the whole Osa study area.

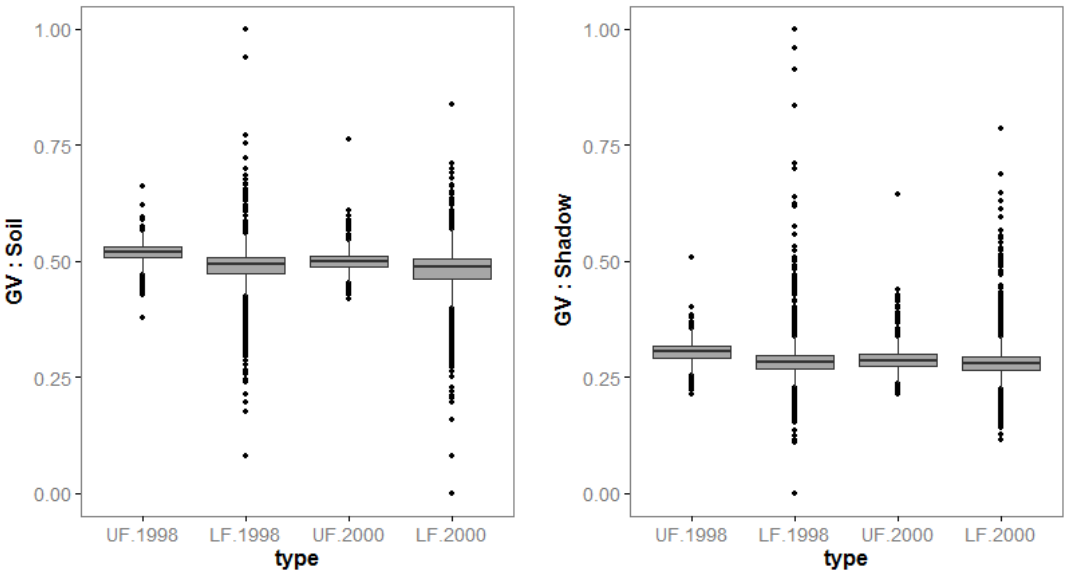

Figure 5.4 Distribution of the values for the GV:soil and GV:shadow ratios, used to determine the threshold values to map forest disturbance, for undisturbed and logged forests in 1998 and 2000 Landsat images.

The central line corresponds to the median, the ends of the boxes correspond to the 25th and 75th percentiles, and the dots represent outliers; values were rescaled 0-1.

UF = undisturbed forest and LF = logged forest

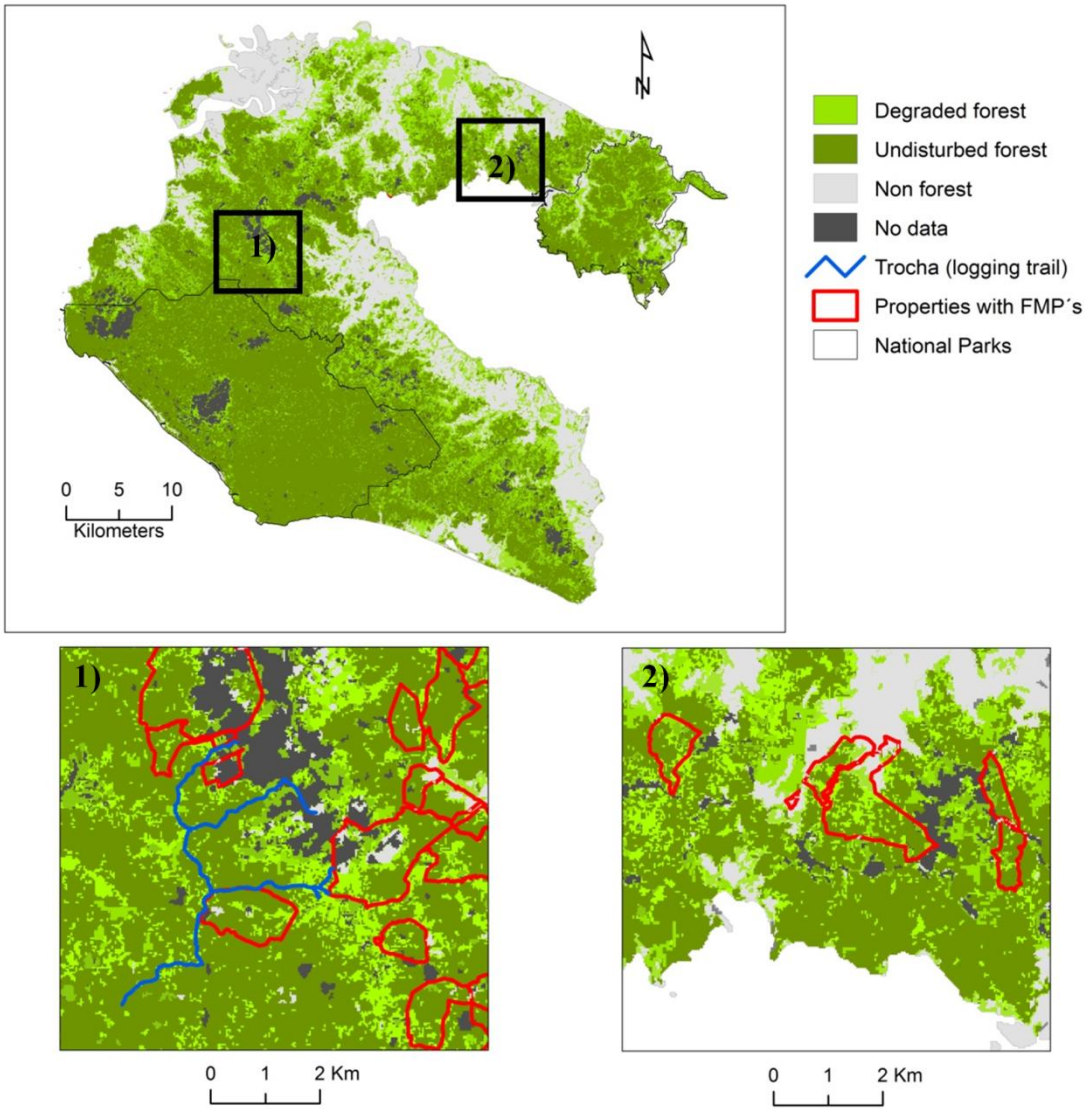

Figure 5.5 Extent of undisturbed forest and degraded forest in the Osa Peninsula, Costa Rica in 2014.

Degraded forests include the area of LF modelled using the information from the FMPs from 1997-1999 and areas of secondary forest regrowth determined from the forest change detection between 1975 and 2000 images, and between 2000 and 2014 images. Greater detail of the map for two areas showing some of the FMPs is given in the boxes marked with 1) and 2) Logging trails in 1, were mapped from GPS field data acquired in July 2013.

5.3.3. Approximation of disturbance intensity using pre-logging inventories and surveys

The weighted mean AGB of undisturbed forest, determined from the 3000 m^2 sample plots used in the pre-logging inventory of each FMP during 1997-1999, which recorded all trees $\geq$ 30 cm DBH, was estimated to be 145.47 ($\pm$ 55.72 SD) Mg ha^{-1}. There is considerable variation in this estimate (Fig. 5.6), as well as that of the number of trees $\geq$ 30 cm DBH per hectare. The average number of trees ($\geq$ 60 cm DBH) marked to be harvested per ha was 5.27 ($\pm$2.68 SD) (Fig 5.7 a), with an estimated volume of 25.53 m^3 ha^{-1} $\pm$ (15.01 SD) (Fig. 5.7 b).On average FMPs retained 4.77 ($\pm$ 1.79 SD) trees $\geq$ 60 cm DBH per ha (Fig. 5.7d, Table S 5.4). Logging removed on average 52.91% ($\pm$ 8.30 SD) of the EAGB of trees $\geq$ 60 cm DBH (Fig. 5.7 c) per ha, with higher removal percentages concentrated in specific areas across Osa (Fig S. 5.4). In addition to the removal of an average of 8.72 ($\pm$ 2.49 SD) (Mg ha^{-1} of above-ground carbon stock in the harvested trees ($\geq$ 60 cm DBH), emissions due to collateral damage were estimated to be 1.49 ($\pm$ 0.12 SD) (Mg C m^{-3}). Logged forests retained on average 72% of the above-ground carbon stock (trees $\geq$ 30 cm DBH) after the first harvest.

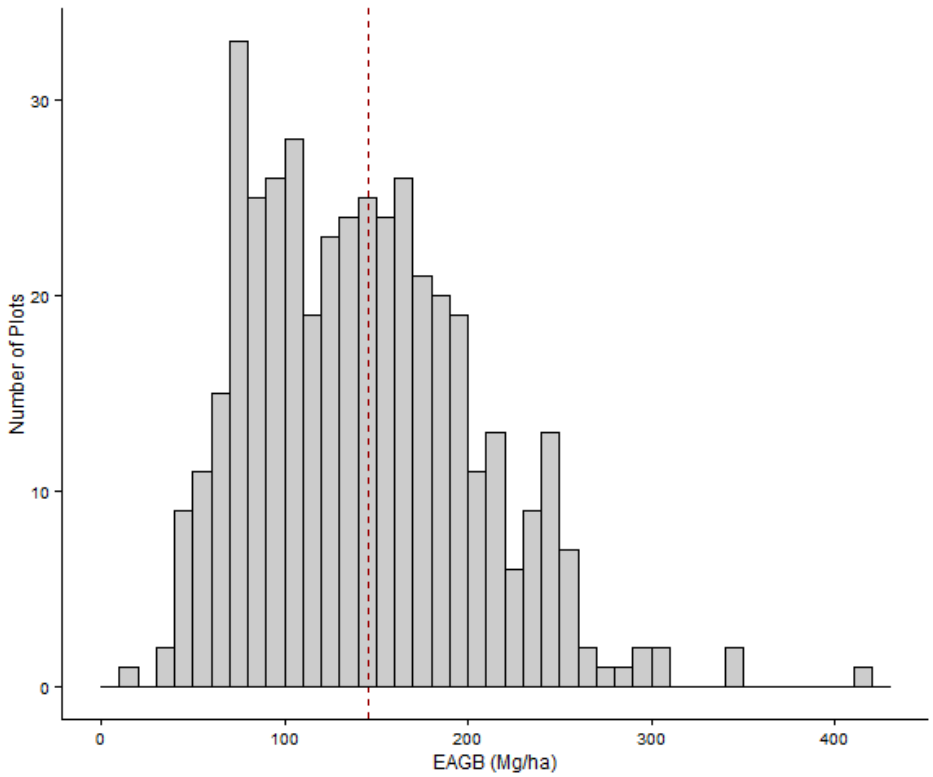

Figure 5.6 Frequency distribution of estimated above-ground biomass (EAGB) from pre-logging inventory plots sampled for the forest management plans (FMPs) registered during 1997-1999 in the Osa Peninsula, Costa Rica (*n*=421).

