

ABSTRACT

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FOR CONSERVATION

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Reducing tropical deforestation has been a primary focus for the implementation of policies that are aimed at biodiversity conservation, and reducing greenhouse gas emissions, as tropical forests have, biologically, the richest ecosystem on Earth, tropical deforestation is one of the largest sources of anthropogenic carbon emission into the atmosphere, and preventing it is the most inexpensive option, in order to reduce carbon emissions and conserve biodiversity. To set the effective policies and conservation plans to reduce emission from tropical deforestation, the evaluation of effectiveness of both the current and previous efforts for conservation is critical. The three studies in this dissertation describe the development of the methods to accurately monitor pan-tropical forest cover change, using satellite remote sensing

data, and their integration with the econometrics approach, to evaluate the effectiveness of the tropical forest conservation practices. The dissertation contributes a method for long-term, global forest cover change estimation from Landsat, and the methods are applied to report the first, pan-tropical forest cover change trends, between the 1990s and the 2000s. The global forest cover change product from 1990 to 2000, which was produced, based on the developed methods which are evaluated to have an overall accuracy of 88%. The results demonstrate that tropical deforestation has accelerated between the 1990s and the 2000s by 62%, which contradicts the assertions of it being decelerating. The results further show that the increased deforestation rate between the 1990s and the 2000s is significantly correlated with the increases in Gross Domestic Product (GDP) growth rate, agricultural production growth, and urban population growth between the two decades. Protected Areas (PA), throughout the tropics, avoided $83,000 \pm 22,000 \text{ km}^2$ of the deforestation during the 2000s. The effectiveness of international aid can be suppressed by weak governance and the lack of forest change monitoring capacity of each country. The conclusions of this dissertation provide a historical baseline for the estimates of tropical forest cover change, and for the evaluation of effectiveness of such conservation efforts.

ESTIMATION OF PAN-TROPICAL DEFORESTATION AND IMPLICATIONS
FOR CONSERVATION

By

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Foreword

Chapters 2-4 contain jointly authored work in which Do-Hyung Kim is the primary author. Methods development, data processing, analysis of the findings and manuscript writing is led by Do-Hyung Kim with the contributions from other co-authors, who are named in the corresponding chapters.

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Chapter 1 Introduction

1.1 Background

Reducing tropical deforestation has been a primary focus for the implementation of policies that are aimed at biodiversity conservation, and reducing greenhouse gas emissions, as tropical forests have, biologically, the richest ecosystem on Earth (Laurance et al. 2012), tropical deforestation is one of the largest sources of anthropogenic carbon emission into the atmosphere (Gibbs et al. 2007), and its prevention is the most inexpensive option, which can help to reduce carbon emissions, and conserve biodiversity (DeFries et al. 2010; Pimm et al. 2001).

In order to effectively target the objects of policies and plans, and to evaluate the effectiveness of such policies and plans, accurate and consistent estimation of forest cover change, over space and time, is critical. Satellite remote sensing data has been used to monitor this over large areas, for its spatial and temporal consistency, and to complement issues in ground-based observations, such as data gaps and incompatibility (Curran et al. 2004; DeFries et al. 2005). However, none have successfully provided a historical baseline of the pan-tropical forest cover, based on the satellite observation, in an appropriate spatial resolution, which is suitable to monitor the majority of anthropogenic change, and with a temporal range which is long enough to depict the effects of policies and conservation practices.

In turn, the lack of accurate and comprehensive spatial data has impeded the estimation of long term trends of tropical forest cover change, which is critical for the

analysis of causal relationships between the climatological, socio-economic factors, and forest loss.

There are many possible applications of the fine spatial resolution, and long term forest cover change data. In this dissertation, the application of those data, to evaluate conservation plans, are presented. This introduction discusses the rationale and challenges in using Landsat data, for setting the historical baseline of global forest cover and its change, the current address of estimation of long-term forest cover change in the tropics, and the challenges in applying the results to the evaluation of policies and conservation plans.

1.2 Landsat based, historical forest cover change estimation

Definition of forest cover

In this dissertation, the term “forest cover” refers to a specified density of trees, and not to the land use which pertains to forestry (Di Gregorio & Jansen 1998; Hansen et al. 2010). The definition is consistent with the United Nations Framework Convention on Climate Change (UNFCCC 2002), United Nations Food and Agriculture Organization (FAO 2002), and International Geosphere-Biosphere Programme (IGBP) (Belward 1996). The term “cover” itself generalizes binary (presence vs. absence), as well as continuous (e.g., percent) scales of representation. Forests and forest cover, thus defined, are relevant to the ecosystem processes, such as chemical (e.g., carbon) and hydrological cycling, energy budgets, and biodiversity, whereas, other definitions might be more applicable to the socio-economic phenomena, such as land tenure. Further, the precision of analyses, based on these

forest cover data, depends upon the consistency of the definition of “forest” versus “non-forest”, over space and time (Kim et al. 2014; Sexton et al. 2013).

Rationale of using Landsat data for monitoring historical forest cover change

Most anthropogenic land cover changes are small in area, and the patterns of change have developed over a long period of time (Lambin et al. 2003; Townshend & Justice 1988). Consequently, the effective monitoring requires longer-term data sets, with fine spatial resolution – ideally, at the sub-hectare spatial resolutions, spanning multiple decades (Kim et al. 2015; Sexton et al. 2013; Townshend & Justice 1988). Since their first launch in the 1970s, Landsat archive represents the only globally comprehensive data record of more than three decades, which is suitable for mapping global forest cover. Landsat data offer a spatial resolution which is appropriate for mapping such changes (e.g. shifting cultivation in the rainforest), with Instantaneous Field Of View (IFOV) of 30 m, and Effective Resolution Element (ERE), which is smaller than 75 m, where the minimum area for which the spectral properties of the center can be assigned with at least 95% confidence (Townshend 1981; Wilson 1988).

Since the public opening of the United States Geological Survey (USGS) Landsat archive (Woodcock et al. 2008), there have been some efforts made to report the global forest-cover, and its changes at the 30-meter resolution of the Landsat sensors. Most of these efforts have concentrated on the recent changes (2000-present) (Hansen et al. 2013; Sexton et al. 2013; Townshend et al. 2012). However, historical baselines are needed, to understand the causes and consequences of forest cover changes, and to assess the effectiveness of land-use policies, most notably for

Reducing Emissions from Deforestation and Degradation (REDD) (Olander et al. 2008). Currently, the geospatial datasets represent Earth's forest cover globally (Hansen et al. 2013; Hansen et al. 2000; Loveland et al. 2000; Potapov et al. 2008; Potapov & Yaroshenko 2008; Sexton et al. 2013), but, none have both the spatial and temporal scale which is required for longer-term (i.e., pre-2000), global monitoring of forest-cover change, at fine spatial resolution.

Challenges in using Landsat data for long-term, global forest cover change monitoring

Provision of appropriately scaled forest cover change data has been hindered by certain constraints, including the acquisition of well-registered imagery, the need for atmospheric correction, incorrect calibration coefficients in some of the data-sets, the different phenologies between the scenes, and the need for terrain correction (Kim et al. 2014; Townshend et al. 2012). Progresses in data processing, and computing technologies, resolved the majority of these problems (Townshend et al. 2012). Especially, the opening of the USGS Landsat archive to the public has released the constraints of data access and expense, thus, enabling the successful production of operational, global scale forest cover change data (Hansen et al. 2013; Sexton et al. 2013). While these efforts have concentrated on the recent changes (2000-present), retrospective mapping of the global forest cover is still limited, by a lack of coincident reference data, required for supervised image classifications, and to assess the accuracy of change detection results.

1.3 Tropical forest cover change trends estimates

Estimation of trends in the tropical forest cover change is important, to evaluate the effectiveness of climate policies and conservation plans. Statistics from

the United Nations Food and Agriculture Organization (FAO), Forest Resource Assessment (FRA) (FAO 2010; FAO 2015) was the only source available to estimate the trends in pan-tropical forest cover change between the 1990s and the 2000s, until recently.

Based on the statistics from the FAO-FRA, the Intergovernmental Panel on Climate Change (IPCC) reported a $1.84 \text{ Gt CO}_2\text{-yr}^{-1}$ global decline in CO_2 emissions, from land-use change between the 1990s and the 2000s, attributed largely to a decreasing rate of deforestation (Stocker et al. 2013). Based on these estimates, certain assertions have been made, and it is widely accepted that the tropical, and even global deforestation rates slowed down during the 2000s (e.g. Anon. 2014).

Nonetheless, the FRA has been criticized for inconsistencies in the definition of forest among countries, and, over time, as well as its dependence on national self-reporting (DeFries et al. 2002; Grainger 2008; Matthews 2001). Previous studies have shown that the FRA overestimated changes in forest area (Achard et al. 2002; DeFries et al. 2002; Houghton 1999; Steininger et al. 2001) in the 1980s and 1990s. In the tropics, especially, the FRA reported a declining rate of deforestation from the 1980s to the 1990s, while some studies, based on satellite data, observed opposite trends (DeFries et al. 2002). FRA has also been criticized for their constant forest change rate, reported for more than half of the tropical countries, over the three periods of 1990-2000, 2000-2005, and 2005-2010 (Figure 1-1).

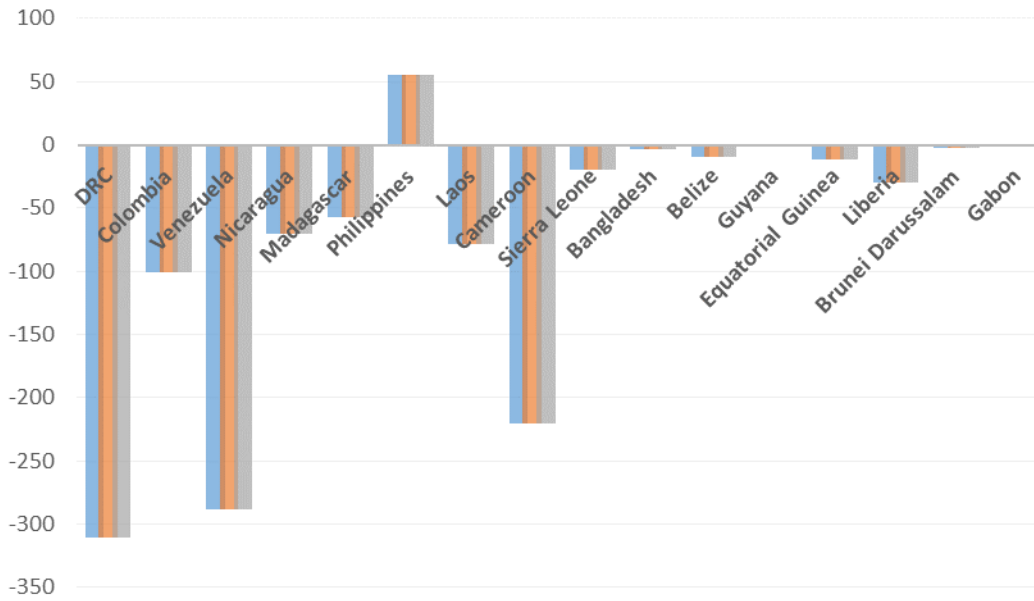


Figure 1-1 Annual net forest cover change of 16 countries from FAO, during 1999-2000 (blue), 2000-2005 (red), and 2005-2010 (gray) (FAO 2010).

These criticisms underscore the necessity to complement FRA with satellite-based estimates of pan-tropical forest cover change trends. Several remote sensing-based estimates of forest change in each time period have been made at the tropical biome level, to complement FRA, as summarized in Table 1-1.

Table 1-1 Recent satellite-based estimates of pan-tropical forest change (1,000 ha·yr⁻¹) in the 1990s and 2000s.

	<i>Area</i>	<i>1990s</i>	<i>2000s</i>	<i>ΔRate</i>	<i>Method</i>	<i>Data</i>
FAO, JRC (2012)	Tropics	-5,648	-9,111	1.3%	Sampling	Landsat
FAO, JRC (2014)	Tropics	-6,000	-7,000	16.7%	Sampling	Landsat
Achard (2002)	Humid Tropics	-5,800	-		Sampling	AVHRR
Achard (2014)	Tropics	-6,050	-5,930	-2%	Sampling	Landsat
	Humid Tropics	-3,960	-3,170	-20%	Sampling	Landsat
DeFries (2002)	Tropics	-5,563	-	-	Wall-to-wall	AVHRR
Hansen (2008,2010)	Humid tropics	-	-5,400 (gross loss)	-	Sampling	Landsat
Hansen (2013)	Tropics	-	-7,100	-	Wall-to-wall	Landsat
	Humid tropics (34 countries)	-	-5,500		Wall-to-wall	Landsat

Estimates of forest change differ among the satellite-based studies. The major differences include the inconsistencies in the definition of forest, resolution of input data, classification accuracy, and sensitivity of algorithms to detect change.