The red dashed vertical line is the weighted mean (145.47 (± 55.72 SD) Mg/ha)

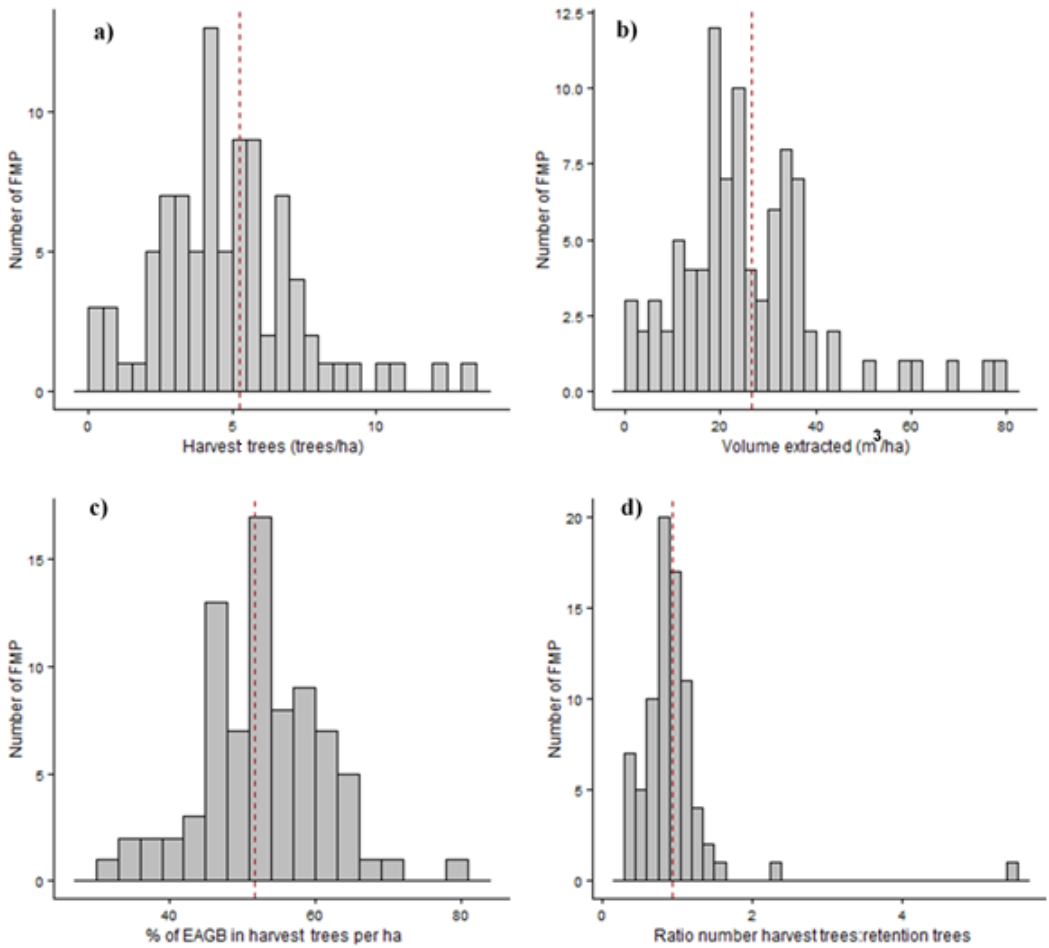

Figure 5.7 Frequency distribution of the number of forest management plan (FMP) areas by number, timber volume, estimated above-ground biomass and ratio of trees ≥ 60 cm DBH marked for harvesting or for retention based on the tree surveys of 79 FMPs registered during 1997-1999 in the Osa Peninsula, Costa Rica.

a) number of trees marked for harvesting per ha, b) timber volume of trees marked for harvesting per ha, c) percentage of the total estimated above-ground biomass (EAGB) of trees ≥ 60 cm DBH represented by trees marked for harvest , d) ratio between the number of trees ≥ 60 cm DBH marked for harvesting and for retention. Each FMP refers to one property.

5.3.4. Evaluation of forest recovery 14-16 years after logging

In 2013 we measured a total of 429 trees in 11 plots in forest that were selectively logged during the 1997-1999 period and 4 plots in undisturbed forest to estimate AGB in order to

evaluate the current state of the forest carbon stocks. Although these results should be interpreted with caution given the small sample and plot size, no significant difference was found between logged and undisturbed forests for any of the variables tested, except for canopy cover (Fig 5.8, Table S 5.5). For trees ≥ 10 cm the median EAGB was 291.1 Mg ha^{-1} in the undisturbed forest plots and 258.0 Mg ha^{-1} in the logged forest plots (a difference of about 12%) (Fig. 5.8). In both, approximately 72% of the EAGB was found in trees ≥ 30 cm DBH (UF, 74.1% and LF, 71.4%) (Table S 5.5). Logging was restricted to trees ≥ 60 cm DBH and, as expected, there was evidence of a greater difference in basal area for trees in this size class: in logged forest the basal area of 15 m^2 ha^{-1} was 20% lower than that in undisturbed forest of 19 m^2 ha^{-1} (Table S 5.5).The mean values of all the other calculated forest stand characteristics (density of tree stems, DBH and BA) were also very similar between the plots in logged forest and those in undisturbed forest (Table S 5.5).

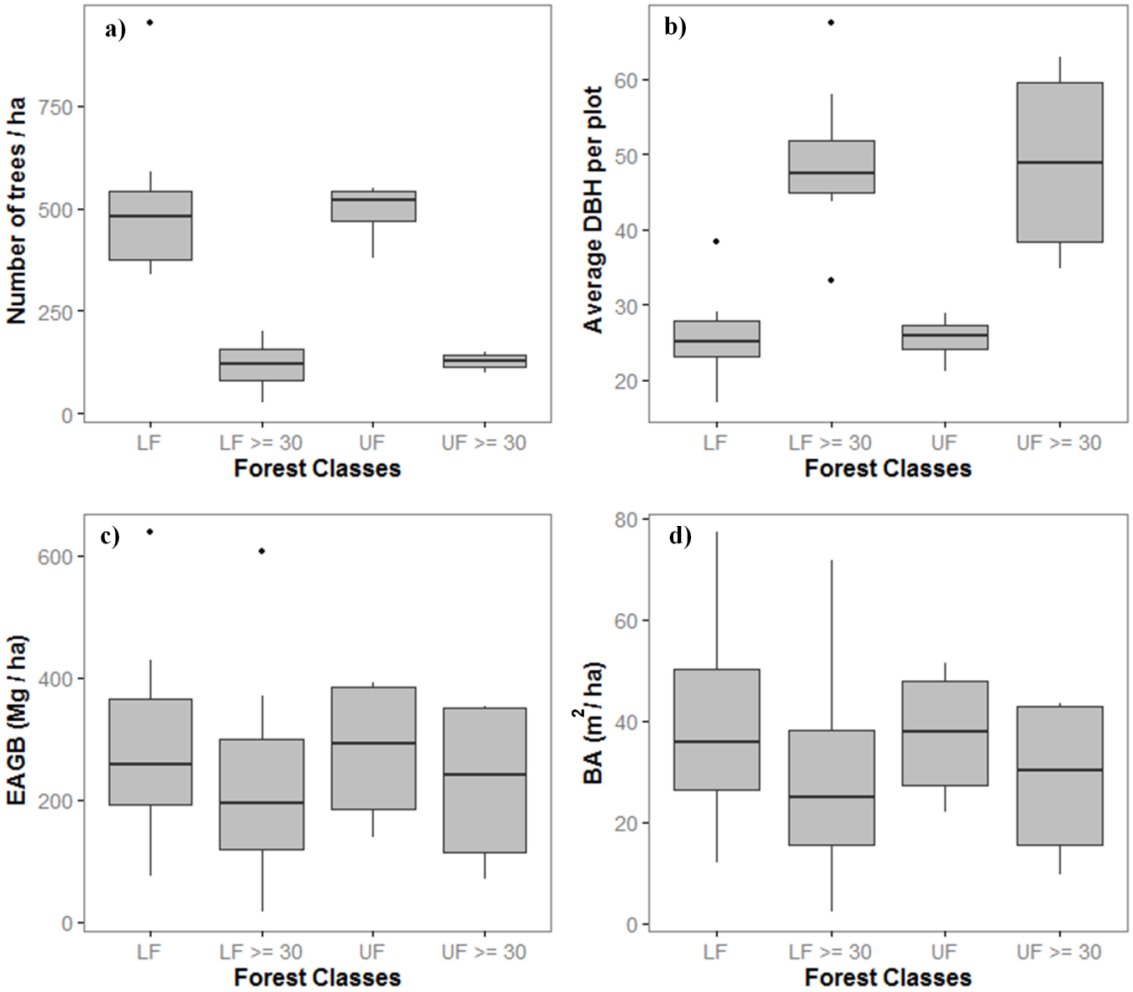

Figure 5.8 Forest structural characteristics of sample plots located in logged (LF) and undisturbed (UF) forest 14-16 years after the occurrence of logging. Values are reported for all trees ≥ 10 cm DBH and only for trees ≥ 30 cm DBH.

a) Density of trees, b) average tree DBH per plot, c) estimated above-ground biomass (EAGB), d) basal area; n = 11 plots for LF and 4 plots for UF. The central line corresponds to the median, the ends of the boxes correspond to the 25th and 75th percentiles, and the dots represent outliers.

5.4. Discussion

5.4.1. The transformation from an undisturbed to a degraded forest landscape

In this study, we obtained estimates of land cover change that are comparable to previous studies in areas that partially overlap our study area. Thus, we consider our results to provide a good estimation of land cover dynamics in the area. For example, Sanchez-Azofeifa *et al.*

(2002) reported high deforestation rates (approx. 1.5% yr^{-1} between 1979 and 1987), which decreased towards the end of the 1990's (approx. 0.83% yr^{-1} between 1987 and 1997) for the southern part of the Osa Peninsula excluding Corcovado National Park. Although we obtained lower deforestation rate estimates for a similar study period (0.41% yr^{-1} between 1975 and 2000), these results are compatible since we included in our analysis the area of two National Parks, which have experienced little deforestation. Thus, we would expect the deforestation rates to be lower in our study. On the other hand, we found an increase in forest cover of 0.43% yr^{-1} for the period 2000-2014, a similar trend to the result of Algeet-Abarquero *et al.* (2014) who found an increase in forest cover between 1998 and 2009 (and a decrease between 1987 and 1998), although their study covered only the northern part of the Osa Peninsula. Both Algeet-Abaraquero *et al.* (2014) and our study observed that the increase in forest cover during this period is linked to regrowth rather than a complete cessation of the deforestation process, and that almost half of the secondary regrowth ("*matorral"*) reported at the beginning of the 2000's was classified as forest approximately ten years later.

Our results, as well as those of the above mentioned studies, confirm that approximately one-third of the Osa Peninsula forest cover has been altered, as it was either classified as secondary regrowth forest, or has been logged within the past 15 years. We estimated that undisturbed (old-growth) forests changed to degraded areas at a rate of 1.1% per year. This conversion of old growth forests is a cause of concern for biodiversity conservation, particularly of forest-dependent species that are sensitive to disturbance (Edwards *et al.*, 2014a), since these forests have different ecological characteristics than undisturbed ones (Gardner *et al.*, 2009; Brown & Zarin, 2013; Ewers *et al.*, 2015; Chaudhary *et al.*, 2016). At the landscape level, the combined effects on biodiversity of converting old-growth forests into secondary and logged forests are often overlooked and not well understood (Barlow *et al.*, 2016). They rarely occur in isolation, and effects on forest state are often magnified over time. For example, logging has been shown to produce fine-scale fragmentation within forest patches that, depending on the harvest intensity, could last for between 5 and 50 years, hence increasing further the edge effects caused by deforestation within the landscape (Broadbent *et al.*, 2008).