Furthermore, none of the studies reported forest cover change rate for both the 1990s and the 2000s, based on fine resolution, wall-to-wall mapping. Recent progress in data availability, processing power, and progresses in classification algorithms have enabled the national and global forest cover change assessments, based on the long-term archives of satellite imagery, in a fine spatial resolution (Hansen et al. 2013; Kim et al. 2014; Sexton et al. 2013; Townshend et al. 2012).

1.4 Challenges in evaluating the effectiveness of forest conservation efforts

As one of the application of fine spatial resolution observation of long term forest cover change, an evaluation of the effectiveness of policies and conservation plans are presented in this dissertation.

In order to evaluate the effectiveness of policies and conservation plans, the assessment of the effectiveness of Protected Areas (PAs), throughout the tropics, is of the utmost importance, as PAs have been central to climate and biodiversity policies (DeFries et al. 2005; Joppa et al. 2008; Pimm et al. 2001).

Satellite remote sensing data has been used, to evaluate the effectiveness of Protected Areas, in reducing deforestation for its spatio-temporal consistency, and to complement the issues in ground-based observations, including data gaps and compatibility issues (Curran et al. 2004; DeFries et al. 2005; Gaveau et al. 2009).

However, long-term, spatially explicit data, on pan-tropical forest cover change, in fine spatial resolution has not been made available beyond satellite analysis in a regional scale (Achard et al. 2002; DeFries et al. 2005). The lack of comprehensive long-term spatial data has precluded pan-tropical scale analysis, on the effectiveness of Protected Areas against their regulating factors.

There are also difficulties in the methods to evaluate the effectiveness of protected areas. Measuring the amount of avoided deforestation by PAs is not straightforward, because it cannot be directly measured (Andam et al. 2008).

Largely, two different types of methods have been used, to estimate the avoided deforestation. Firstly, the method of comparing the differences in forest change rate, between the inside and outside of PAs (Curran et al. 2004; DeFries et al. 2005; Joppa et al. 2008). This method has been criticized for its inability to account for the spillover effect from PAs, to the adjacent outside area, and for the selection bias, due to un-randomized selection of PAs, and inherently different deforestation probability, between the inside and outside of PAs (Stern et al. 2001). Second, statistical matching approaches to match the difference of deforestation probability between the samples inside and outside PAs (Andam et al. 2008; Joppa & Pfaff 2011). The statistical matching of the samples are robust, but hard to implement, especially when the PAs network cover large continuous tracts of lands (Soares-Filho et al. 2010), and some important factors which contribute to the deforestation probability, such as policies (e.g. concession), can be overlooked. For the evaluation of the effectiveness of PAs in pan-tropical scale, a new approach is required, to maximize the advantages of fine resolution (30m), spatially explicit data, and which is suitable for application to large areas.

1.5 Priority questions regarding the estimation of tropical deforestation and the effectiveness of protected area

Spatially and temporally comprehensive evaluation, of the effectiveness of conservation efforts, to reduce tropical deforestation, remain critical areas for effectively targeting the objects of policies, and the distribution of available resources. Several priority research questions, that need to be answered, in order to achieve the goal, include:

1. How can historical global forest cover change be estimated, using Landsat?
Landsat based, accurate wall-to-wall mapping of historical forest cover change is critical, to estimate the trends in tropical deforestation over decades, as well as to estimate the effectiveness of conservation efforts, to reduce tropical deforestation.
2. What are the forest cover change trends in the tropics? Is tropical deforestation decelerating since 1990? With consistent definition of forest cover, data and processing algorithm, a comparison between the decades is made possible.
3. How are conservation efforts, including designation of protected areas, and international monetary aid for biodiversity conservation effective in reducing tropical deforestation?

This dissertation seeks to take advantage of the most advanced data processing algorithms and computer technology, to derive a baseline of global forest cover change, using Landsat, and integrate with econometrics, to specifically address the priority research areas that are outlined above.

1.6 Objectives

The specific objectives of the dissertation were

1. To develop a method for historical forest cover change estimation, from 1990 to 2000, using Landsat, and to produce a global-scale forest cover change dataset.
2. To estimate the forest cover change between 1990, 2000, and 2010, in pan-tropical countries, and to estimate the trends in tropical deforestation, between the 1990s and 2000s, in those countries.
3. To analyze the correlations between the trends in forest cover change, and the socio-economic factors, from the 1990s and 2000s in the tropical countries.
4. To evaluate the effectiveness of pan-tropical protected areas, and international aid, on reducing deforestation.

1.7 The dissertation and its organization

Chapter 1 (this chapter) presents a brief overview of the historical, current estimates of the tropical forest cover change methods and trends, and the status of the evaluation of conservation efforts.

Chapter 2 demonstrates the feasibility of extending global, Landsat-resolution mapping, and the change detection, up to 1990. Chapter 2 presents a method to retrieve the historical maps of forest cover, and change from 1990 to 2000, based on

the archival Landsat images, and reference data hind-cast, from the more recent (i.e., post-2000) periods. This chapter reports the first results of this retrospective classification, and the change-detection algorithm, including: (1) a map of circa-1990 forest cover at 30-m resolution and global extent, with a correspondingly scaled layer estimating classification uncertainty, and (2) a global map of forest-cover and change between circa-1990 and 2000, also with a corresponding uncertainty layer. To assess the quality of the forest-cover and the change estimates, this chapter reports the error estimates relative to the samples of independent reference data, collected over the United States and across the globe, and this study compares these validation results to those, from the previous change-detection efforts. Given the sensitivity of the empirical classifiers, special attention is paid to assess the efficacy of methods, to minimize the impact of the sampling bias.

Chapter 3 summarizes a consistent series of forest-change datasets, based on satellite observations in the 1990, 2000, and 2005 “epochs” (Kim et al. 2014; Sexton et al. 2013), to estimate the changes in the tropical forest area at high (30-m) spatial resolution, in 34 tropical countries, from circa-1990 to 2005. Using a consistent definition of forest throughout, the data enable a spatio-temporally comprehensive alternative to the FAO reports, and other sample-based satellite analyses (e.g. Achard et al. 2014; FAO 2012). This study extends the series forward as well, from 2005 to 2010, to estimate the changes in tropical forest area in the latter part of that decade, and to complete the first fine scale satellite-based estimates of change in humid tropical deforestation, spanning the turn of the millennium.

Chapter 4 estimates 1) the avoided deforestation by PAs in the tropics, during the 2000s, based on long term, large-scale forest cover change, from high spatial resolution (30-m) data that has been recently made available (Kim et al. 2014), 2) estimate the effect of international aid on avoided deforestation by PAs, and 3) to analyze the correlations between the socio-economic variables on the increase in deforestation, avoided deforestation by PAs, and effects of international aid.

Chapter 5 presents the conclusions and implications of the results, as presented in the previous chapters. The dissertation concludes with a discussion of the directions for future research.

Chapter 2 Global, Landsat-based Forest-Cover Change from 1990 to 2000¹

2.1. Introduction

2.1.1 Background

Climatological and anthropogenic factors are causing widespread changes in Earth's forest cover. Since the public opening of the USGS Landsat archive (Woodcock et al. 2008), there have been efforts to report global forest-cover and its changes at the 30-meter resolution of the Landsat sensors. Most of these efforts have concentrated on recent changes (2000-present) (Townshend et al. 2012; Sexton et al. 2013; Hansen et al. 2013). However, historical baselines are needed to understand the causes and consequences of these changes and to assess the effectiveness of land-use policies, most notably for Reducing Emissions from Deforestation and Degradation (REDD) (Olander et al. 2008).

Consistent with the United Nations Framework Convention on Climate Change (UNFCCC 2002), United Nations Food and Agriculture Organization (FAO 2002), and International Geosphere-Biosphere Programme (Belward 1996), here the term “forest cover” refers to a specified density of trees, and not to land use as

¹ The presented material has been previously published in D.H. Kim, J. O. Sexton, P. Noojipady, C. Huang, A. Anand, S. Channan, M. Feng, and J. R. Townshend, Global , Landsat-based forest-cover change from 1990 to 2000, *Remote Sens. Environ.*155, 178–193 (2014).

pertaining to forestry (Hansen et al. 2010; Di Gregorio & Jansen 1998). The term “cover” itself generalizes binary (presence vs. absence) as well as continuous (e.g., percent) scales of representation. Forests and forest cover thus defined are relevant to ecosystem processes such as chemical (e.g., carbon) and hydrological cycling, energy budgets, and biodiversity, whereas other definitions might be more applicable to socio-economic phenomena such as land tenure.

Most land-cover changes are small in area, and regional patterns develop over long (e.g., decadal) time scales (Townshend & Justice 1988; Lambin et al. 2003). Consequently, effective monitoring requires longer-term data sets with fine spatial resolution - ideally at sub-hectare spatial resolutions spanning multiple decades (Townshend & Justice 1988; Sexton et al. 2013). Further, the precision of analyses based on these data depends upon consistency of the definition of “forest” versus “non-forest” over space and time (Sexton et al. 2013). Several geospatial data sets represent Earth’s forest cover globally (e.g. Loveland & Reed 2000; Potapov & Yaroshenko 2008; Sexton et al. 2013; Hansen et al. 2013), but none have both the spatial and temporal scale required for longer-term (i.e., pre-2000), global monitoring of forest-cover change at fine spatial resolution.

Provision of appropriately scaled data has in the past been hindered by two constraints: (1) access to large volumes of satellite imagery and (2) the coincident reference observations required to translate image pixels into estimates of cover. Given their global coverage, spatial resolution (30- to 60-m), and temporal extent (1972-present), the archive of Landsat data are the best source of information for retrieving historical baselines of forest cover (Olander et al. 2008). But whereas the

2009 opening of the USGS Landsat archive has released the constraint of data access, retrospective mapping of forest cover is still limited by a lack of coincident reference data required for supervised image classifications.

2.1.2 Objectives

This study demonstrates the feasibility of extending global, Landsat-resolution mapping and change detection to 1990. This study presents a method to retrieve historical maps of forest cover and change from 1990 to 2000 based on archival Landsat images and reference data hind-cast from more recent (i.e., post-2000) periods. This study reports the first results of this retrospective classification and change-detection algorithm, including: (1) a map of circa-1990 forest cover at 30-m resolution and global extent with a correspondingly scaled layer estimating classification uncertainty and (2) a global map of forest-cover change between circa-1990 and -2000, also with a corresponding uncertainty layer. To assess the quality of the forest-cover and –change estimates, this study reports error estimates relative to samples of independent reference data collected over the United States and globally, and this study compares these validation results to those from previous change-detection efforts. Given the sensitivity of empirical classifiers, special attention is paid to assessing the efficacy of methods to minimize the impact of sampling bias.

2.2. Methods

2.2.1 Data and processing

Landsat-based Surface Reflectance

Landsat images from the 1990 Global Land Survey (GLS) collection (Gutman et al. 2008) were the primary source of imagery of the 1990 “epoch”. Representing conditions around the nominal years of 1975, 1990, 2000, 2005, and 2010, the GLS was selected to optimize cloud-free conditions during the growing season for land-cover change studies. The 1990 epoch ranges from 1984 to 1997; images were taken preferentially from years near the target year 1990, but images far from 1990 were chosen by necessity in cloudy or otherwise poorly sampled regions. GLS coverage over the high northern latitudes and over western India and the surrounding region was prevented by gaps in the USGS archive. Also, nearly half of the original GLS-1990 dataset did not have correct radiometric gain and bias coefficients at the time of data acquisition; thus atmospheric correction and conversion to surface reflectance were not possible (Chander et al. 2004; Chander et al. 2009; Townshend et al. 2012). These un-calibrated GLS images were replaced after the original GLS compilation with substitutes from the updated USGS archive within the epoch wherever possible (Figure 2-1).

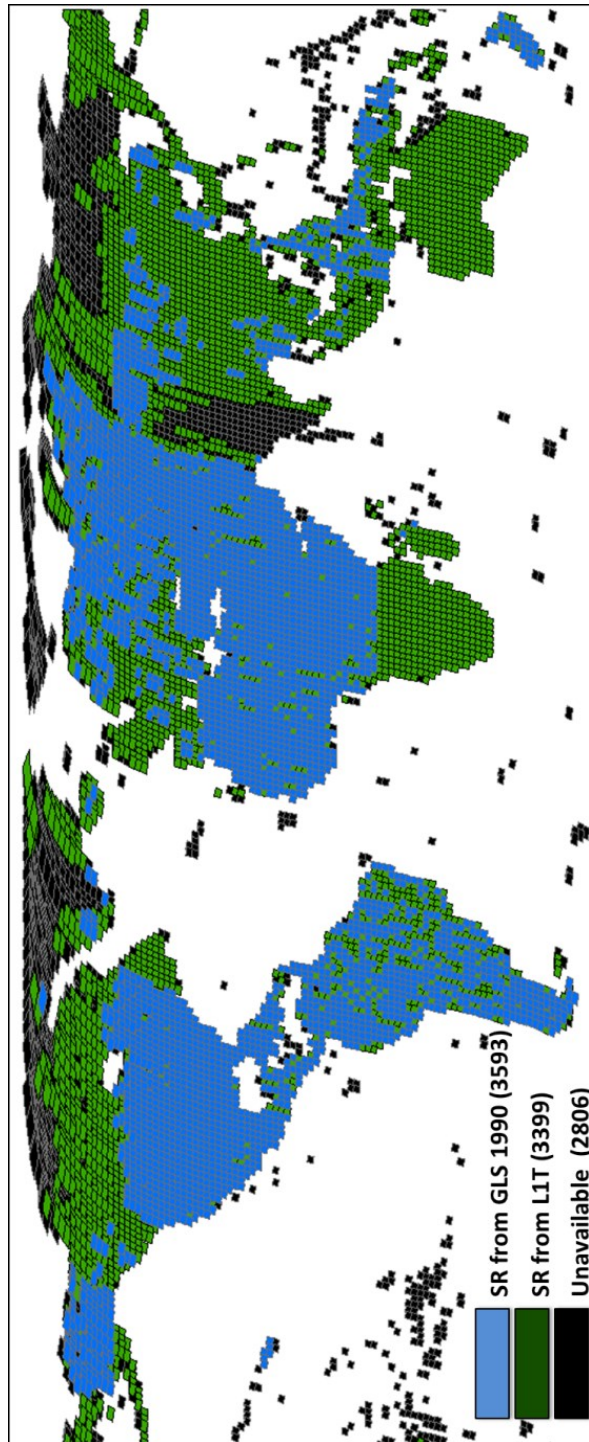


Figure 2-1 Sources of calibrated Landsat images for estimating surface reflectance (SR). Blue tiles represent SR images from the 1990 Global Land Survey collection of Landsat images, and green tiles represent SR images from downloaded LIT images. Black tiles represent areas with no available data in the USGS archive for the 1990 epoch (1984-1997).

To perform the selection of replacement imagery while minimizing phenological or atmospheric noise, a tool was constructed to query the USGS Global Visualization Viewer (GloVis) database (glovis.usgs.gov/) for appropriate images based on phenological time series of Normalized Difference Vegetation Index (NDVI) from the MODerate-resolution Spectroradiometer (MODIS) (Townshend et al. 2012; Kim et al. 2011).

Each image of this enhanced GLS dataset was then atmospherically corrected to surface reflectance using the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) (Masek et al. 2006). The surface reflectance data set from the enhanced version of GLS-1990 is available from the Global Land Cover Facility (www.landcover.org) and use of these data is strongly recommended for studies based on the GLS-1990 data (Channan et al. 2015). Clouds were identified in a spectral-temperature space (Huang et al. 2010) and removed from subsequent analysis. This “aggressive” cloud-detection algorithm’s low rate of omission error makes it suitable for masking pixels from forest-cover change analysis. Cloud shadows were identified by projecting cloud masks onto a digital elevation model through solar geometry at the time of image acquisition (Huang et al. 2010) and were also removed from analysis.

Forest cover maps in 2000 and 2005 GLS epochs

This study used tree-cover and error estimates from a global, Landsat-based tree-cover dataset for 2000 and 2005 GLS epochs (Sexton et al. 2013) available from the Global Land Cover Facility (www.landcover.org). Following the International Geosphere-Biosphere Programme (IGBP) definition of forests (IGBP 1992), forest cover maps for 2000 and 2005 epochs were derived by imposing a 30 % threshold of

tree-cover for discriminating forest from non-forest. Forest-cover change maps between 2000 and 2005 epochs were derived by image differencing (Sexton et al. 2015; data available at www.landcover.org). The overall global accuracy was approximately 89%. More details on accuracy assessment are presented in the results section.

2.2.2 Forest-cover retrieval using stable pixels

For the purpose of large-area mapping, extrapolation of models beyond the immediate temporal and spatial domain in which they were trained has been explored by many researchers (e.g. Botkin et al. 1984; Woodcock & Macomber 2001; Pax-Lenney et al. 2001; Sexton et al. 2013; Gray & Song 2013). Termed as “generalization” or “signature extension”, this approach to extend spectral signatures through time and space has been successfully applied for the classification of forest cover (Pax-Lenney et al. 2001) and change (Woodcock et al. 2001) using Landsat data. This approach has been implemented by deriving training data from one date and using it to train a classifier on a different image from the same path/row scene but different acquisition date (Pax-Lenney et al. 2001). Complementary to the traditional signature extension method, Gray and Song (2013) combined a procedure to identify stable pixels to deal with irregular time-series images. This approach has been found to be effective for the automated classification of large areas, especially when there are actual changes in class spectral signatures from phenological variability, atmospheric differences, or land cover changes (Fortier et al. 2011; Gray & Song 2013).

Reference forest/non-forest data

Persistent forest (F) and non-forest pixels (N) were sampled from forest-cover change maps between 2000 and 2005 GLS epochs and then filtered so that only “stable” pixels—i.e., those whose class did not change between 1990 and 2000 epochs—were retained for analysis. The details of the filtering process are presented below.

For each WRS-2 scene, an annual rate of forest-cover (F) change, $\frac{dF}{dt}$, and an annual rate of non-forest-cover (N) change, $\frac{dN}{dt}$, were calculated as:

$$\frac{dF}{dt} = \frac{|F_{t2} - F_{t1}|}{t2 - t1} \quad (1)$$

$$\frac{dN}{dt} = \frac{|N_{t2} - N_{t1}|}{t2 - t1} \quad (2)$$

where F and N are the percentage of forest and non-forest pixels, respectively, and t_1 and t_2 were respectively the acquisition years of the Landsat images for 2000 and 2005 GLS epochs.

The spectral difference (ΔSR) - quantified as the Euclidean distance between two pixels over time in the spectral domain— was calculated for 1990-2000 (ΔSR_1) and 2000-2005 (ΔSR_2). To minimize impact from accelerating or decelerating rates of forest-cover change between two periods, a parameter α was defined as the ratio of the sums of spectral difference of all persistent pixels and was calculated as:

$$\alpha = \Sigma \Delta SR_1 / \Sigma \Delta SR_2, \quad (3)$$

Given the large number of available pixels within the overlapping portion of two Landsat images within the same WRS-2 scene, α was doubled to increase the selectivity of filtering for stable pixels. A percentage of forest equaling $\alpha \times 2 \times 100$

$\times \frac{dF}{dt}$ and non-forest pixels equaling $\alpha \times 2 \times 100 \times \frac{dN}{dt}$ were thus removed per year of difference between 1990- and 2000-epoch images in the order of spectral difference (ΔSR). Limiting the sample to pixels that were stable from 2000 to 2005 minimized inclusion of erroneous data, and filtering the most spectrally different pixels from 1990 to the later epochs removed the pixels most likely to have changed over that period (Figure 2-2).

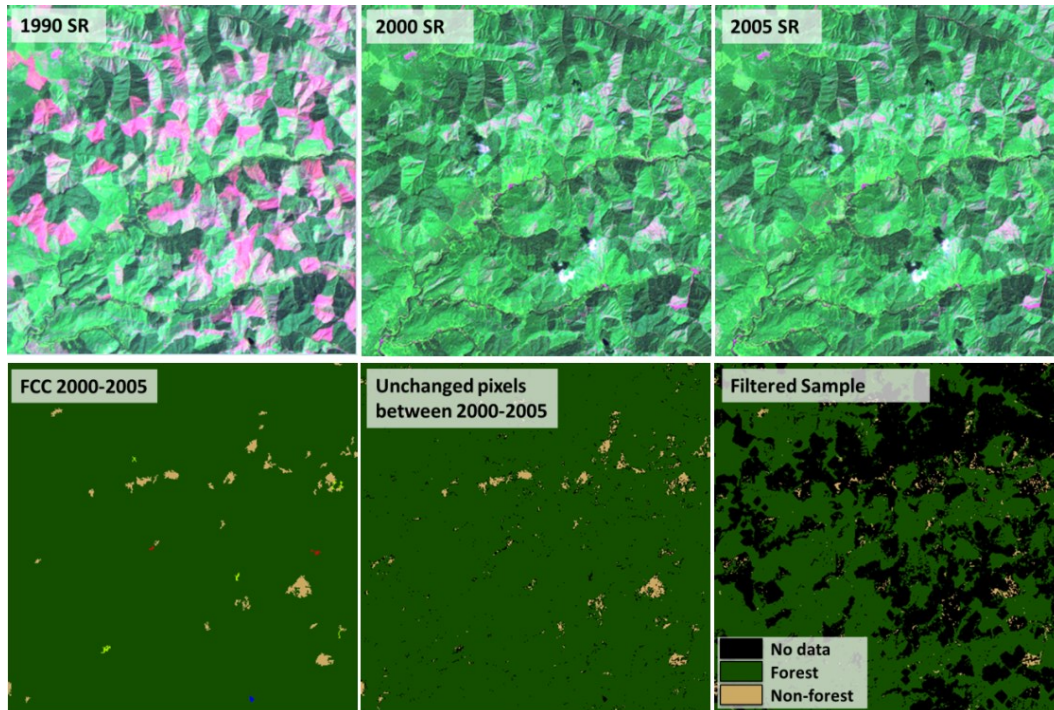


Figure 2-2 Example of training data selection from existing forest covers data (path 47 row 27). Upper three 7, 4, 2 band composite images are surface reflectance from Landsat images acquired for the 1990, 2000 and 2005 epochs respectively. The lower left image is forest cover change map from the 2000 to 2005 epoch, the central lower image depicts only persistent forest and non-forest samples selected from 2000-2005 change map and the right-hand image in the lower row is the final training data after the filtering procedure based on surface reflectance covariance.

A positive relationship between given α for each scenes and estimated change between 1990 and 2000 epoch for selected WRS-2 scenes are demonstrated in Figure 2-3. Figure 2-3 shows the relationship between alpha, the ratio of the sums of spectral difference of all persistent pixels and change rate between 1990 and 2000 epochs for persistent pixels.