Our results showed, furthermore, that most of the forest cover change was concentrated in lowland flat areas, increasing forest fragmentation there, which could potentially exacerbate the negative effects of cover change on biodiversity and ecosystem processes. The observed change in land cover produced a forest cover with lower connectivity between protected forest areas, and between them and the palm forest located in the northern part of the Osa Peninsula (Fig. 5.5). This connectivity has been shown to be important for the movement of

many large mammal species in the area (Yaap *et al.*, 2014). Loss of connectivity through changes in forest cover and quality at the landscape level can also have direct effects on timber species' populations. In Osa many tree species characteristic of old-growth forests, including endemic species, have low population densities (< 0.2 individuals per hectare) and/or a complex reproductive biology (e.g. dioeciousness) (Quesada *et al.*, 2010).The observed clustering of logging concessions in a number of adjacent properties (or forest patches) together with clearance that occurred in the area of Mogos (Fig 5.5.subset 2) may fragment the populations of certain trees (e.g *Peltogyne purpurea*). to the extent of reducing their viability (Lobo *et al.*, 2007).

We estimated that approximately 18% of the forest area found in the year 2000 within Osa had been disturbed by logging, and that on average 53% of the EAGB of commercial trees ≥ 60 cm DBH was removed during these activities. Arguably, taking these extraction estimates into account, these areas could still be considered altered in structure and species composition, and hence as degraded when compared with old-growth forest. There is evidence that some logged areas can take up to 100 years to recover their timber stocks (Sist et al. 2003). That being said, there has been a major shift in perceptions of the impact of selective logging of tropical forests on their biodiversity and ecosystem services. Evidence of high rates of AGB recovery after logging (Gourlet-Fleury *et al.*, 2013), and of the use by fauna of logged areas (Sheil *et al.*, 1999; Edwards *et al.*, 2014a), indicate that to an extent significant impacts of logging may only be temporary, especially if carried out according to careful guidelines, such as reduced impact logging (Putz *et al.*, 2008b; Burivalova *et al.*, 2014; Bicknell *et al.*, 2015; Rutishauser *et al.*, 2015; Kleinschroth *et al.*, 2016). However, while the increasing similarity with old-growth forests in forest structure and biodiversity during recovery after logging is well documented for some case studies, these studies do generally still find detectable differences between logged and unlogged forests (Chapman & Chapman, 2004; Edwards *et al.*, 2011, 2014a; Putz *et al.*, 2012; Cazzolla Gatti *et al.*, 2014; Osazuwa-Peters *et al.*, 2015).

Despite the limitation of the small sample size used in our study, our field observations suggested an agreement with studies indicating rapid AGB recovery after logging (but not of forest structure). After only 14-16 years since logging the field plots have on average similar level of EAGB to unlogged forest, though there was evidence that basal areas of trees ≥ 60 cm DBH may not yet have fully recovered (TS 5.5). Similarly, Quesada *et al.* (2012) found using four 1-ha experimental monitoring plots in Osa, that 19 years after logging, basal area (> 10 cm DBH) was similar to pre-logging values, however the density and basal area of trees ≥ 70 cm DBH was still lower in all the plots. Rutishauser *et al.* (2015) provided evidence that recovery of AGB is highly dependent on the initial AGB lost by timber

harvesting. We estimated from the FMPs that 72% of the overall above-ground carbon stocks was retained after selective logging that removed on average 25 m^3 ha^{-1} of timber volume. At similar logging intensities in Brazil (23 and 30 m^3 ha^{-1}) retained AGB was found to be 63% and 88% respectively (Asner *et al.*, 2005; Miller *et al.*, 2011), while it has been estimated that logged tropical forests retained on average 76% (Putz *et al.*, 2012). Applying the Rutishauser *et al.* (2015) model to our data, with an average of 25 m^3 ha^{-1} extracted volume, AGB will require approximately 16 years to recover, thus explaining our field results. Caution is needed to interpret these results, as clearly larger replication and size of sample plots distributed over the whole study area is required to overcome the effects of patchy distribution of large trees, environmental variability, natural canopy gaps etc., and so improve the reliability of our results on the recovery of AGB (and other variables) after logging. Nonetheless, the estimates of approximate recovery from our results coincide with those in the literature, showing a rapid recovery of forest carbon stocks after logging but a slower recovery of stocks of timber in larger diameter trees.

The potential negative effects highlighted above are the reason why it is important that monitoring is not limited to forest cover but that it includes monitoring of forest quality. As suggested by our results, the quality and characteristics of forest areas varies greatly across the landscape, due to either previous clearing or selective logging, creating a mosaic of forest patches under different degrees of forest degradation. The common approach to obtain forest cover statistics with the use of remote sensing in many tropical regions is just to classify the images between forest and non-forest (GOFC-GOLD, 2013). By incorporating information on previous disturbances our study provided additional information on the quality of the forest of this key area for biodiversity conservation in Costa Rica.

5.4.2. Methodology for assessing forest degradation in combination with deforestation

Our study evaluates the state of forest cover in Osa by combining supervised image classification techniques with existing data from FMPs. Our results showed that mapping forest disturbance based on decomposing the best available satellite images into a series of reference materials (linear spectral unmixing), although limited in its precision, is a feasible method. This is particularly valuable given its suitability for Landsat data that are, in most areas, the only satellite data available for previous decades to study disturbance processes over a sufficiently long time period to quantify trends over time. The study of forest degradation with remote sensing is very challenging, particularly because the disturbance signal caused by logging is hard to detect after 42 months following selective logging because of rapid forest regrowth, and as in any remote sensing analysis this detectability is

also affected by topography (Asner *et al.*, 2002, 2005, 2013; Souza *et al.*, 2005). Contrary to studies carried out in large flat areas of the Amazon or the Congo Basin, Osa has a complex topography with about 30% of the area having slopes greater than 10º (Fig S 5.1), which makes disturbance to the canopy cover even harder to detect. In combination with the hilly terrain, the lack of higher resolution data for the area constrains the mapping of logging roads based only on image interpretation, as has been attempted in other studies (e.g. Gaveau et al. 2014; Kleinschroth et al. 2015; Margono et al. 2012).

The method presented here builds on previous research that demonstrated the utility of analyzing fraction images to map disturbed areas in tropical forests (Souza *et al.*, 2005; GOFC-GOLD, 2013). Considering the accuracy obtained here, and comparing with other studies, indicates that the estimate obtained with our model of the forest area disturbed most likely due to logging (18.1%) is reasonable. In just a sub-set of the total study area, the Reserva Forestal Golfo Dulce (Fig. 5.1), Barrantes et al. (1999) analysing only the area given on the FMPs reported that 8.5% of the forest was demarcated for logging. Nonetheless their field evaluation revealed that 16% more trees were harvested than reported in the FMPs. This suggests that the area affected by logging was in fact larger. Although there are limited studies to compare with, and logging intensities vary widely from region to region, in a study area in the Brazilian Amazon Matricardi et al. (2010), also using linear spectral unmixing analysis, reported that about 31% of the area was affected by logging, with removal of around 40-50% of the tree canopy cover.

Although our approach achieved a classification accuracy for the disturbance map of 77%, and its estimate of the logging area is reasonable, the approach is subject to a series of limitations, particularly linked with the available data. Firstly, the lack of data on the exact location of the logging concessions precludes establishing a more precise threshold of values to extract from the image fractions. This limits the precision of differentiation between logged and undisturbed areas. Instead, we had to use an indirect approach, based on the observation that the GV component is higher in undisturbed areas (Souza *et al.*, 2005), and rely on comparing the distributions by using the median value as a threshold, which clearly has an associated error where values of UF and LF overlapped (Fig 5.4). Secondly, the method makes no direct distinction between anthropogenic and natural disturbances when analyzing the ratios GV:Soil and GV:Shadow. As a result the differentiation is based on the context, i.e. whether the pixel is inside or outside a protected area *versus* an area subject to recent logging. However, the assumption that forest within protected areas is not subject to notable anthropogenic disturbance will not always hold since, in Costa Rica, although protected areas are less disturbed than unprotected areas, they are not completely unaffected by human impacts (Sanchez-Azofeifa *et al.*, 2002).

The image classification of the present study showed that some areas found inside the national parks, particularly the Corcovado National Park, were classified as degraded (Fig. 5.5). The evidence does not enable determination of the extent to which this degradation was due to human activity, as many of these areas are adjacent to a river course, and might naturally have a more open canopy. However, human disturbance of forest connected with illegal gold mining that has been practiced inside the national park is also concentrated on land adjacent to rivers (Vaughan, 2012). The other national park in the study area (Piedras Blancas National Park) had a smaller percentage of its forest area classified as degraded, coinciding with human incursions being known to be less frequent in this protected area (Sierra *et al.*, 2003). The difficulty of separating natural from anthropogenic disturbance is not exclusive to the method applied in this study; it has also been discussed in other studies that have mapped forest degradation (Matricardi *et al.*, 2010; Negrón-Juárez *et al.*, 2011; Gaveau *et al.*, 2014), and remains one of the biggest challenges in monitoring forest degradation (Birdsey *et al.*, 2013; GOFC-GOLD, 2013). Despite these limitations, we believed that our approach is an improvement over existing methods for determining degraded areas, such as the use of visual interpretation of roads to determine logged areas or degraded areas (e.g. Mollicone et al. 2007), mainly because it is derived directly from the spectral values of the forests that vary according to forest structural characteristics.

Future improvements to detect areas affected by logging will benefit from including other data sources that are now available, such as LiDAR and higher resolution data. LiDAR has the potential to improve logging detection because it provides direct information on forest structure comparable to that obtained from field plots. For instance, its use in combination with optical data to model AGB over regional scales has resulted in models with substantial lower errors than those derived using optical data alone (Zolkos *et al.*, 2013; Vaglio Laurin *et al.*, 2014; Marvin & Asner, 2016). Nonetheless, LiDAR data is relatively recent, therefore no long-term historical data is available; moreover, it is currently only available via airborne sensors, thus it can only provide data for small areas. For these reasons, it needs to be used in conjunction with optical satellite data to cover larger areas.

An important remaining benefit of time series of optical data is their value to provide information on forest disturbance legacy (the process of degradation) with which to interpret the forest attributes obtained with LiDAR data. A recent study by Taylor *et al.* (2015) carried out in Osa provides an example of this benefit. Their study used LiDAR in combination with topographic and geological information to study the factors determining AGB, and found that abiotic factors explained only 34% of the variation in AGB. It is highly likely that most of the remaining variation in AGB is explained by disturbance history, in particular by the logging and the regrowth processes that have occurred in the area, which are the focus of our

study. Furthermore, the classes defined in our study can potentially be used as strata for multistage sampling, to select sampling points for field plots and LiDAR flights stratified between undisturbed, logged and secondary forests to improve AGB estimates.

In addition to the inclusion of other data sources, future research to improve the detection of degraded forests in Osa should attempt to make the separation between natural and human-induced disturbance more efficient, for which further field work using stratified sampling between areas of logged and undisturbed forests is also required. The classes defined in this research (LF and UF) can potentially be used as strata for selecting sampling points, which could include undisturbed areas outside protected areas, that might help refine this analysis. Additional priorities for future research should further explore the temporal dimension of forest degradation with the aim of understanding how forests recover in the area, the spatial variability that results from logging, and potential impacts that logging might have on forest quality at the landscape level (Pfeifer *et al.*, 2016).

5.4.3. Implication for policy of improved methods to assess forest degradation

In Costa Rica there has been little assessment of the effects of logging and secondary forest regrowth on carbon stocks and biodiversity conservation at the landscape scale. This is a major gap and challenge for a small-area country, given its commitments to sustain and improve forest-based ecosystem services, while both sustainable management of natural forests and an increase in consumption of wood are included within the proposed national REDD+ forest strategy (Sáenz-Faerrón *et al.*, 2010). Two main issues should be addressed to move forward towards achieving these commitments: development of a landscape level spatial planning of forest uses and improvements in the forest monitoring capacity.

Our approach of combining historical data on FMPs, field-evaluation of recovery and long-time-series Landsat data provides an example of the kind of integrated methodology required to monitor forest-based ecosystem services and to improve spatial planning of forest management at a landscape scale, in areas with poor data sources. Mapping degraded forests can specifically provide information for decisions about where, when, and with what intensity, new logging cycles should be permitted, and where to spare large areas from logging (Edwards et al. 2011). Although we could not identify all the management plans in the cadastral database, visually inspecting our results in combination with the author's knowledge of the area, suggested some degree of clustering of logging concessions. As the impacts on biodiversity at a larger scale and within the context of heterogeneous landscapes are different from those at the scale of a single forest management unit (in Osa, the property) (Chaudhary *et al.*, 2016), coordinating logging operations based on spatial planning using information of the extent of degraded areas, is clearly needed. Such coordination should aim

to reduce the risks of harming the delivery of ecosystem services, biodiversity, and specifically the populations of timber species. Moreover, mapping the extent of degraded areas can support the much needed evaluation of tradeoffs between logging and other land uses for biodiversity conservation, which is key in the study area because of the increasing importance of nature-based tourism.

Low capacity for monitoring selective logging in Costa Rica is one of the arguments against the country's forest policy allowing a continuation of logging activities (Sáenz-Faerrón *et al.*, 2010), and is one of the reasons why FMPs were banned in Osa after 1999 (Barrantes *et al.*, 1999; Arroyo-Mora *et al.*, 2014). However, information sources and monitoring capabilities to which forest and conservation managers have access are now substantially better than when logging was last carried out in Osa 15 years ago. Most importantly, information availability and new analyses, such as that presented in this study, can facilitate spatial planning of logging and restoration at the landscape level. This is particularly true now with the availability of an updated cadastral database, high resolution remote sensing data and the higher accuracy of current GPS technologies, as well as the improved capacity to systematize this information in consistent databases (Svob *et al.*, 2014).

Besides improvement in monitoring methodology, access to better information sources and the planning of forest uses at the landscape scale is needed. A major difficulty in performing the analyses in the present study was the use of historical data that were not systematically collected (e.g. the data from the tree surveys and forest inventories carried out as part of the previous prescribed forest management planning process). This situation is not restricted to Costa Rica: in many other places in Latin-America reliable data on past forest management is limited (Nasi *et al.*, 2011). Many of the legal requirements for selective logging are often not being enforced, thus the information that would be required to provide good evidence of the actual forest exploitation carried out is not systematically documented and contains major irregularities (Barrantes *et al*. 1999). This lack of well-documented information on logging concessions makes it difficult to evaluate in more detail than the present study the variability in forest quality and the legacy of past disturbances across the landscape.

The need for adequate landscape planning for implementation of REDD+ is evident, particularly if forest management is incorporated as a mitigation activity, or if enhancing carbon sequestration at the landscape level by avoiding forest conversion to competing land uses is attempted (Sayer *et al.*, 2013; Venter *et al.*, 2013). The type of spatial information on the extent of degraded forests presented in this study could play a valuable role in targeting priority areas for forest restoration, but also as reference information for monitoring future changes in the spatial distribution of degraded areas. This would be relevant, for example if

permission is given to resume selective logging in an area after a period of time during which it has been prohibited (such as in Osa) and for evaluating policy interventions (e.g. effectiveness of PES schemes) (Rosendal & Schei, 2014). Through the methodology developed and tested in this paper, we hope to provide an approach that can be used to produce data on the state and changes of both forest cover and degradation level that is needed to improve landscape planning processes towards sustainble forest management and enhancing the delivery of forest ecosystem services.

5.5. Conclusions

Our study sought to map degraded forest areas by combining the limited available information on previous selective logging activities with a spatial analysis to detect both secondary regrowth and areas that could have been potentially affected by logging. Four decades ago, about 80% of the landscape of the Osa Peninsula was covered by an almost continuous block of undisturbed tropical moist forest. High conversion rates of forest cover were experienced until two decades ago, when a process of forest recovery started. Our study estimated that about 30% of the forest of the Osa Peninsula is to some extent degraded because it has been logged in the past or is the result of secondary regrowth after clearance. This implies that the current landscape is formed by a mosaic of forest patches that differ in their level of degradation, and presumably in their structure and composition, connected to the past and present distribution of human activities.

Mapping degraded areas with optical remote sensing is challenging, and is a process that commonly relies on secondary data sources such as records of logging concessions, which were not specifically designed for this purpose, thus increasing the difficulty of applying them in spatial analysis. Despite these methodological challenges, it is important to understand the history of disturbance that an area has been subject to in a spatially explicit manner. Commonly, the effects of disturbance history go unnoticed, because remote sensing analysis is limited to assessing only the extent of forest against non-forest cover. In the case of the Osa Peninsula, one application of the information on the extent of degraded areas presented in this study is to serve as the input for a stratification process to improve the precision of forest carbon inventories. In turn, this would allow identification of synergies between carbon and biodiversity conservation initiatives.

The transformation of undisturbed tropical forest landscapes into other land cover/land uses is the result of complex interactions between multiple processes. The observed extent of degraded forest in the Osa Peninsula has resulted from changes in forest policies that first promoted forest clearing for agriculture, and then opened up the possibility of extensive

logging activities. Our satellite data analysis showed that forest cover has recovered at least in terms of area. However, at present, the circumstances of the Osa Peninsula are changing again, with the opening of a new highway in 2010, real estate development and an increase in the area of oil palm, all processes that can potentially affect forest ecosystems negatively. Therefore, it is important that government incentives, in particular through its REDD+ strategy, can provide attractive options to conserve forest and its carbon stocks, and enhance the conservation of biodiversity and delivery of other ecosystem services, and thus promote sustainable development. Two such alternatives could be providing incentives for applying reduced impact logging and for accelerating the recovery of secondary forest. If such options are to be attempted in the near future as part of REDD+ or the national PES scheme, their design and implementation could benefit greatly from the landscape-scale forest cover and degradation change assessment methods presented in this paper.

5.6. Appendices

Table S 5. 1 Confusion matrix at pixel level from the random forests classification for each year based on out-of-bag error. Classification results are the columns, and reference categories are the rows. Accuracy refers to the number of correctly classified pixels relative to all reference pixels in that class, Reliability refers to the number of correctly classified pixels relative to all pixels classified as that class. Overall accuracy is equal to the number of correctly classified pixels with respect to the total number of pixels.

1975	Forest	Non-forest	Mangrove	Cloud/ shadow	Water	Palm forest	Total	Accuracy
Forest	1978	4	2	0	0	29	2013	0.98
Non-forest	1	1001	1	1	0	6	1010	0.99
Mangrove	0	0	912	0	0	0	912	1.00
Cloud/shadow	0	0	0	2005	0	0	2005	1.00
Water	0	0	0	0	1000	0	1000	1.00
Palm forest	15	5	1	0	0	984	1005	0.98
Total	1994	1010	916	2006	1000	1019	7945	0.99
Reliability	0.992	0.991	0.996	1.000	1.000	0.966		
Overall accuracy							7880	**0.99**

1998	Forest	Non-forest	Mangrove	Cloud/ shadow	Water	Palm forest	Secondary regrowth	Forest plantation	Total	Accuracy
Forest	1391	1	7	5	0	40	17	6	1467	0.95
Non-forest	3	678	0	0	0	1	26	1	709	0.96
Mangrove	8	0	684	0	0	3	0	4	699	0.98
Cloud/shadow	0	0	0	1381	0	1	0	0	1382	1.00
Water	0	0	0	0	69	0	0	0	69	1.00
Palm forest	5	1	10	0	0	687	2	0	705	0.97
Secondary regrowth	8	8	0	0	0	13	675	2	706	0.96
Forest plantations	4	0	1	0	0	0	0	689	694	0.99
Total	1419	688	702	1386	69	745	720	702	6431	
Reliability	0.98	0.99	0.97	1.00	1.00	0.92	0.94	0.98		
Overall accuracy									6254	**0.97**

2000	Forest	Non-forest	Mangrove	Cloud/ shadow	Water	Palm forest	Secondary regrowth	Forest plantation		Total	Accuracy
Forest	1582	3	29	1	0	24	21	7		1667	0.95
Non-forest	0	785	0	0	0	0	20	4		809	0.97
Mangrove	12	0	791	0	0	2	0	0		805	0.98
Cloud/shadow	0	0	0	1418	0	0	0	0		1418	1.00
Water	0	0	0	0	609	0	0	0		609	1.00
Palm forest	11	0	11	0	0	777	4	0		803	0.97
Secondary regrowth	10	9	0	0	0	9	778	0		806	0.97
Forest plantations	8	0	0	0	0	0	2	787		797	0.99
Total	1623	797	831	1419	609	812	825	798		7714	
Reliability	0.97	0.98	0.95	1.00	1.00	0.96	0.94	0.99			
Overall accuracy										7527	**0.98**
2014	**Forest**	**Non-forest**	**Mangrove**	**Cloud/ shadow**	**Water**	**Palm forest**	**Secondary regrowth**	**Forest plantation**	**Oil palm plantation**	**Total**	**Accuracy**
Forest	1551	2	23	22	0	25	6	11	27	1667	0.93
Non-forest	1	701	0	0	0	1	8	3	0	714	0.98
Mangrove	2	0	798	0	0	0	0	0	0	800	1.00
Cloud/shadow	9	0	0	1583	0	0	0	0	1	1593	0.99
Water	0	0	0	0	68	0	0	0	0	68	1.00
Palm forest	11	0	0	2	0	777	0	0	4	794	0.98
Secondary regrowth	7	5	0	0	0	4	776	0	2	794	0.98
Forest plantations	3	0	0	0	0	0	0	637	0	640	1.00
Oil palm plantation	25	5	0	0	0	2	2	0	737	771	0.96
Total	1609	713	821	1607	68	809	792	651	771	7841	
Reliability	0.96	0.98	0.97	0.99	1.00	0.96	0.98	0.98	0.96		
Overall accuracy										7628	**0.97**

Table S 5.2 Proportion of forest area change by elevation and slope.

	Forest cover (ha)			Forest cover change (%) during periods		
	1975	2000	2014	1975-2000	2000-2014	1975-2014
Elevation (m a.s.l.)						
0-100	9614	7800	9049	-18.9	16	-5.9
100-200	62 648	53 400	59 127	-14.9	10.8	-5.6
200-400	45 131	43 652	44100	-3.3	1.0	-2.3
>400	14 283	14 610	14 612	2.3	0	2.3
Slope (degrees)						
0-5	69 847	59 974	65 614	-14.1	9.4	-6.1
5-10	22 193	20 851	21 799	-6.0	4.5	-1.8
10-20	23 336	22 581	23 239	-3.2	2.9	-0.4
20-30	11 470	11 262	11 396	-1.8	1.2	-0.7
>30	4574	4520	4541	-1.2	0.5	-0.7

Table S 5.3 Validation results for the disturbance map based on the classification of 157 random field data points between degraded forest, which was identified in the field as areas of logged forest and secondary regrowth forest, and undisturbed forest, which was identified in the field as areas that had not been logged or cleared.

Classification results /Ground truth points	Undisturbed forest	Degraded forest	Total	Accuracy*
Undisturbed forest	76	29	105	72.4
Degraded forest	7	45	52	62.5
Total	83	74	157	
Reliability**	91.6	60.8		
Overall accuracy				77.1

*Accuracy (producer's accuracy) refers to the number of correctly classified pixels relative to all the pixels of the ground points in that class, **Reliability (user's accuracy) refers to the number of correctly classified pixels relative to all pixels classified as that class. Overall accuracy is equal to the number of correctly classified pixels with respect to the total number of pixels.