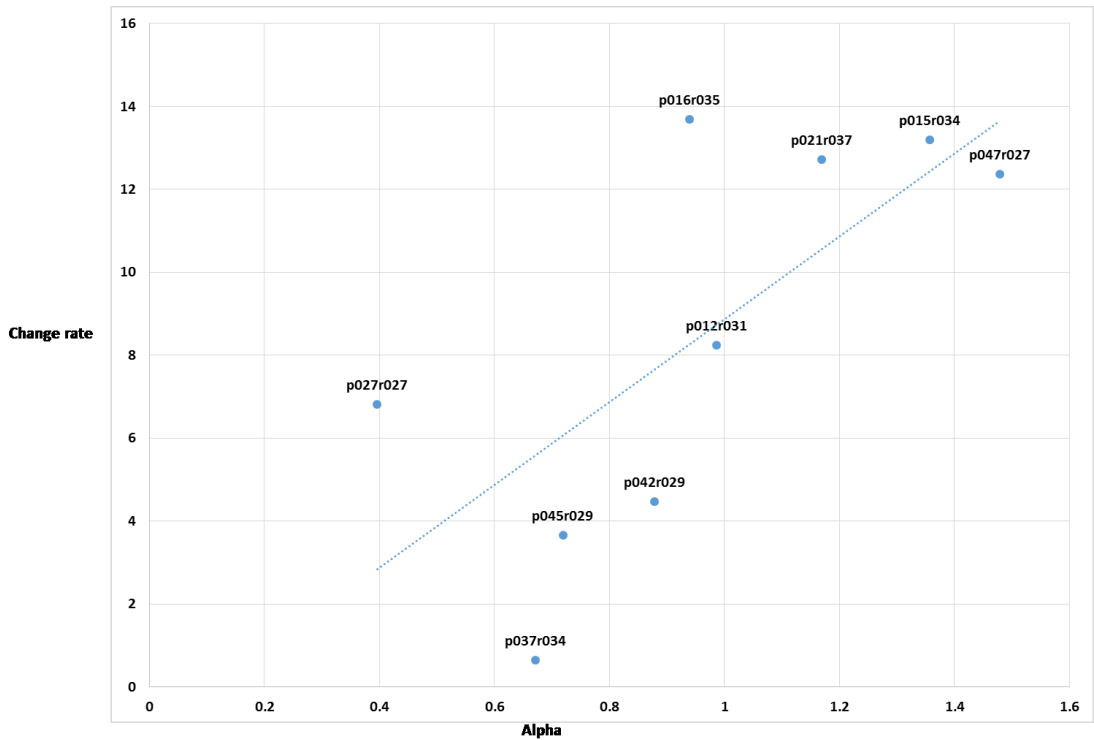


Figure 2-3 The relationship between alpha, the ratio of the sums of spectral difference of all persistent pixels and change rate between 1990 and 2000 epochs for persistent pixels.

Forest cover classification

Using the sample of stable-pixel locations, a forest/non-forest reference sample was extracted from forest-cover maps in 2000 and 2005. This sample was then filtered to maximize certainty and minimize change between observation periods (Figure 2-4).

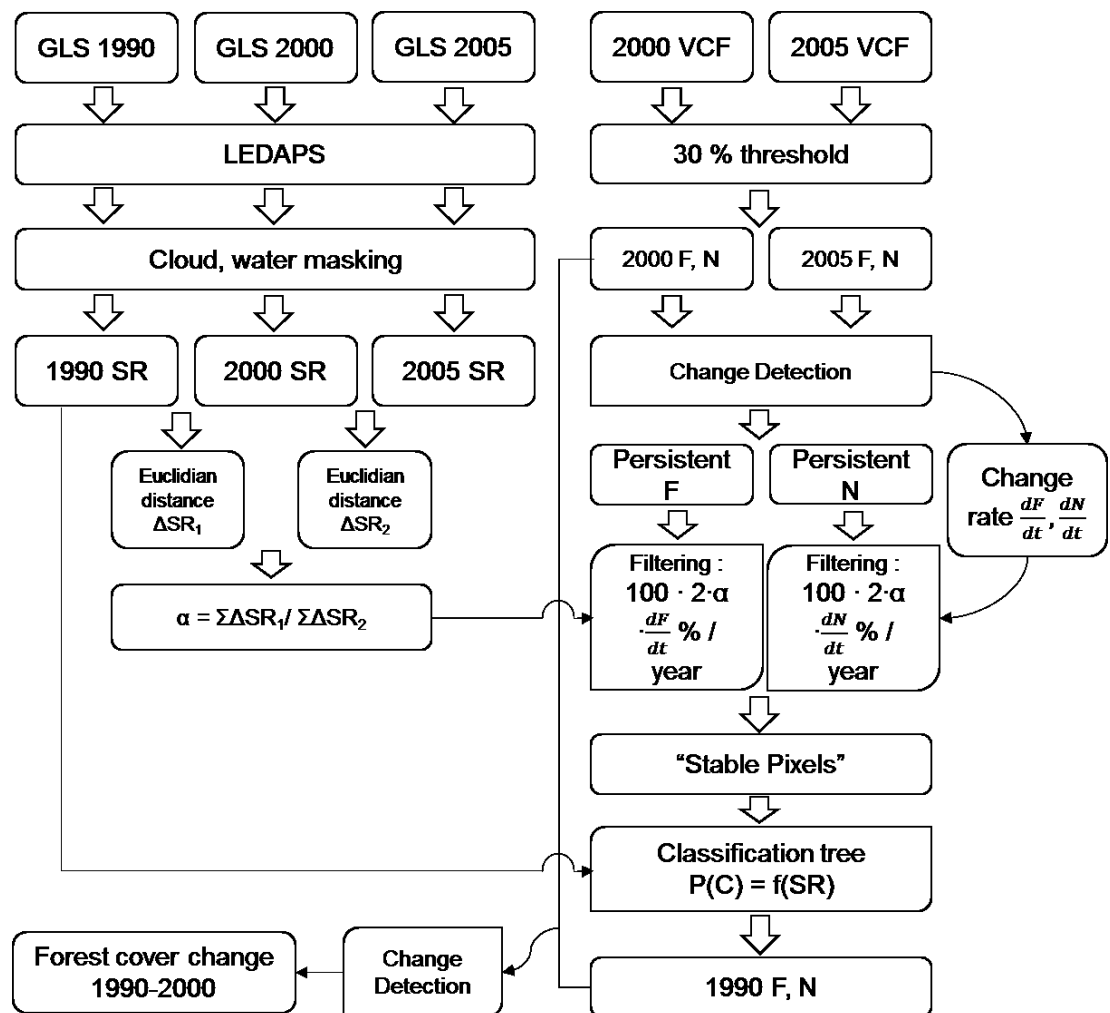


Figure 2-4 Hind-cast training and classification procedure to retrieve historical forest cover estimates. SR = surface reflectance, C = cover, $t_1 \approx 1990$, and $t_n \approx 2000$ or 2005.

Forest cover in circa-1990 was retrieved by a classification-tree algorithm. The probability of forest cover, $p(F)$, in each pixel i at time $t \approx 1990$ was estimated by a conditional relationship (g) to remotely sensed covariates (X):

$$\hat{p}(F)_{i,t} = g(X_{i,t}), \quad (4)$$

where X is a vector of surface reflectance and temperature estimates; subscripts i and t denote the pixel's location in space, indexed by pixel, and time indexed by year. The relation g was parameterized using the C 5.0™ classification-tree software (Quinlan 1986), trained on a sample of pixels within each Landsat image; the model was thus fit locally within each Landsat World Reference System 2 (WRS-2) scene. Reflectance and temperature covariates were acquired from the 1990-epoch Global Land Survey collection of Landsat images (Gutman et al. 2008) and other Landsat images selected from the USGS archive, each of which was atmospherically corrected to surface reflectance and converted to radiant temperature by the LEDAPS implementation of the 6S radiative transfer algorithm (Masek et al. 2006). Whereas retrievals from within the period of overlap between the Landsat-5, Landsat-7, and MODIS eras may be based on general—even global—models based on phenological metrics that require dense image samples within each year (e. . Hansen et al. 2013), this local fitting instead maximizes use of the single-image coverage characteristic of much of the history of Earth observation. Use of atmospherically corrected surface reflectance fulfills the conditions for signature extension in space (Woodcock et al. 2001; Pax-Lenney et al. 2001).

2.2.3 Forest-cover change

Classification trees estimate the probability $p(C)$ of each class in each pixel as a conditional relative frequency. Given $C = \text{“F”}$ (i.e., “forest”), each pixel was labeled either “forest” or “non-forest” based on $p(F)$:

$$F \equiv p(F) \geq 0.5 \quad (5)$$

$$N \equiv p(F) < 0.5 \quad (6)$$

Forest-cover change between 1990 and 2000 epochs was detected given the joint probabilities in 1990 and 2000 epochs (Sexton et al. 2015):

$$p(FF_i) = p(F_{it_1}) \times p(F_{it_2}) \quad (7)$$

$$p(NN_i) = (1 - p(F_{it_1})) \times (1 - p(F_{it_2})) \quad (8)$$

$$p(NF_i) = (1 - p(F_{it_1})) \times p(F_{it_2}) \quad (9)$$

$$p(FN_i) = p(F_{it_1}) \times (1 - p(F_{it_2})) \quad (10)$$

That is, given the probability of forest $P(F)$ vs. non-forest $P(N)$ in a pixel i in the 1990-epoch (t_1) and 2000-epoch (t_2), four classes were derived: stable forest (FF), stable non-forest (NN), forest gain (NF), and forest loss (FN). A categorical map of change classes was then produced by assigning each pixel the class with the highest probability.

2.2.4 Weighting

Decision trees and other empirical classifiers are sensitive to bias in training samples relative to class proportions within their population of inference (Borak 1999; Carpenter et al. 1999; Song 2009; Sexton et al. 2013; Woodcock et al. 2001;

Song 2010) and to uncertainty in the training data set (McIver & Friedl 2002; Strahler 1980). To minimize these effects, this study maintained a large sample with representative class proportions by removing a small, but equal fraction of the least stable pixels from each class while maintaining the class proportions from reference epoch to training sample. Further, this study weighted each pixel's contribution to the classifier's parameterization based on the pixel's classification certainty in the reference data. A weight w was adopted for each pixel as the classification probability of the estimate (p_{max}) of forest- or non-forest cover (C) from the 2000-epoch dataset:

$$W_i = p_{max}(C_i). \quad (11)$$

The weights were then applied to adjust the objective (i.e., purity) function maximized by the iterative binary recursion algorithm employed by C5.0™ (Quinlan 1986).

2.2.5 Accuracy assessment

Accuracy assessment for the conterminous United States

A sample of nine Landsat World Reference System 2 (WRS-2) scenes across the conterminous United States were selected to assess the accuracy of 1990 forest-cover and 1990-2000 forest-cover change estimates (Figure 2-5).

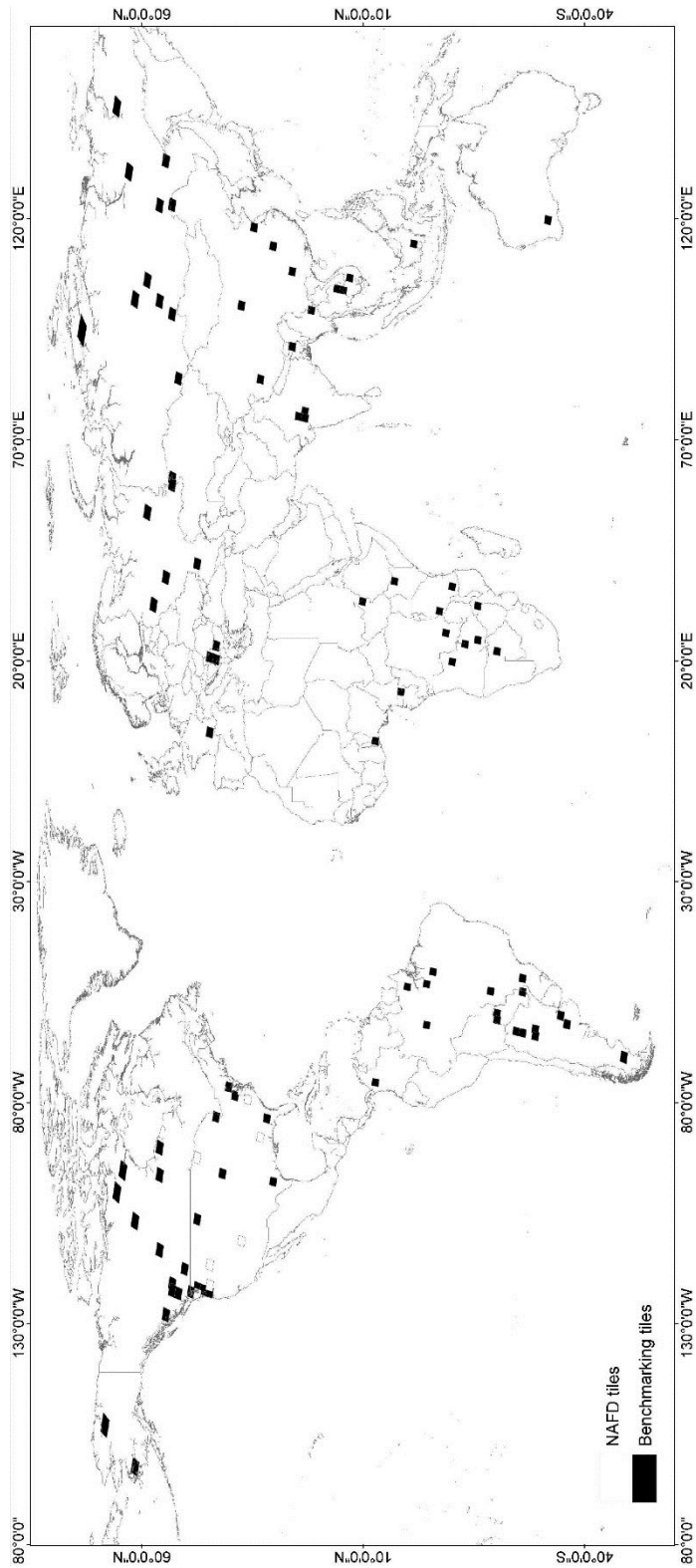


Figure 2-5 LandsatWRS-2 tiles used for error assessment including 9 North America Forest Disturbance (NAFD) tiles (Thomas et al. 2011) and 89 tiles for global accuracy assessment.