Table S 5.4 Summary statistics from pre-logging inventory and survey data from the forest management plans registered for the period 1997-1999 in the Osa Peninsula, Costa Rica.

	Mean (±SD)	Min	Max
AGB (Mg ha^{-1})§	142.50 ± 61.07	15.07	413.74
Number trees ha^{-1}§	70.26 ± 23.67	26.67	170
AGB of harvested trees (Mg ha^{-1})	17.45±4.98	9.13	35.52
Basal Area of harvested trees (m^2 ha^{-1})*†	2.07 ± 0.56	1.11	4.07
Number of harvested trees ha^{-1}*†	5.27 ± 2.68	0.25	13.16
AGB of retained trees†(Mg ha^{-1})**	16.19 ± 8.34	2.31	63.47
Basal Area of retained trees (m^2 ha^{-1})†**	1.96 ± 1.00	0.28	7.62
Number of retained trees ha^{-1}*†	4.77 ± 1.79	0.89	10.02

FMP = forest management plan, each FMP corresponds to a property; § based on inventory data (trees ≥ 30 cm DBH, *n* = 421 plots); * harvested trees refers to trees marked for harvesting in the survey; ** retained trees refers to the marked as retained in the survey; † based on FMP pre-logging survey data (trees ≥ 60 cm DBH, *n* = 79 FMPs).

Table S 5.5 Comparison of the mean value of the plots located in undisturbed (UF, n = 4) and logged (LF, n = 11) forest in the Osa Peninsula, Costa Rica.

Parameter	Mean UF ± (SD)	Mean LF ± (SD)	*t*-value	d.f.	*P*
Number of trees ≥10 cm DBH ha^{-1}	492.5 ± 78.0	501.3 ± 171.4	0.135	12	0.89
Number of trees ≥ 30 cm DBH ha^{-1}	127.5 ± 22.2	121.8 ± 55.19	-0.284	13	0.78
Mean DBH ≥ 10 cm	25.4 ± 3.2	25.8 ± 5.4	0.150	9	0.88
Mean DBH ≥ 30 cm	48.9 ± 13.8	48.9± 8.7	0.001	4	0.99
BA of trees ≥30 cm DBH (m^2 ha^{-1})	37.25 ± 13.9	38.4± 18.5	0.130	7	0.89

BA of trees ≥ 60 cm DBH (m^2 ha^{-1})	18.9± 24.2	14.7 ± 17.8	-0.315	5	0.76
EAGB (Mg ha^{-1})	278.3 ± 128.6	291.8 ± 156.1	0.169	7	0.87
Percentage of EAGB in trees ≥ 30 cm DBH	74.1 ± 20.4	71.4 ± 20.4	-0.223	5	0.83
Elevation (m a.s.l.)	317.8 ± 166.3	220.3 ± 104.9	-1.095	4	0.34
Slope (º)	31.2 ± 30.6	20.36 ± 15.57	-0.680	4	0.54
Canopy cover (%)	89.12±1.7	62.8 ± 7.8	-10.470	12	< 0.001*

BA = basal area, EAGB = estimated above ground biomass, * denotes significant difference ($P < 0.05$) between UF and LF.

Table S 5.6 Comparison of the mean estimated above-ground biomass (EAGB) from field plots with other studies conducted in the region. Piro and La Gamba are within the Osa Peninsula.

Site	Basal Area (m^2 ha^{-1})	EAGB (Mg ha^{-1})	Method	DBH range	Reference
Osa region	NA	25 - 225	Remote sensing		Taylor et al. (2015)
Lowland rainforests for the whole of Costa Rica	32.4	244	Field plots	≥ 10 cm	NFI (2015)
Piro-Friends of the Osa reserve	NA	260	Field plots	≥ 10cm	Winrock (2006)
La Gamba	NA	218.46 ± 29.01	Field plots	≥ 30 cm	Hofhansl et al. (2012)
This study (Osa Peninsular)	37.25 ± 13.9 38.4 ± 18.5	278.3 ± 128.6 (UF) 291.8 ± 156.1 (LF)	Field plots	≥ 10 cm	

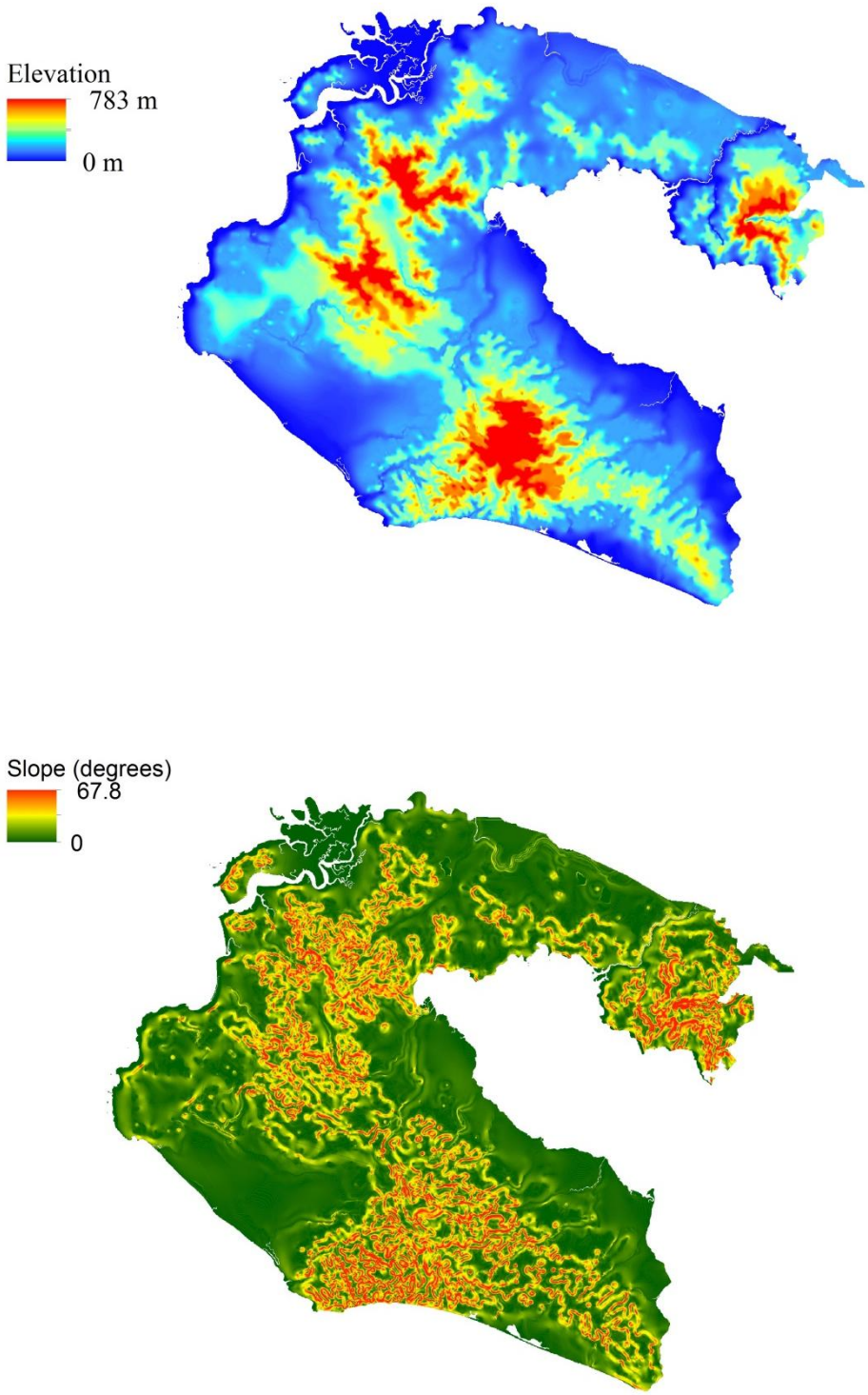

Figure S 5.1 Terrain elevation (top panel) and slope (bottom panel) in the study area region, as obtained through the Digital Elevation Model (30-m resolution) from the Digital Atlas of Costa Rica (ITCR, 2008).

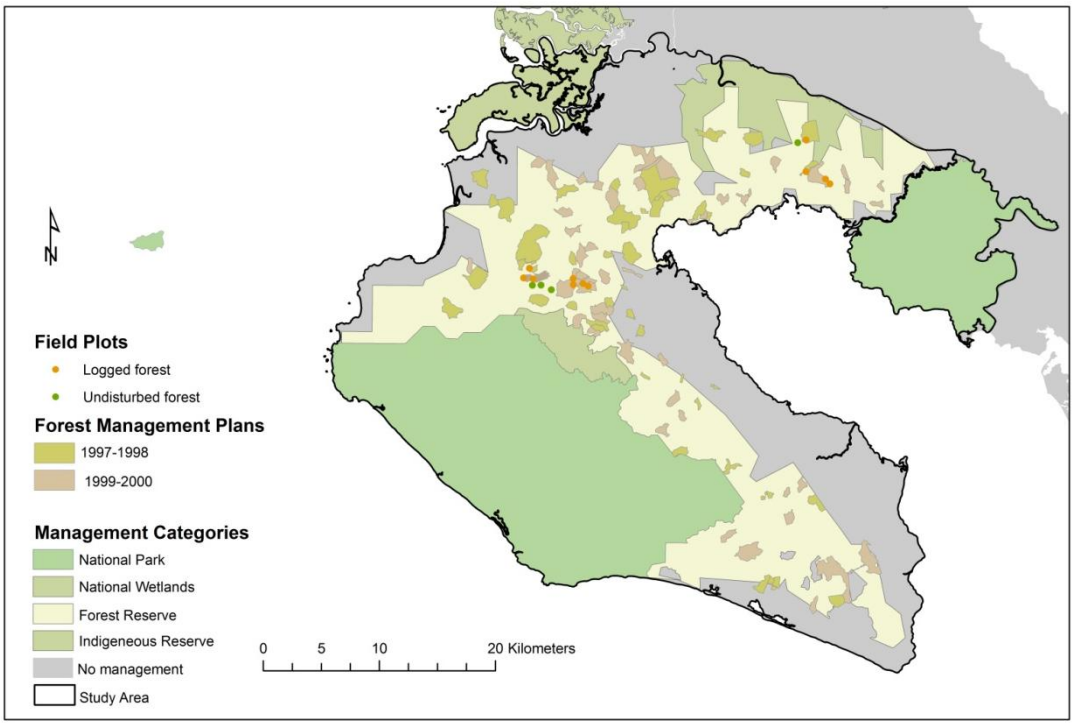

Figure S 5.2 Distribution of the forest management plans registered between 1997 and 1998, and the field plots sampled in July 2013, in the Osa Peninsula.

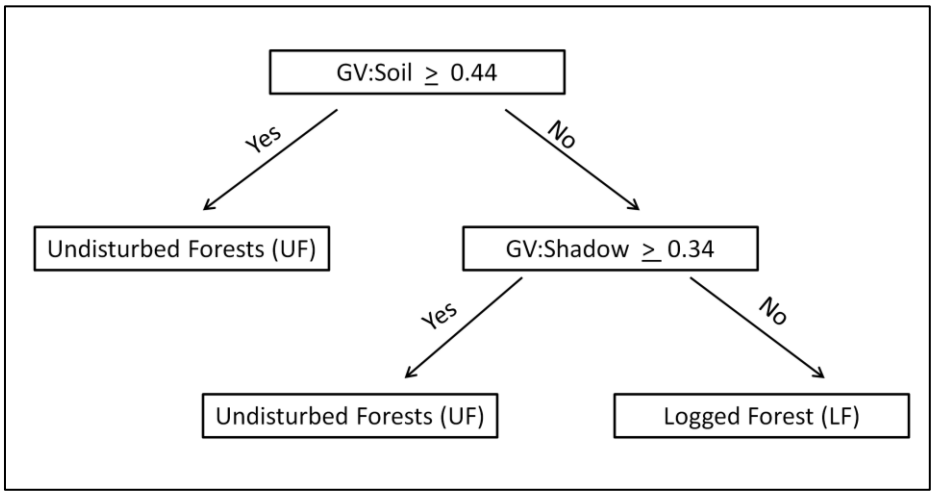

Figure S 5.3 Decision tree classifier used to classify the 1998 and 2000 fraction images into logged and undisturbed forests based GV (green vegetation). Soil and shadow refer to the image endmembers obtained through the linear unmixing analysis.

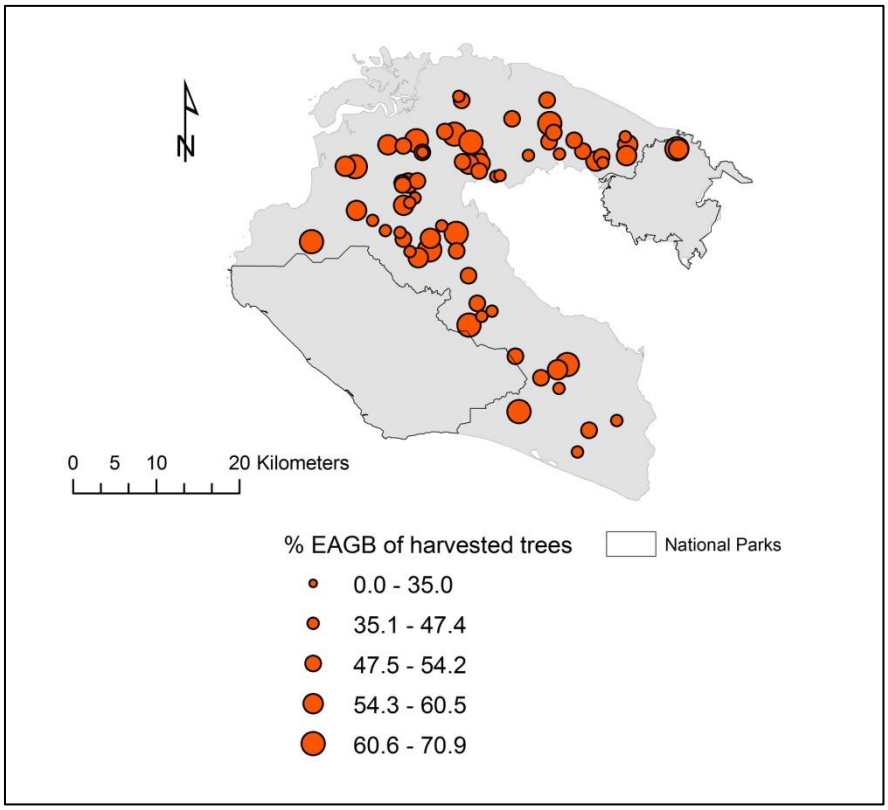

Figure S 5.4 Spatial distribution of the percentage of the total estimated above-ground biomass (EAGB) of harvested trees (≥ 60 cm DBH) based on the forest management plans registered during 1997-1999 in the Osa Peninsula, Costa Rica.

Chapter 6. Synthesis and Conclusions

There is a consensus about the difficulty of measuring and monitoring tropical forest degradation in comparison with deforestation, particularly with remote sensing, which is reflected in most of the literature on this topic (Joseph *et al.*, 2010; Herold *et al.*, 2011; GOFC-GOLD, 2013; Goetz *et al.*, 2015). Particular attention has been given to measuring and monitoring forest degradation with respect to above-ground biomass (AGB), due to the international priority of implementing climate change agreements(Gibbs *et al.*, 2007; Tyukavina *et al.*, 2015). Nonetheless, multiple challenges remain in improving understanding of the full range of processes that affect AGB dynamics at the scale of human modified landscapes and methods to monitor them (Mertz *et al.*, 2012; Birdsey *et al.*, 2013; Houghton, 2013; Thompson *et al.*, 2013; Dons *et al.*, 2015). Dealing with these challenges is likely to require different approaches to conceptualize forest degradation, and for these approaches to be effective in reducing forest degradation they should be clearly linked to the type of human activity that is causing it (Skutsch & Balderas-Torres, 2012; Salvini *et al.*, 2014).

The research presented in this thesis aimed to address these challenges from a technical perspective, by characterizing the spatial and temporal patterns of the extent of forest degradation at a landscape scale in relation to disturbance caused by shifting cultivation and logging. This study analysed forest degradation with respect to the disturbance agents, rather than limiting its analysis to the quantification of carbon stocks. Overall my research has substantially advanced methodology to use remote sensing to evaluate landscapes continuously subject to the degradation processes of grazing, fuelwood collection and small-scale logging. This topic has previously been neglected in the literature. My method to evaluate the impacts of selective logging through the use of historical logging information in order to provide a landscape-scale approach is an innovative new contribution to the assessment of degradation in tropical moist forests. I hope that this research will contribute to a far more comprehensive discussion of how best to integrate evaluation of the specific effects of different types of disturbance into the monitoring of tropical forest degradation in the socio-ecological landscapes. Such a discussion should be based on three elements: monitoring aims, current ecological knowledge and available data sources, which I sought to integrate in the methodology developed in this study.

In this chapter, I refer to the main findings of the preceding chapters and discuss their combined significance for future research directions and for policy formulation, particularly in relation to carbon mitigation schemes and tropical forest conservation. I reflect as well on some the limitations of the research.

6.1. Use of benchmarks as a way of bridging the gap between policy and ecological science to measure tropical forest degradation

Carbon mitigation schemes have tended to define forest degradation as a loss of forest biomass below a reference condition (Cadman, 2008; Simula, 2009; FAO, 2011). Clearly, such an approach responds to a carbon-trading perspective, which attempts to deal with tropical forest carbon and other ecosystem services as a commodity. This has transformed the concept of forest degradation, fabricating the term within a geo-political context specifically related to climate mitigation, drawing attention away from the original ecological context, in which changes in forest ecosystems arising from anthropogenic disturbances were studied (Chazdon *et al.*, 2007). This discrepancy between the political and ecological dimensions of forest degradation is what motivated Chapter 2 of this thesis.

In Chapter 2, a detailed literature-based analysis of the technical and political capabilities of assessing forest degradation was carried out, using Mexico as an example. Mexico, in contrast to most other tropical countries, has much better developed forest monitoring systems and institutional frameworks to assess forest resources (Bucki *et al.*, 2012; Skutsch *et al.*, 2013). Nonetheless, my analysis concluded that there is limited capacity to assess forest degradation in the country. Therefore, recognizing the limitations in the potential to detect forest degradation with available remote sensing data, and that there is a lack of historical biomass data in most developing countries for setting reference levels (Skutsch *et al.*, 2011; Olander *et al.*, 2012), in Chapter 2 I advocated the use of local benchmarks as a quick-start option to measure forest degradation. Local benchmarks refer to undisturbed areas or areas with minimum human intervention that represent the potential AGB against which to compare, in order to establish levels of forest degradation, within landscapes which have comparable biophysical characteristics.

One potentially cost-effective solution to the setting of benchmarks, that I proposed on the basis of this research, is to base them on the disturbance history of the area. In the case of the shifting cultivation TDF landscapes used as an example in Chapter 2, the stand age, defined as the number of years since an area was cleared for the last time, was used as an explanatory variable for AGB, as it has been observed that it is a strong predictor of biomass in other TDF (Laurance, 2005; Kauffman *et al.*, 2009; Dupuy *et al.*, 2012; Aryal *et al.*, 2014; Becknell & Powers, 2014). The analysis based on land-use history of TDF within two elevation gradients (Fig. 2.1) showed that there is a high degree of overlap between degradation levels that are adjacent in the classification. This supports the widely acknowledged finding that multiple factors control/determine AGB in TDF (Kauffman *et al.*,

2003; Baker *et al.*, 2004; Poorter *et al.*, 2016). Some of these factors are related to the current use that communities make of the TDF resources, which are further explored in Chapter 4, where a strong correlation (r = -0.62, P < 0.001) was found between AGB and indicators of cattle grazing, logging and fuelwood collection. These findings, on the one hand, support the possibility of using the least disturbed areas in the TDF landscape (those with the lowest levels of disturbance indicators) as a reference against which to measure forest degradation. On the other hand the findings also showed that setting local benchmarks in tropical forest landscapes is a complex process. Within the site of my study all of the plots had some degree of disturbance, including low biomass values in many of the least disturbed plots. The AGB values for undisturbed TDF reported in the literature, along with the measured *in situ* indicators, suggested that the use of these least disturbed plots as benchmarks will imply setting the reference level below that which it could be (for truly undisturbed forest). Therefore, as in the case of this study, the nearest examples of undisturbed forest that are suitable for use as a reference may be a considerable distance away, and therefore stretch the definition of local. This raises more questions, and as explained below the need for further research.

These analyses illustrate the complex reality that tropical forests are inherently dynamic systems that lose and gain biomass constantly (Attiwill, 1994; Cole *et al.*, 2014; Ghazoul *et al.*, 2015), and that AGB is influenced by a series of environmental, biophysical and disturbance-history related factors that are not well understood, including unexplained variation (Chazdon *et al.*, 2007; Asner *et al.*, 2008; Norden *et al.*, 2015). They also show that AGB variability within landscapes is large (as shown for example in Fig. 2.2 and Fig 5.8 c) (Chave *et al.*, 2003; Mitchard *et al.*, 2013) and as a result it is difficult to detect changes in biomass due to management interventions. The few studies that have attempted long-term monitoring of changes in estimated biomass using permanent plots in the context of carbon emissions reduction, e.g. Chidumayo (2013), have shown that changes tend to fall within the uncertainty limits of the estimates. However, policy design tends to overlook these realities in its simplification of the definition, measurement and monitoring of forest degradation to a carbon accounting approach. By failing to quantify and monitor losses of AGB more precisely, this simple accounting approach risks a failure to detect the changes in carbon stocks that do result from successful interventions designed to avoid forest degradation. Given the high uncertainty range of biomass accounting (Avitabile *et al.*, 2012; Langner *et al.*, 2012), such subtle changes will often go unnoticed. As a result the opportunity for new sources of funding (Venter & Koh, 2012) linked to avoided forest degradation that could be used to enhance tropical forest ecosystems and improve livelihoods will be lost. To avoid this, consistent, yet simple, protocols, to define and measure forest degradation within

countries, such as the benchmark approach presented here, need to be developed further, and included within policy frameworks, acknowledging the several limitations of such an approach. Then, basing carbon accounting on biomass losses or gains becomes more reasonable and less isolated. This approach has the potential to improve equitability and long-term sustainability, as the socio-economic dimension of natural resource utilization and ecological characteristics of forests need to be incorporated in order to decide on benchmarks and to identify the management alternatives that create least risk of forest degradation.