These scenes were originally used as reference data for the North American Forest Disturbance (NAFD) program of the North American Carbon Program. Collection of reference data for accuracy assessment was described by Thomas et al. (2011). A design-based, stratified random sample for the four classes of forest cover change detection (FF, NN, NF and FN) was gathered to represent rare change classes (FN and NF) as well as the more common stable classes (FF and NN). Stratification was based on initial classes identified by the Vegetation Change Tracker algorithm (VCT) (Huang, Goward, et al. 2009), and selection probabilities were used to remove sampling biases in the error matrix. Each sample pixel was examined by expert interpreters and labeled as changed or persistent forest/non-forest pixel after a visual evaluation of Landsat time series imagery and high resolution imagery from TerraServer (www.terraserver.com) and/or Google Earth (www.earth.google.com). Knowledge of the spectral properties, temporal changes, and spatial context of the pixel within the context of the surrounding landscape over time were used together to label each sample pixel.

Global accuracy assessment

Global accuracy was estimated based on a confusion matrix between collected reference data and the forest-cover change detection results. Similar to the NAFD assessment, sampling bias at the scene level as well as at individual pixels was corrected by assigning weights based on inclusion probability (Stehman et al. 2003). Global accuracy assessment was performed using reference data collected from 89 WRS-II tiles (Figure 2-5). These sites were selected using a stratified random sampling scheme to represent major biomes identified by Olson (2001). Sampling and

response design were similar to those of the NAFD protocol used for the US accuracy assessment. The number of observations per scene varied between 350 and 625, totaling > 25,000 samples globally. Each observation was labeled as either forest or non-forest for each epoch, including 1990, 2000, and 2005, using a web-based forest-change labeling tool (Feng et al. 2012). This tool facilitates rapid labeling of forest cover and change using fine-resolution imagery automatically co-registered to multi-temporal Landsat images.

2.3. Results and discussion

2.3.1 Accuracy assessment for the conterminous United States

Accuracy of forest cover maps

Accuracy estimates for the 1990 global forest cover map (“FC 1990”) relative to the NAFD sample is are presented in Table 2-1.

Table 2-1 Accuracy assessment of (static) forest and non-forest classes. Accuracy estimates for the 1990 forest cover map were based on reference data from North American Forest Disturbance (NAFD) program (Thomas et al. 2011). For comparison, accuracy estimates from coincident data taken from the US 1990 National Land Cover Database (NLCD 1992) are included in parentheses.

<i>p045r029</i>			Kappa	0.65(0.41)
		N	F	
	N	14(16)	3(28)	82.4(36.4) %
	F	11(9)	350(325)	97(97.3)%
		56(64)%	99.1(92)%	96.3(90.2)%
<i>p012r031</i>			Kappa	0.78(0.57)
		N	F	
	N	82(93)	5(71)	94.3(56.7)
	F	31(21)	452(390)	93.6(94.9)
		72.6(81.6)	98.9(84.6)	93.7(84)
<i>p021r037</i>			Kappa	0.76(0.36)
		N	F	
	N	176(115)	12(66)	93.6(63.6)
	F	53(118)	432(379)	89.1(76.3)
		76.9(49.4)	97.3(85.2)	90.3(72.9)
<i>p047r027</i>			Kappa	0.81(0.62)
		N	F	
	N	34(27)	1(8)	97.1(77.1)
	F	14(21)	527(525)	97.4(96.2)
		70.1(56.2)	99.8(98.5)	97.4(95.1)
<i>p015r034</i>			Kappa	0.76(0.39)
		N	F	
	N	143(96)	40(80)	78.1(54.6)
	F	18(66)	369(331)	95.4(83.4)
		88.8(59.2)	90.2(80.5)	89.8(74.5)
<i>p027r027</i>			Kappa	0.63(0.45)
		N	F	
	N	57(75)	5(80)	91.9(48.4)
	F	49(32)	438(366)	89.9(92)
		53.8(70.1)	98.9(82.1)	90.2(79.8)
<i>p042r029</i>			Kappa	0.85(0.82)

		N	F	
	N	94(93)	13(15)	87.9(86.1)
	F	10(14)	248(278)	96.1(95.2)
		90.4(87)	95(95)	93.7(92.8)
<i>p016r035</i>			Kappa	0.87(0.5)
		N	F	
	N	70(53)	15(61)	82.4(46.5)
	F	4(21)	624(579)	99.4(96.5)
		94.6(71.6)	97.7(90.4)	97.3(88.5)
<i>p037r034</i>			Kappa	0.38(0.52)
		N	F	
	N	84(43)	86(6)	55.9(87.8)
	F	2(47)	122(206)	81.4(81.4)
		62.6(47.8)	76.8(92.2)	72.3(82.5)

For precedent, accuracy estimates comparing the US 1992 National Land Cover Database (NLCD 1992) against the NAFD sample are included in parentheses. The average accuracy and kappa coefficient of FC 1990 for all 9 WRS-2 tiles were 93 % and 0.72, demonstrating a strong relationship between the reference data and classified maps overall. The FC 1990 map was most accurate in areas dominated by closed-canopy forest (e.g., WRS-2 path 16 row 35, path 45 row 29 and path 47 row 27) but had comparatively low accuracy in sparsely forested areas (e.g., path 37 row 34). The FC 1990 was slightly biased towards the “forest” class, with errors of commission toward forest greater than those toward non-forest. Overall, the FC1990 map showed higher accuracy than NLCD 1992, with only one exception in sparse forests (path 37 row 34).

Weighting the training sample proportional to certainty had a positive effect on accuracy of the final estimates. Accuracy of forest cover maps estimated from un-

weighted training data was 88.57 %, approximately 3 % lower than those derived from weighted training data (Table 2-2).

Table 2-2 Accuracy measurement of FC 1990 without being weighted by certainty for training pixels

<i>p045r029</i>			Kappa	0.65(0.41)
		N	F	Producer's (%)
	N	173	3	98.29
	F	32	105	76.64
User's (%)		84.39	97.22	88.81
<i>p012r031</i>			Kappa	0.78(0.57)
		N	F	
	N	228	1	99.56
	F	21	38	64.4
		91.56	97.43	92.36
<i>p021r037</i>			Kappa	0.76(0.36)
		N	F	
	N	215	6	97.28
	F	25	93	78.81
		89.58	93.93	90.85
<i>p047r027</i>			Kappa	0.81(0.62)
		N	F	
	N	265	1	99.62
	F	37	62	62.62
		87.74	98.41	89.58
<i>p015r034</i>			Kappa	0.76(0.39)
		N	F	
	N	187	18	91.21
	F	10	72	87.8
		94.92	80	90.24
<i>p027r027</i>			Kappa	0.63(0.45)
		N	F	
	N	223	2	99.11
	F	45	55	55
		83.2	96.49	85.53
<i>p042r029</i>			Kappa	0.85(0.82)
		N	F	
	N	125	5	96.15

	F	20 86.2	172 97.17	89.58 92.23
<i>p016r035</i>			Kappa F	0.87(0.5)
	N	316	4	98.75
	F	17 94.89	75 94.93	81.52 94.9
<i>p037r034</i>			Kappa F	0.38(0.52)
	N	60	42	58.82
	F	36 62.5	147 77.77	80.32 72.63

Improvement in accuracy was greatest in path 47 row 27, where forests are characterized by dense, tall trees, and lowest in path 37 row 34, characterized by short and sparse woody vegetation.

Accuracy of forest cover change map

Compared against the NAFD reference data, the FCC 1990-2000 forest-change map showed similar or even higher accuracy than the NLCD change product. The change map produced in this study had greatest accuracy in persistent forest and non-forest classes and had accuracy comparable to the NLCD change product in forest gain and loss classes. Accuracy of the FCC 1990-2000 forest cover change map and spatially corresponding NLCD 1992-2001 Retrofit Land Cover Change Product are presented in Table 2-3.

Table 2-3 Accuracy assessment of forest-cover change. Accuracy estimates for the 1990-2000 forest cover change map were based on reference data from North American Forest Disturbance (NAFD) program (Thomas et al. 2011). For comparison, accuracy estimates from coincident data taken from the NLCD 1992/2001 Retrofit Land Cover Change Product are included in parentheses.

<i>p045r029</i>		<i>Kappa 0.6(0.57)</i>			
	NN	NF	FN	FF	%
NN	14(17)	0(0)	0(14)	0(3)	100(50)
NF	0(0)	0(0)	1(0)	1(0)	0(0)
FN	0(0)	0(0)	7(5)	2(10)	77.8(33)
FF	4(1)	3(3)	14(3)	201(191)	90.5(96)
%	77.8(94)	0(0)	31.8(23)	98.5(94)	90(86)

<i>p012r031</i>		<i>Kappa 0.74(0.53)</i>			
	NN	NF	FN	FF	
NN	67(87)	0(1)	1(31)	0(60)	98.5(49)
NF	8(0)	3(0)	0(0)	4(2)	20(0)
FN	16(9)	1(0)	83(52)	12(14)	74.1(69)
FF	10(6)	3(6)	20(22)	302(245)	90.2(88)
	66.3(85)	42.9(0)	79.8(50)	95(76)	85.9(72)

<i>p021r037</i>		<i>Kappa 0.69(0.31)</i>			
	NN	NF	FN	FF	
NN	97(96)	3(2)	0(38)	0(69)	97(47)
NF	8(1)	67(14)	0(0)	10(3)	78.8(78)
FN	9(1)	0(0)	58(14)	26(13)	62.4(50)
FF	3(21)	41(95)	30(36)	315(266)	81(64)
	82.9(81)	60.4(13)	66(16)	89.7(76)	80.5(58)

<i>p047r027</i>		<i>Kappa 0.58(0.36)</i>			
	NN	NF	FN	FF	
NN	28(30)	0(1)	0(14)	1(42)	96.6(35)
NF	1(0)	5(0)	0(0)	0(1)	83.3(0)
FN	0(0)	0(0)	7(2)	6(2)	53.8(50)
FF	2(1)	11(15)	29(20)	318(285)	88.3(89)
	90.3(97)	31.3(0)	19.4(6)	97.9(57)	87.8(77)

<i>p015r034</i>		<i>Kappa 0.69(0.44)</i>			
	NN	NF	FN	FF	

NN	79(79)	4(3)	3(22)	4(35)	87.8(57)
NF	4(0)	54(2)	0(0)	32(1)	60(67)
FN	3(1)	0(1)	38(18)	18(7)	64.4(67)
FF	6(12)	8(60)	21(23)	273(284)	88.6(75)
	85.9(86)	81.8(3)	61.3(29)	84(87)	81.2(70)

p027r027 Kappa 0.47(0.22)

	NN	NF	FN	FF	
NN	29(43)	3(13)	0(21)	0(55)	90.6(33)
NF	4(3)	16(6)	1(6)	4(6)	66.7(29)
FN	7(0)	0(0)	46(1)	21(1)	39.1(50)
FF	25(20)	15(15)	55(74)	267(232)	81.7(68)
	44.6(65)	47.1(18)	45.1(1)	91.4(79)	72.6(57)

p042r029 Kappa 0.77(73)

	NN	NF	FN	FF	
NN	83(81)	2(0)	1(4)	7(11)	89.3(84)
NF	1(0)	0(0)	0(0)	0(0)	0(0)
FN	2(1)	0(0)	9(6)	8(0)	47.4(86)
FF	5(12)	0(2)	6(8)	123(148)	91.8(87)
	91.2(86)	0(0)	56.2(33)	89.1(93)	87(86)

p016r035 Kappa 0.8(0.6)

	NN	NF	FN	FF	
NN	64(63)	0(0)	1(8)	1(47)	94.1(53)
NF	2(0)	4(0)	0(0)	11(8)	23.5(0)
FN	1(2)	0(0)	21(17)	12(5)	61.8(70)
FF	3(5)	0(4)	8(5)	449(413)	97.6(97)
	91.4(90)	100(0)	70(56)	94.9(87)	93.2(85)

p037r034 Kappa 0.38(0.81)

	NN	NF	FN	FF	
NN	74(67)	1(0)	0(0)	64(2)	53.2(97)
NF	4(0)	0(0)	0(0)	13(0)	0(0)
FN	0(3)	0(0)	0(0)	3(0)	-(-)
FF	2(14)	0(1)	0(0)	81(163)	97.6(92)
	92.5(80)	0(0)	-(-)	50.3(99)	64(92)

Overall accuracy of FCC 1990-2000 for all nine NAFD sites was 83 %, and

average kappa coefficient was 0.64—greater than the NLCD change product by 7 %

and 0.14, respectively. Similar to the accuracy of the forest cover maps, the accuracy of the forest cover change map was higher in closed-canopy forest (WRS-II path 16 row 35, path 45 row 29, and path 47 row 27) and lower in sparsely forested areas (e.g., path 37 row 34). Omission errors were slightly less than commission errors in the persistent forest class. With the exception of path 37 row 34, commission errors in persistent forest ranged from 1.5 % to 16 % while omission error ranged from 2.4 % to 19 %. Most errors in persistent forest were from misclassification of forest loss as persistent forest. These errors have been attributed to sub-pixel scale disturbance such as partial or non-stand clearing (Thomas et al. 2011). Errors committed to persistent non-forest (9-40%) were more frequent than errors committed to persistent forest. Path 27, row 27 had the largest commission error rate, mainly caused by confusion between wetland and forest, which was also observed in the NAFD assessment (Thomas et al. 2011). The omission error rate of persistent non-forest was less than that of persistent forest, ranging from 0 to 12.2 % with the exception of path 37 row 34. The rate of commission error to forest loss was 34 % and to forest gain was 32 % across all 9 NAFD sites. For both forest change classes, omission from persistent forest class was the largest source of error.

2.3.2 Global accuracy assessment

The overall accuracy for the 2000-2005 forest cover change map was about 89 percent globally (Table 2-4), and the overall accuracy for the 1990-2000 forest cover change map was approximately 88 percent (Table 2-5).

Table 2-4 Global accuracy of forest cover change maps for 2000-2005 epoch. The global scale accuracy was estimated based on a confusion matrix between reference data collected from 89 WRS-II tiles and the forest cover change detection results. Similar to the NAFD assessment, sampling bias at the scene level as well as at individual pixels was corrected by assigning weight based on inclusion probability.

		Change map				Total (n)	samples	Producer's Accuracy
		FF	FN	NF	NN			
Reference	FF	0.35	0.00	0.00	0.09	0.45	13562	0.78
	FN	0.00	0.00	0.00	0.00	0.01	1632	0.48
	NF	0.00	0.00	0.00	0.00	0.01	933	0.20
	NN	0.00	0.00	0.00	0.53	0.54	10624	0.99
	Total	0.36	0.01	0.00	0.63	1.00	26751	
User's Accuracy		0.98	0.50	0.32	0.84		Overall :	0.89

Table 2-5 Global accuracy of forest cover change maps for 1990-2000 epoch.

		Change map				Total (n)	samples	Producer's Accuracy
		FF	FN	NF	NN			
Reference	FF	0.34	0.01	0.01	0.07	0.43	12876	0.80
	FN	0.00	0.01	0.00	0.01	0.01	1956	0.45
	NF	0.00	0.00	0.00	0.02	0.03	1583	0.16
	NN	0.00	0.00	0.00	0.52	0.53	9153	0.99
	Total	0.35	0.02	0.01	0.62	1.00	25568	
User's Accuracy		0.97	0.39	0.28	0.85		Overall :	0.88

This study also report the accuracy of the results for 1990-2000 by major forest biomes (Table 2-6). Among the forest biomes, tropical evergreen forest and temperate evergreen forest showed highest accuracy of 95 and 90 percent, respectively, while tropical deciduous forest showed the lowest accuracy, 70 percent (Table 2-6).

Table 2-6 Global accuracy of forest cover change maps for 1990-2000 by biomes

	Image	FF	FN	NF	NN	totalC	ProdAccu
<i>Boreal forest</i>	Reference						
	FF	0.61	0.03	0.02	0.08	0.73	0.83
	FN	0.01	0.01	0.00	0.00	0.02	0.45
	NF	0.01	0.00	0.01	0.01	0.03	0.37
	NN	0.01	0.00	0.00	0.20	0.22	0.94
	totalR	0.63	0.04	0.03	0.30	1.00	NA
	UsersAccu	0.96	0.22	0.39	0.67	Overall	0.83
<i>Temperate deciduous forest</i>	Image	FF	FN	NF	NN	totalC	ProdAccu
	Reference						
	FF	0.30	0.01	0.01	0.03	0.35	0.86
	FN	0.00	0.00	0.00	0.01	0.02	0.26
	NF	0.00	0.00	0.00	0.05	0.05	0.04
	NN	0.01	0.00	0.00	0.57	0.58	0.98
	totalR	0.31	0.01	0.01	0.66	1.00	NA
UsersAccu	0.96	0.35	0.16	0.86	Overall	0.88	
<i>Temperate evergreen forest</i>	Image	FF	FN	NF	NN	totalC	ProdAccu
	Reference						
	FF	0.61	0.01	0.01	0.02	0.65	0.93
	FN	0.00	0.02	0.00	0.00	0.03	0.80
	NF	0.01	0.00	0.02	0.01	0.05	0.39
	NN	0.01	0.01	0.01	0.24	0.27	0.90
	totalR	0.64	0.04	0.04	0.28	1.00	NA
UsersAccu	0.95	0.56	0.46	0.88	Overall	0.90	
<i>Tropical deciduous forest</i>	Image	FF	FN	NF	NN	totalC	ProdAccu
	Reference						
	FF	0.34	0.01	0.01	0.21	0.57	0.60
	FN	0.00	0.01	0.00	0.02	0.03	0.36
	NF	0.01	0.00	0.00	0.04	0.05	0.04
	NN	0.00	0.00	0.00	0.35	0.35	0.98
	totalR	0.35	0.02	0.01	0.61	1.00	NA
UsersAccu	0.97	0.44	0.18	0.56	Overall	0.70	
<i>Tropical evergreen forest</i>	Image	FF	FN	NF	NN	totalC	ProdAccu
	Reference						
	FF	0.81	0.01	0.01	0.01	0.84	0.97
	FN	0.00	0.01	0.00	0.00	0.02	0.68

NF	0.00	0.00	0.00	0.01	0.02	0.27
NN	0.00	0.00	0.00	0.11	0.12	0.94
totalR	0.83	0.03	0.01	0.14	1.00	NA
UsersAccu	0.99	0.58	0.38	0.83	Overall	0.95

This pattern of uncertainty, also evident in the global distribution of classification and change-detection certainty (Figure 2-6), suggests the global distribution of classification and change-detection certainty was driven primarily by the density and height of tree cover. Dense forests in the tropics and temperate zones were associated with relatively high classification certainty, and treeless deserts (e.g., central Australia and the Sahara desert), grasslands (e.g., Mongolia and Patagonia), and tundra (e.g., Northern Canada) also showed very high certainty of non-forest cover. However, sparse and/or short forests, such as the boreal forests of North America and Eurasia, the Sahelian and Miombo woodlands of Africa, and the Chaco and Atlantic dry forests of South America, were associated with relatively low certainty in the forest/non-forest classification. Anthropogenically fragmented forests in ecologically productive regions—e.g., the southeastern United States, southeastern China and eastern Brazil—were mapped with intermediate certainty.

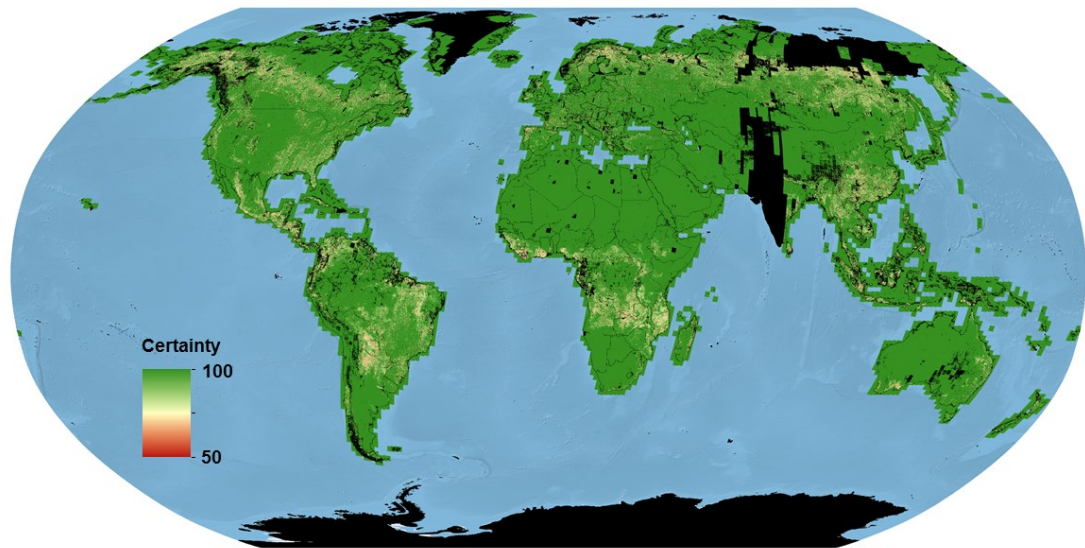
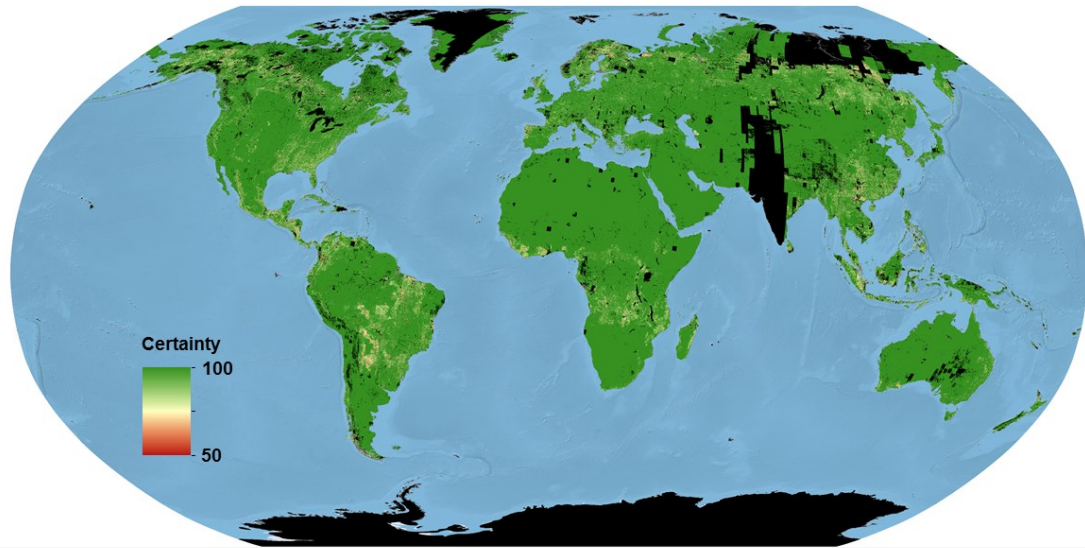


Figure 2-6 Global distribution of classification certainty of forest cover (top) and forest-cover change (bottom).

Sources of confusion in semi-arid regions

In spite of the overall efficacy of the algorithm, the Utah site (path 37, row 34) showed comparatively low accuracy for both forest cover and change maps. Located in a semi-arid, mountainous, sparsely vegetated region, forest signatures here could be confused by terrain shadowing and understory vegetation, which varies in space and time in response to rainfall and temperature (Thomas et al. 2011). The gradient of height and cover of woody vegetation also likely resulted in semantic confusion between shrubs vs. trees and between forests vs. savannas (Sexton et al. 2013).