6.2. The measurement of forest degradation should be guided by the spatial and temporal scales

The study of the patterns of shifting cultivation landscapes in western Mexico presented in Chapter 3 provided evidence of the importance of conceptualizing forest degradation as a landscape process, instead of limiting it to a stand level process or analyzing it only at a national scale. By using high spatial resolution data (10 x 10 m), I found similar amounts of TDF clearance and regrowth over the study period, both at a regional and at a community level. This may indicate indirectly that at the landscape level no net carbon emissions are being produced if emissions due to clearance are offset by secondary regrowth. This implies that the estimated carbon balance of the landscape would be very different if such an analysis is carried out at different spatial and temporal scales. At lower spatial resolutions (> 30 m), which are normally used for mapping forest cover at national and global levels, clearings due to shifting cultivation (approximately 2 ha) will not be detected and are therefore are ignored in the overall carbon budget.

In areas where small-scale agriculture is the predominant form of land use, cycles of forest clearance and regrowth are a major component of the uncertainties in the overall carbon budget (Defries *et al.*, 2002; Houghton, 2012; Pelletier *et al.*, 2012b) and create challenges for setting baselines (Grainger, 2008). Two recommendations for monitoring can be derived from my research to detect small clearings and regrowth that was reported in Chapter 3. Firstly, to fully capture the dynamics of forest degradation occurring due to shifting cultivation, assessments should be made at the landscape level, or at the management unit level, and to achieve consistent results the limits should be clearly defined. Secondly, to improve monitoring of forest cover and consequently of activity data, there is a need for spatially explicit linkage of coarser estimations of clearance-regrowth done at national or even global scales, with those obtained locally using higher spatial resolution.

Similar considerations apply to assessment of the impacts of selective logging. Carbon emissions from selective logging clearly vary depending on the temporal and spatial scales that are used in the carbon accounting. In Chapter 5 I found that the area affected by logging compromises a substantial proportion of the studied landscape (approx. 18%), however the field data suggested , despite the small sample size, that AGB had recovered in the approximately 15 years since logging was carried out. As discussed in chapter 5, other recent studies provide evidence that the time required for tropical forests to recover their AGB will vary depending on the logging intensity. Under most common timber extraction rates, recovery of AGB will take between more than decade and 75 years (Rutishauser *et al.*, 2015). After the first decade logged areas generally become a carbon sink (Blanc *et al.*, 2009; Gourlet-Fleury *et al.*, 2013), suggesting that assessed over a sufficient temporal and spatial scale forest subject to selective logging could even be carbon neutral. However, this will vary depending on the spatial unit used as the basis for the carbon accounting. Given that the effect of spatial scale has received relatively little attention in the context of carbon emissions from selective logging there is no basis for a more detailed evaluation of the specific effects of the scale of evaluation on the results of the carbon accounting. This issue is therefore a priority for future research, e.g. to compare the relative net emissions (and other environmental impacts) resulting from low intensity logging carried out over a wide area with those from higher intensity logging carried out in smaller areas (Healey *et al.*, 2000; Edwards *et al.*, 2014b)

These findings raise the difficult question of what is the appropriate scale for monitoring the dynamics of carbon stocks for REDD+ projects, or other payment for ecosystem services schemes. Firstly, the appropriate scale should be directly linked to the type of disturbance activity that has been causing carbon emissions. Secondly, the scale should be appropriate for the detection of change, which is clearly limited by data availability. Thirdly, any incentive program should considered explicitly the constraints on efficient monitoring of outcomes due to practical limitations of the temporal and spatial resolution at which change can be measured.

6.3. Disturbance type and data availability as limiting factors for methods to monitor the extent of forest degradation

In this study I evaluated, both at the ground level and with remote sensing, the detectability of the area of degraded forest in two different ecosystem types. Despite the context of the two analyses being different, some general conclusion can be drawn. The performance of remote sensing in monitoring forest degradation seems to be higher for moist forest than for dry forests. While in moist forest mapping degraded areas based on historical

information, achieved a relatively high accuracy (Chapter 5); the remote sensing analysis of dry forests presented in Chapter 4 achieved only limited success. This suggests that in dry forest ground-level measurements might play a more important role than purely remote sensing-based methods, and therefore monitoring of forest degradation might benefit from more indirect approaches (as further discussed in 6.4 below). However, this situation might change in the near future for dry forests, as better data become available enabling multi-temporal analyses to be made using reliable field data on carbon stocks. Nonetheless, remote sensing and ground measurements should not be seen as separated competing monitoring systems but as complementary ones (Herold *et al.*, 2011; Birdsey *et al.*, 2013; Tokola, 2015).

Analyzing the above-mentioned findings in a broader context, and from a practical perspective, the definition and capacity to monitor tropical forest degradation is to a great extent determined by the type of disturbance, and this affects how forest degradation is defined. The majority of the research on forest degradation had focused on moist forests, mostly analyzing discrete disturbance events, in particular logging (De Sy *et al.*, 2012; Dons *et al.*, 2015; Goetz *et al.*, 2015). This is despite the suggestion that the area of dry forests that are degraded could be greater than the area affected by logging in moist forests (Herold *et al.*, 2011). While it is possible to use historical satellite data to establish baselines or reference conditions in moist forests, as I did in Chapter 5, my results in dry forest and other recent work suggest (Ryan *et al.*, 2012; Dons *et al.*, 2015), that this is not the case in that biome .

The more gradual and persistent changes that characterize forest degradation in TDF are difficult to relate to a specific date in order to compare with any available satellite data. Thus, in the case of TDF, gathering information on the current state in order to set a reference condition, as I carried out in Chapter 4, seems to be of the utmost important. Although having a series of generic guidelines for measuring forest degradation in all types of forest for all types of disturbances (e.g. FAO 2011) would be ideal as a basis for comparison between forest types, and to maximise credibility amongst stakeholders, this is not yet possible with current knowledge and technology. In the meantime, monitoring methods that are feasible and achieve sufficient accuracy to meet their purposes will need to be fitted to the characteristics of each biome and critically assessed before being used for any comparison between systems.

6.4. The use of alternative methods to measure forest degradation that are linked with the type of disturbance

The difficulties of detecting changes in tropical forests AGB with enough precision (Chidumayo, 2013; Aryal *et al.*, 2014; Cartus *et al.*, 2014; Marvin & Asner, 2016), motivated my research into understanding which factor and/or indicators can link, simultaneously, biomass and management practices in an area, as a potentially efficient solution to monitor forest degradation. The research presented in Chapters 3 and 4 explores this idea for TDF. In Chapter 3, I found that the use of forest resources by communities, along with socio-economic and biophysical factors, can predict the changes in forest cover related to shifting cultivation systems, which I used as a proxy of forest degradation in TDF. One of the main drivers of forest degradation in this study site was the degree of marginalization, which is a measure of the socioeconomic level of a community. Another important factor was the amount of forest area available for each person in the community, and to a lesser extent the amount of livestock and of fence posts harvested. In particular, the community's socioeconomic level will have an effect on the dependency or use that it makes of forest resources. This suggests that highly marginalized communities will rely more on shifting cultivation, while also using the forest as a source of fuelwood and land for livestock grazing. Therefore, at the community level, measuring these factors might be an efficient way to monitor forest degradation once projects are implemented that can complement field inventories and remote sensing analysis (Skutsch, 2011; Skutsch & Balderas-Torres, 2012).

The importance of the use of forest resources by communities is further explored in Chapter 4. In this Chapter the relationship is explored between forest attributes and indicators of state that are linked with the use of forest for livestock grazing, as a source of fuelwood and for building materials. A series of ecologically meaningful indicators that can be associated with disturbance process, such as the percentage of small and large stems, and the type and quantity of ground cover, were combined and correlated with the estimated actual AGB and potential AGB of the area. This provided evidence that supported the utility of *in situ* indicators that are easy to measure for the monitoring of forest degradation in TDF. Taken together these *in situ* indicators provide an assessment of the disturbance intensity of an area and how this has affected the AGB. Although I recognized that repeated measurements as part of longer monitoring efforts are needed to come to definitive conclusions; in the case of the TDF of the Ayuquila Watershed, indicators related to the impact of livestock seem to be the most important to monitor, especially the cover of bare soil and the density of small stems.

Taken together these findings have interesting implications for policy design, since they suggest that it will be advantageous and feasible to design monitoring protocols that directly measure the use of forest resources as an alternative and/or complementary measures to the time-consuming and costly process of measuring AGB using forest inventories (Böttcher *et al.*, 2009; Birdsey *et al.*, 2013). Countries are encouraged to use monitoring systems that are most appropriate to their national circumstances (Mora *et al.*, 2012). For countries with large areas of TDF this represents a major challenge, since disturbances in TDF tend to be gradual and persistent, thus there is little information on their effects on AGB and consequently designing monitoring efforts, or establishing any type of baseline, is difficult (Kalacska *et al.*, 2008; Dons *et al.*, 2015). In this regard, protocols that collect data on the disturbance and management of an area, such as the one presented in Chapter 4, will provide much needed information for detecting the effect of project activities implemented for REDD+, and in identifying which interventions have the biggest impact on AGB or other forest attributes. In this way, including indicators related to disturbance and management represent an efficient way to assess degradation in TDF where changes in AGB between measurements tend to be small, often within a wide uncertainty range (Ryan *et al.*, 2012; Chidumayo, 2013). They will provide the evidence needed to link any changes in AGB to management and therefore justify any carbon payment.

To make the use of disturbance indicators in forest monitoring more cost-effective, a possible way forward could be to perform complete forest inventories, including information on disturbance indicators on a set of field plots. In order to increase the sampling area measurement of just disturbance indicators could also be made in a larger set of plots. This sampling effort could greatly benefit from involving communities in the monitoring (Skutsch *et al.*, 2011; Pratihast *et al.*, 2013), as discussed below. If communities are involved, not only can this reduce costs but it can also potentially improve management as communities could identify activities that are degrading their forests (Skutsch *et al.*, 2013). For the latter purpose indicators related to activities such as livestock grazing or fuelwood collection are likely to be easier to understand than more abstract concepts as biomass (Skutsch *et al.*, 2015).

6.5. Multi-temporal analysis as a way to define forest strata and to guide carbon accounting in the landscape

The results of multi-temporal analysis of cover with remote sensing data in dry and moist forest presented in Chapters 3 and 5 respectively have important applications for evaluating the heterogeneity found within landscapes and for developing stratification systems that can assist with better monitoring of forest resources. In Chapter 5 specifically, I found that

through the combination of long time series of medium-resolution satellite data with historical sources of data on logging concessions it was possible to distinguish degraded forests from undisturbed forest within the landscape with a 77% accuracy (Fig. 5.5). A potential application of these result is to use the determined areas of degraded and undisturbed forest as strata for future assessment of forest resources and to derive the activity data for degraded areas.

To monitor forest degradation at the landscape level, it would be ideal to map using remote sensing, the areas that are expected to be gaining carbon and those losing carbon due to human activities, and those that are not affected. Such an approach would allow the application of the IPCC's carbon stock accounting methods to estimate the effects of forest degradation which, as far as I know, has not previously been achieved. Therefore, using multi-temporal analysis as input for the stratification can offer an approximation to this, mainly because it is incorporating information on disturbance processes (Mohren *et al.*, 2012). In the case of the Osa Peninsula moist forest study area, the combination of change detection analysis to determine areas of secondary regrowth and the mapping of logging activity based on the management plan records allowed the determination of the areas within the forest that are in a recovery phase and therefore presumably sequestering carbon. It also allowed the differentiation, to a great extent, of undisturbed areas that can be considered comparatively 'stable' in terms of carbon, because their carbon gains or losses will be linked only to natural processes. Similarly, the detailed mapping of shifting cultivation in TDF landscapes that was presented in Chapter 3 can be used to define strata. The detection of the areas that have undergone shifting cultivation can be used to define the areas that are gaining carbon, as well as those that are losing carbon, due to human activities.

Defining land cover strata can be very important, particularly if default values are being used to establish the amount of carbon that is present per land cover class (as specified in the IPCC Tier 1 approach to emission estimation (Pearson *et al.*, 2005; GOFC-GOLD, 2013; Langner *et al.*, 2014)). Refining these land cover classes can potentially increase accuracy, but a default value for this needs to be determined accordingly (Gibbs *et al.*, 2007; Langner *et al.*, 2014); for this the use of half of the total forest carbon stocks found in undisturbed areas has been proposed by Mollicone *et al* (2007) and Bucki *et al.* (2012). The use of strata, however, is really an (over-) simplification of the heterogeneity revealed by the spatial variability of the AGB that is seen on the "ground" throughout a landscape. For instance, the results obtained from the field plots in logged and undisturbed forests in Chapter 5, contrary to my expectations, showed similar values of the measured forest attributes (Fig. 5.8), suggesting that the logged forest has already recovered after approximately 15 years and that these two strata are not different enough to be usefully distinguished. This result must,

however, be treated with considerable caution because of the limited number of plots, along with potential problems of spatial autocorrelation that are commonly reported in comparisons between logged and undisturbed forests (Ramage *et al.*, 2013). The spatial variability in the distribution of harvested trees (Fig S 5.4) and in the AGB estimated from the pre-logging inventories (Fig. 5.6) suggests that there is actually a large range of variation in the state of the forest across the Peninsula since the logging intensity was much higher in some areas than in others.

6.6. A retrospective look at categorizing forest as degraded

As discussed in several parts of this thesis, defining tropical forest degradation is extremely problematic (Putz & Redford, 2010). Thus, it has even been argued that due to this difficulty no definition is needed (Guariguata *et al.*, 2009; Goetz *et al.*, 2015)or that no forest that is able to recover without human intervention should be classified as degraded (Ghazoul *et al.*, 2015). All these arguments have validity in many respects. Once the degradation process stops, the inherent resilience of tropical forests means that tree biomass and cover will recover, though the rate is highly dependent on the intensity of the disturbance (Kauffman *et al.*, 2009; d'Oliveira *et al.*, 2011; Rutishauser *et al.*, 2015). Where the soil and sources of tree propagules have remained sufficiently intact the recovery could be relatively rapid (e.g. over one or two decades) (Chazdon, 2003; Chazdon *et al.*, 2016). Therefore, the categorization of a forest as degraded or not degraded will be highly dependent on when the assessment of the state of a forest is carried out, if the criteria used is restricted to AGB. This is particularly evident for logging, where there is usually a discrete identifiable disturbance event. In this case, whether a forest is classified as degraded is likely to depend on whether the assessment is made shortly after timber was harvested or a decade later (Putz & Romero, 2015). As an example, the results presented in Chapter 5 of my assessment showed similar AGB values between plots in forest logged 15 years previously and unlogged forest, despite my small sample and plot size. This assessment suggests that AGB did recover quickly after logging, and some stakeholders would therefore consider that these forests should not be classified as degraded.

Such grey areas are inherent when we try to apply a purely ecological-biophysical definition to categorize forest degradation. Thus, given that production of timber from tropical forest is going to continue over large areas (Blaser *et al.*, 2011; Putz & Romero, 2015), and the difficulties of establishing clear guidelines to operationalize forest degradation (discussed in detail in Chapter 2), incorporating a forest spatial planning and management perspective in the categorization of degraded forests might be a sensible and pragmatic path to move this issue forward. There is substantial evidence that under certain

logging practices (e.g. reduced impact logging) loss of carbon stocks is only temporary (Miller *et al.*, 2011; Putz *et al.*, 2012) and that its extent and duration can be estimated with reasonable accuracy (Griscom *et al.*, 2014; Pearson *et al.*, 2014). Therefore, within the context of carbon markets, payments can be allocated based on the desired management outcomes that could be predicted with reasonable certainty, supported by the use of a benchmark approach (i.e. comparing areas under improved management against areas that are not managed). Outcomes of alternative forms of forest management should be assessed considering spatial aspects of planning as well as the management practices. Integrating this information into monitoring systems, such as that developed in Chapter 5, could help in systematic planning of when, how and where logging is carried out. This should enable a clear distinction to be made between sustainable forest management (as a well-planned land use) and forest exploitation that results in degradation.

6.7. Limitations of the study and suggestions for future research

6.7.1. Limitations

In my research two main limitation are found. First in chapter 4, a limitation of the analysis was that, the closest available site with a suitable area of comparable undisturbed forest was located 150 km away from the study site. This selection of the comparator site was based on the best available data of the distribution in the region of intact forests of the study type (western Mexico TDF). For this selection it was necessary for the site to have a well-documented history, so there was certainty that the forest was undisturbed and had well documented (and peer reviewed) measurement of its AGB. Even though the selected comparator site had similar bio-physical characteristics to my study area, it would have been preferable if it had been much closer, to provide a genuinely local value for potential forest AGB. In this respect, further research is needed on the criteria use to select benchmarks and their effects, and how big the contribution of distance is as a source of error. It will be particularly valuable to focus research efforts on modelling approaches that could evaluate potential AGB under different management scenarios and environmental characteristics, and use this to set benchmarks at a local level. Future availability of AGB estimates from new planned satellites (Goetz *et al.*, 2015) could support such modelling approaches and consequently the approach of using local benchmarks of least-disturbed forest, as advocated in this study.

The second limitation is the sample number and plot size used to evaluate forest recovery after logging. As discussed in Chapter 5, one limitation of that study was that the field

assessment of recovery from logging was based on very few plots of inadequate size. Future work to evaluate the state of forest resources in the Osa Peninsula should use a much larger number of larger plots distributed across the peninsula. The spatial analysis of degraded areas presented in Chapter 5 would be of value to guide the sampling design for such a future forest inventory.

6.7.2. Recommendations for future research

Given the complexity of factors that interact to determine the distribution of AGB, and the widespread occurrence of forest degradation, particularly in TDF, there is a clear need for effective forest monitoring, which is likely to involve repeated field inventories over large areas. A cost-effective way to collect such information on AGB and disturbance-related indicators, such as the ones that I tested in Chapter 4, is through the involvement of communities in the monitoring process (Skutsch *et al.*, 2011; Larrazábal *et al.*, 2012). While substantial recent work has demonstrated the utility and benefits of involving communities in forest monitoring, and its importance in the context of REDD+ has been discussed (Danielsen *et al.*, 2011), the integration of local community- (or any other citizen-science-) based monitoring into national monitoring has not, as far as I know, been properly addressed. Therefore, the design of monitoring systems that can successfully link the information collected by communities at the local project or subnational scale , with national scales at which reporting to the UNFCCC process occurs remains a major challenge (Skutsch & Balderas-Torres, 2012). The collection and analysis of more data over larger areas would enable better calibration and validation of remote sensing models, which may be key to the integration of local, sub-national and national scales of assessment. Therefore, this is a priority for future research.

With the availability of higher resolution satellite images (in particular the 10 x 10 m resolution of Sentinel-2) that allow the crowns of individual trees to be distinguished, are acquired with a higher frequency, and are free, will enable improvements in local-scale models. Specifically, it will be possible to develop models, similar to the one I presented in chapter 3, to predict the likelihood of change in tree cover and the density of trees. Other approaches that need to be tested with higher resolution data include the feasibility of developing models that link canopy gaps caused by logging activity and (short-term) AGB loss. Thus development of methods that can improve the linkage between the location of AGB loss across the landscape and the location of human activities, making use of newly available satellite data, is also a priority for future research.

Methodology to assess forest degradation would be improved by better methods to stratify forest landscapes by AGB, with the aim of refining benchmark reference values for undisturbed areas. In the last five years many tropical countries that are implementing REDD+ have developed, or are developing, national forest inventories (Mora *et al.*, 2012; Tokola, 2015). This will make it feasible to estimate emissions more accurately by determining activity data for degraded forests through methods similar to the ones developed in this thesis, in combination with default values of AGB for the different strata (Langner *et al.*, 2014). Therefore, more work is needed on analyzing the spatial variability of AGB in the different strata at different scales and also on determining benchmark reference values.

More research effort should be focused on the effects of combined disturbances, particularly in TDF, in areas that are actively used by communities. Such research is difficult to carry out since many factors (e.g. the number of livestock) cannot easily be controlled, but is clearly needed for designing effective interventions to reduce forest degradation.

Finally, now that REDD+ has been implemented on the ground for more or less five years, this provides a valuable opportunity for comparative analysis on the definitions of forest degradation that projects/countries that are being used, as well as how it is being measured by different projects/countries are measuring it.

6.8. Final comments on the capacity to monitor forest degradation in the context of REDD+

In the context of REDD+ projects, it is possible that monitoring requires reframing to enable development and application of methods that are more precise, pragmatic and produce more consistent results through time. It is expected that technological improvements will solve, or at least make a substantial contribution to, the need for an accurate accounting method for carbon emissions. This may make an important contribution to increasing investment in forest-based emissions reduction projects through carbon market mechanisms. Even if technological advances improve the accuracy of carbon stock and emissions estimates in the near future, the cost and feasibility of applying such new technologies at project and regional levels still needs to be seen (Böttcher *et al.*, 2009; De Sy *et al.*, 2012). Appropriate methods to deal with generation of reference or baseline data will remain an additional challenge.

It has recently been suggested that the planned new satellites will enable direct operational monitoring of AGB, and that such monitoring will be independent of any definition of forest and/or forest degradation (Goetz et al. 2015). While it is true that

improvements in AGB estimation will be important, this does not address the root of the problem, which relates to understanding the causes and/or factors that account for the temporal and spatial variation of AGB in tropical forest landscapes, and how to counteract the most important causes of forest degradation.

The context of current international REDD+ policy dictates that payments will be made at the national level. However, countries have the right to decide what type of activities will be included in REDD+ and how they will evaluate performance of those activities. Furthermore, countries are encouraged to develop monitoring systems that are appropriate for their particular circumstances and sub-national monitoring systems are acceptable (UNFCCC 2010). This is where the methods presented in this thesis can make an important contribution, by providing alternative approaches for countries to evaluate the state of their forest resources, that take into consideration previous use of the forest.

Combining conditionality with equitability in local REDD+, or other payment for ecosystem services schemes, depends on sufficiently accurate monitoring methods to allow, for instance, a positive change of X Mg of carbon stocks in a pixel to be translated into a payment to a community at the local level. Of even more importance for communities in poverty, would be the reliability of negative carbon stock change evidence used to justify depriving them of an expected payment following their forest management actions that caused an opportunity cost to the community. Solving this is a complex issue that requires an interdisciplinary perspective to be used in monitoring tropical forests. This could be key to reduce the gap between science and policy.

Although it is challenging, to overcome forest degradation and restore the ecosystem services delivered by tropical forest landscapes, the effects that the different causes of forest degradation have on forest ecosystem structure and processes needs to be better characterized. Therefore, advances on the methods currently available for the assessment of forest degradation are urgently needed. I have made new contributions to conceptualizing 'degraded tropical forests' within the context of the monitoring required for carbon emissions mitigation schemes, to the process of determining, measuring and monitoring forest degradation with remote sensing techniques, and to establishing a link between human activities and the state of forest resources. Forest degradation is an extremely complex topic that is full of unresolved questions, contradictory perspectives and a diversity of expectations by different stakeholders. However, it is important not to lose within all this complexity the main objective of improving the state of tropical forest landscapes.

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