Visual assessment of forest cover change map

The regional drivers of forest dynamics were readily observable in the 1990-2000 forest-cover change map. Figure 2-7 shows examples of visual assessments observed within the accuracy assessment sites. Forest cover changes in Path 21 row 37 (Mississippi) and path 47 row 27 (Oregon) are characterized by even-aged silviculture of evergreen needle-leaf trees, including clear-cut harvesting. Small clearings due to urbanization were the dominant pattern in Path 12 row 31 (New England) and path 27 row 27 (Minnesota), where wind damage and timber harvest dominated losses (Huang, Goward, et al. 2010; Thomas et al. 2011).

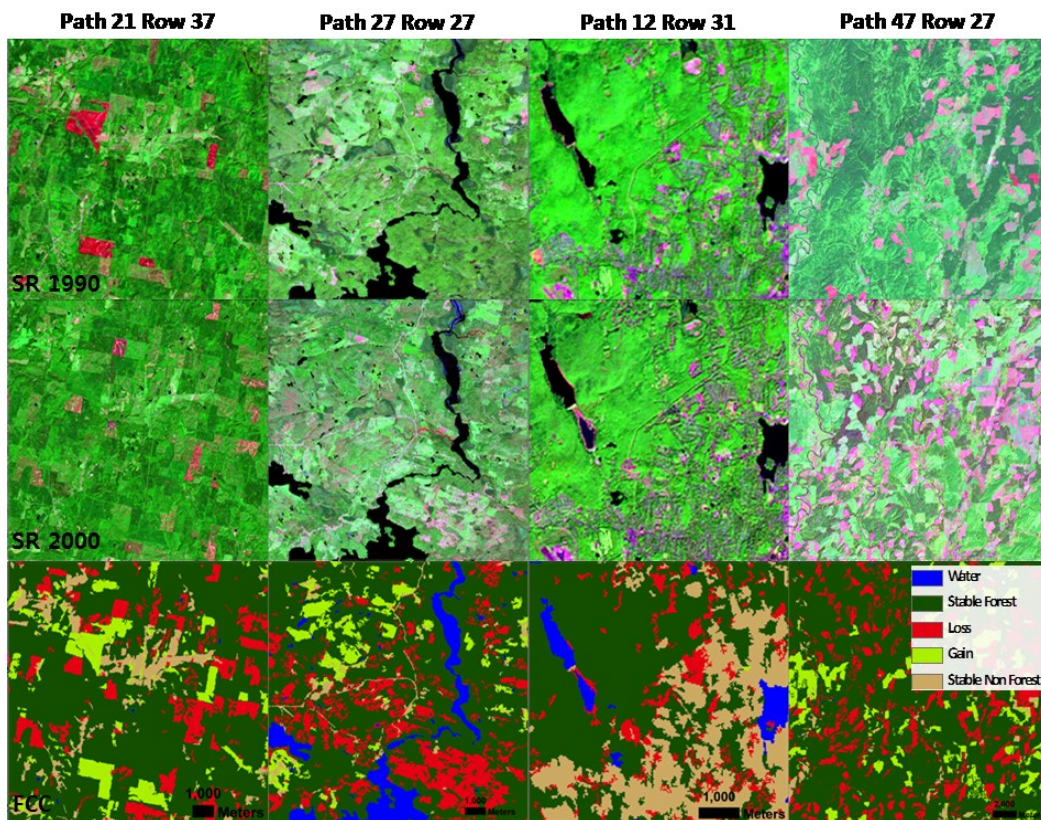


Figure 2-7 Visual examination of forest cover change; the top and middle rows of each column are the surface reflectance composites (SWIR2, NIR, G) from the 1990 and 2000 epochs, and the

Improvement by sample weighting

Weighting based on input classification certainty (as classification probability) improved accuracy by ~3%. Weighting was more effective at minimizing the influence of uncertain training data in patchily heterogeneous landscapes, but less effective in landscapes comprising continuous gradients of woody vegetation height and cover. Accuracy increases due to weighting were highest in the Oregon site (path 47 row 27), characterized by tall, dense forests with extensive logging and regrowth, and were lowest in the Utah site (path 37 row 34), characterized by low, sparse forest and relatively low anthropogenic forest-cover change rates. The scene-level mean uncertainty (Root Mean Square Error - RMSE) of the 2000-epoch Landsat tree-cover layer (Sexton et al. 2013) at path 47 row 27 was 12.55 %-about ten times higher than the scene-level mean uncertainty of 1.28 % at path 37 row 34. Although there appears to be a limit to which such weighting schemes can improve accuracy, the improvements are encouraging. Increasing the classification accuracy of heterogeneous landscapes is considered among the most challenging tasks for improving global land cover mapping (Herold et al. 2008; Gong et al. 2013). I expect that, where sample selection criteria are less effective at filtering unstable pixels, weighting the sample based on prior certainty can contribute modest improvements in accuracy.

2.3.2 Global, circa-1990 distribution of forest cover, change, and uncertainty



Figure 2-8 Global distribution of forest cover, circa-1990.

Figure 2-8 demonstrates the feasibility of extending global, Landsat-resolution mapping and change detection to 1990. Several studies have described recent, i.e., post-2000, global patterns of forest cover and change (Hansen et al. 2013; Gong et al. 2013), and others have noted regional patterns of forest loss prior to 2000 (Achard et al. 2002; Achard et al. 2005; Achard et al. 2006; Achard et al. 2014; Bodart et al. 2013; Ernst et al. 2013; Eva et al. 2012; Mayaux et al. 2005; Mayaux et al. 2013; H. J. Stibig et al. 2014; DeFries et al. 2002; Hansen et al. 2009). Except for gaps remaining due to data availability, the results of this study extend the historical record of Earth's forest cover to the previous decade and globally.

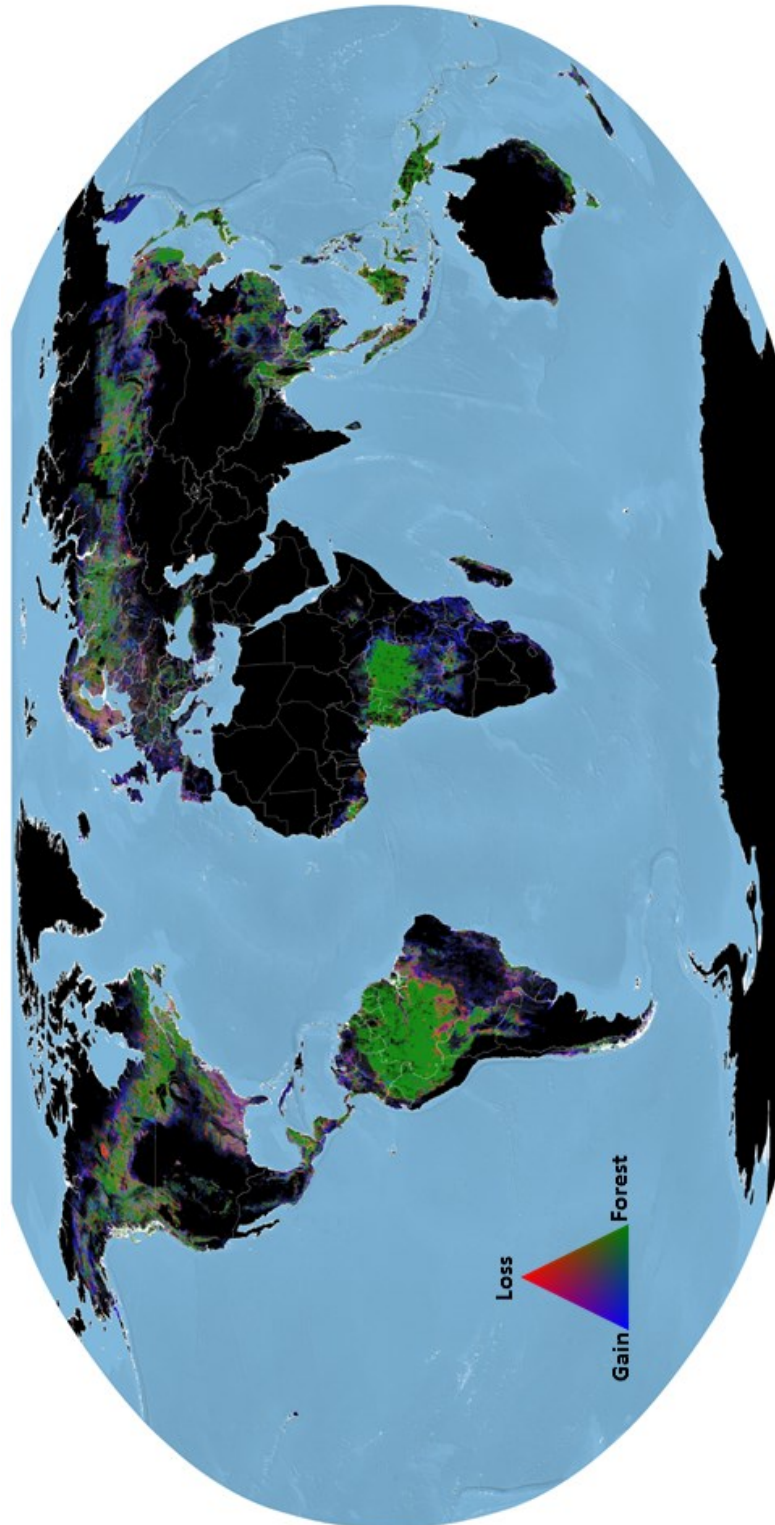


Figure 2-9 Global distribution of forest-cover change, circa-1990 to -2000. The false-color composite was aggregated from 30-m to 5-km grid cells. Forest loss is represented in red, forest gain in blue and persistent forest in green.

The global distribution of forest cover in 1990 was similar to that reported for subsequent years (Hansen et al. 2000; Loveland et al. 2000; Potapov et al. 2008; Mayaux et al. 2005, 2013; Sexton et al. 2013; Hansen et al. 2013). Although the global distribution continues to be constrained primarily by climate, the fine-scale changes responsible for altering that distribution over time were predominantly anthropogenic (Figure 2-9). The land-use effect was strongest in temperate and tropical regions over the period, while wildfire dominated in the boreal zone. Regions of high net forest loss (e.g., Amazonia) were associated with land-use changes from wilderness to agriculture, and regions of high gross gains and losses (e.g., southeastern US) were associated with intensive forestry. These generalities are discussed in the following paragraphs. Quantitative discussion of observed changes will be the subject of subsequent papers. However, I do note several instances of the various trajectories of change from the last decade of the 20th century to the first decade of the 21st: (i) long-term forest stability, (ii) gains and/or losses continuing steadily from the previous decade into the next, and (iii) acceleration of change between the decades.

Remote regions that exhibited little forest change in the first decade of the 21st century also experienced stability in the previous decade. The most stable forests from 1990 to 2000 tended to be those which were both at the core of their climatological regions as well as distant from human pressure. The central Amazon and Congo basins were relatively undisturbed, experiencing neither large losses nor gains as a fraction of their respective areas. This was also true for some part of boreal forest in Northern Canada and Russia. Even regions in relatively close proximity to

areas of harvest and regeneration or to conversion of forests to other land uses—i.e., the Appalachian mountains of the eastern US, highlands of southeastern Asia—exhibited relatively low rates of disturbance and regrowth.

Many areas in temperate and boreal zones that were known to have experienced change in the 21st century were already showing major changes in the 1990s. In the boreal zone, including northern Canada, Europe, and Russia, extensive wildfires were the dominant driver of forest cover change. These disturbances were characterized by large patches of loss with no apparent relation to roads or other human infrastructure. This extends the findings of Pan et al. (2011), who attributed these losses to fire and of Hansen et al. (2010), who attributed the region's losses to both fire and pathogens. In the temperate zone, the greatest changes were due to intensive forestry. For example, subtropical forests in the southeastern U.S. showed notable gains and losses from 1990 to 2000, corroborating previous studies that found high gross gains and losses but relatively low net change in this region (Masek et al. 2008; Sleeter et al. 2013) (Figure 2-10A).

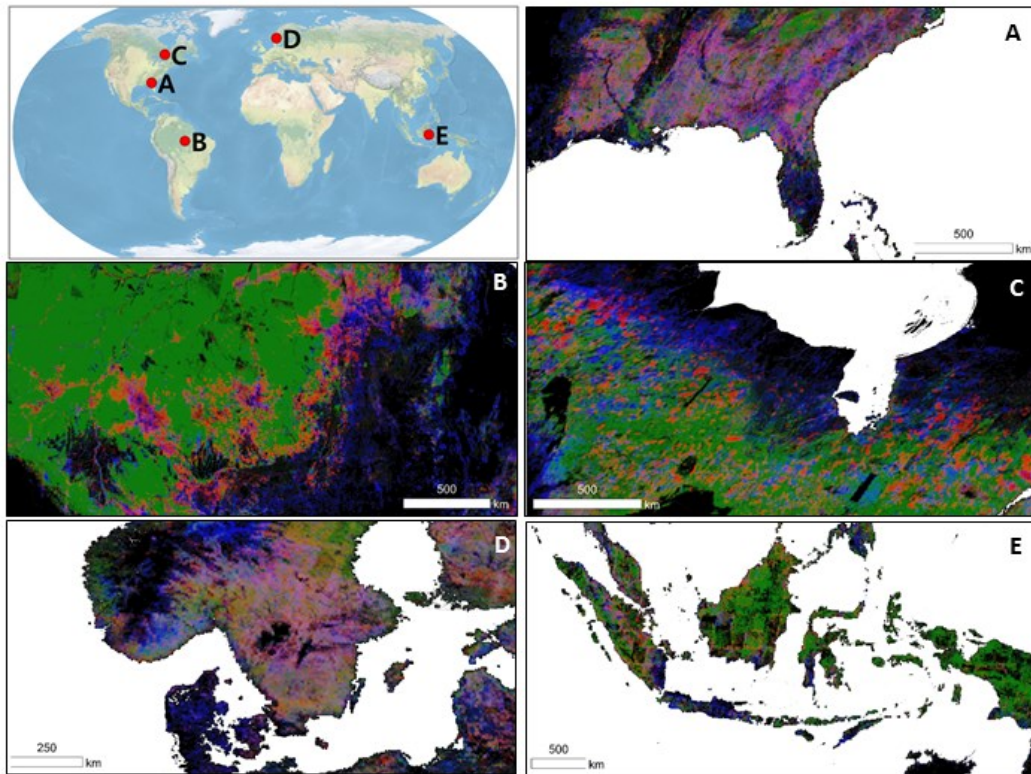


Figure 2-10 Regional forest-cover change in: (A) the Southeastern United States, (B) Amazon Basin, (C) Northern Canada, (D) Southern Sweden, and (E) Indonesia.

In this region, pulp- and timber-production were becoming increasingly dominant at the time due to shifting of the American timber industry from the Pacific Northwest region following listing of the Northern Spotted Owl as “Threatened” under the US Endangered Species Act in 1990 and the subsequent passing of the Northwest Forest Plan in 1994. Similarly, intensive forestry was also apparent in Northern Europe, including Southern Sweden (Figure 2-10D) and Finland over the period. Widespread changes were found over Sweden and Finland, corroborating previous studies(Achard et al. 2005, 2006). In these regions, forest gain and loss were in close spatial proximity due to intensive regional forest-management practices (Achard et al. 2006; Hansen et al. 2013; Loman 2010; Ylitalo 2011).

Many areas that underwent forest clearing in both decades exhibited changing rates of clearing around the turn of the century. In the tropics, losses were by majority due to changes in land use from wilderness to agriculture, which was impacted by shifting economic and conservation policies. Although recent studies have reported decreasing rates of forest-cover loss in the Brazilian Amazon resulting from policies to slow deforestation (Souza, Jr et al. 2013; Hansen et al. 2013; Nepstad et al. 2014), the 1990's cover the period of rapid deforestation prior to the policies' enactment (Figure 2-10B) when clearing was mainly due to expansion of large-scale cattle ranching (Kanninen 2007; Gibbs et al. 2010). Likewise, although observations over much of Indonesia and the Malaysian archipelago were obscured by clouds, the forest losses of the region appear to have been relatively large, including the expansion of oil palm plantations over the 1990-2000 period before a sharp drop in losses in the early 2000s (Hansen et al. 2009). Conversely, in inland Southeast Asia, including Thailand, Vietnam and Cambodia, the results show much lower deforestation rates than post 2000 period, in contrast to FAO estimates (FAO 2010) showing rather monotonic forest cover change trends between the two periods. Although Africa shows overall low rates of forest cover change, the Democratic Republic of Congo shows the highest forest cover loss among the African countries, showing elevated deforestation rate later on which may suggest the expansion of agro-industry in this region.

2.4. Conclusions

This study has produced a global map of circa-1990 forest cover and circa-1990 to -2000 forest-cover change from the USGS archive of Landsat images, using

training data hind-cast from the 2000 and 2005 Global Land Survey (GLS) epochs. With overall accuracies for the US of 93% for circa-1990 forest cover in 1990 and 84% for circa-1990 to -2000 forest-cover change, the maps are of equal or greater accuracy than 1992-2001 retrofit change product of the 2001 US National Land Cover Database over the conterminous United States. Globally, forest-cover change accuracy was 88 %. My method gained its strength from the use of stable pixels over time and from the minimization of influence from training data uncertainty. Given their slow rate, and thus poor detectability, forest gains were less apparent than were losses.

The maps depict the global distribution of gross gains and losses in forest cover, as well as their net change. Whereas some regions (e.g., the Amazonian arc of deforestation, Indonesia) have been perennial centers of forest loss and others (e.g., the southeastern United States and southern Sweden) have retained relatively rapid rates of both gains and losses from 1990 to 2000. While some regions (e.g. inland Southeast Asian countries) exhibiting rapid change of deforestation rates around 2000, most of Africa exhibited persistent and relatively slow rates of forest cover change except for some regions (e.g. Democratic Republic of Congo).

These findings will be important for inferring the efficacy of policies and for analyzing causal relationship between socio- economic drivers and forest cover changes. The global forest cover and change maps will be made available for free download at the Global Land Cover Facility (www.landcover.org).

Chapter 3 Accelerated Deforestation in the Humid Tropics from the 1990s to the 2000s²

3.1 Introduction

Tropical deforestation was among the largest anthropogenic sources of greenhouse gas emissions in the 1990's (Gibbs et al. 2007). Based on statistics from the United Nations Food and Agriculture Organization (FAO) Forest Resource Assessment (FRA) (FAO 2010), the Intergovernmental Panel on Climate Change (IPCC) reported a 1.84 Gt CO₂·yr⁻¹ global decline in CO₂ emissions from land-use change from the 1990's to the 2000's, attributed largely to a decreasing rate of deforestation (IPCC 2013).

However, estimates of forest-area changes across the tropics prior to 2000 remain uncertain. The FAO-FRA has been criticized for inconsistencies in the definition of forest among countries and over time, as well as its dependence on national self-reporting (Matthews 2001; DeFries et al. 2002; Grainger 2008). Previous studies have shown that FAO-FRA overestimated changes in forest area (Houghton 1999; Steininger et al. 2001; Achard et al. 2002; DeFries et al. 2002) in the 1980s and the 1990s. In the tropics especially, the FAO-FRA reported a declining rate of deforestation from the 1980s to the 1990s while studies based on satellite data observed opposite trends (DeFries et al. 2002).

² The presented material has been previously published in D.H. Kim, J. O. Sexton, and J. R. Townshend, Accelerated Deforestation in the Humid Tropics from the 1990s to the 2000s, *Geophys. Res. Lett.* 42, 3495-3501 (2015).

Recent progress in data availability and processing power have enabled national and global forest cover change assessments based on long-term archives of satellite imagery (Townshend et al. 2012; Hansen et al. 2013; Sexton et al. 2013; Kim et al. 2014). Importantly, these satellite assessments are now possible at sub-hectare resolution, the scale at which most anthropogenic changes occur (Townshend & Justice 1988). Landsat data offer a spatial resolution suitable to map such changes (e.g. shifting cultivation in the rainforest) with Instantaneous Field Of View (IFOV) of 30 m and Effective Resolution Element (ERE) smaller than 75 m, the minimum area for which spectral properties of the center can be assigned with at least 95% confidence (Townshend 1981; Wilson 1988).

This study summarizes a consistent series of forest-change datasets based on satellite observations in circa-1990, -2000, and -2005 “epochs” (Kim et al. 2014; Sexton et al. 2013) to estimate changes in tropical forest area at high (30-m) spatial resolution in 34 tropical countries from circa-1990 to -2005. Using a consistent definition of forest throughout, the data enable a spatio-temporally comprehensive alternative to the FAO-FRA reports and other sample-based satellite analyses (e.g. FAO 2012; Achard et al. 2014). This study extend the series forward as well, from 2005 to 2010, to estimate changes in tropical forest area in the latter part of that decade and to complete the first fine scale satellite-based estimates of change in humid tropical deforestation spanning the turn of the millennium.

3.2 Methods

3.2.1. Study area

The study area comprises 34 countries spanning the humid tropics, each of which is covered at least 50% by forest biomes (Olson et al. 2001). These countries' forests comprise over 80 percent of forest area in the tropics (Hansen et al. 2013) and dominates the forest area of the humid tropics.

3.2.2. Definitions

Consistent with the United Nations Framework Convention on Climate Change (UNFCCC 2002), United Nations Food and Agriculture Organization (FAO 2002), and the International Geosphere-Biosphere Programme (Belward 1996), this study defined forest *cover* (as opposed to forest *use* (Belward 1996; Hansen et al. 2010)) as parcels >1 ha in area and comprising pixels with >30% tree cover. The definition used in this study corresponds with the definitions of IGBP classes for forest (> 60% tree cover) and woody savannas (> 30 % tree cover) combined.

Table 3-1 Definitions of “forest” used by various sources.

<i>Basis</i>	<i>FAO FRA 2010</i>	<i>Hansen et al 2013</i>	<i>FRA RSS, TREES</i>	<i>This study</i>
	Land use, Land cover	Land cover	Land cover	Land cover
tree-cover threshold	10 %	25 %	30 %	30 %

Table 3-1 shows the differences in forest definition for each set of estimates compared in this study. It is notable that among the sources, only the FAO definition relies on dominant land use (Stibig et al. 2014).

3.2.3. Data & analysis

5,444 Landsat scenes were collected from the 1990, 2000, 2005, and 2010 epochs of the GLS collection of Landsat images. The GLS is intended to provide full, multi-temporal coverage of Earth's terrestrial surface in service of land-cover mapping and change detection (Gutman et al. 2008). The original GLS data were augmented with additional images to improve radiometric calibration, reduce cloud cover, and maximize spectral discrimination of forests (Kim et al. 2011). Each image of this augmented GLS dataset was atmospherically corrected to estimate surface reflectance using the LEDAPS (Masek et al. 2006). Forest cover in the 2000 and 2005 epochs was estimated by translation of percent-tree cover to categorical forest cover and change (Sexton et al. 2015; Sexton et al. 2013), using probability thresholds of 0.5 to detect forest loss and 0.7 to detect forest gain to account for their different detectabilities. Stable pixels identified in the 2000 and 2005 epochs were then used to extend the classification and change estimate of forest cover to the 1990 and 2010 epochs (Kim et al. 2014). Each GLS epoch spans a range of years focused on the nominal year (Gutman et al. 2008), so the forest/non-forest layer in each year was accompanied by the year of image acquisition to estimate changes over time as rates. Forest-cover data in 1990, 2000, and 2005 epochs are publicly available from the Global Land Cover Facility (www.landcover.org).

Forest-cover change statistics—including gross forest (cover) loss, gross forest gain, and net change—were generated for the periods between the four epochs. Those estimates were adjusted from the raw estimates to account for missing data due to clouds and shadows. The forest-cover change statistics in each period were adjusted using error matrices from global accuracy assessment (Kim et al. 2014) to avoid the incompatibility due to the different level of biases in forest-cover change statistics for each periods. Forest cover change statistics from 2000 to 2010 were estimated by averaging the estimates for 2000-2005 and 2005-2010 periods.

3.3 Results and Discussion

Satellite analysis revealed forest-cover totals of $1,340 \times 10^6$ ha in 1990, $1,300 \times 10^6$ ha in 2000, and $1,240 \times 10^6$ ha in 2010 across the 34 countries. These estimates are broken down by continent and by country in Table 3-2.

Table 3-2 Landsat based estimates of forest area (10⁶ha) in 1990, 2000 and, 2010 by continent and country.

	1990	2000	2010
Belize	1.93	1.85	1.79
Bolivia	57.95	56.05	53.06
Brazil	431.47	412.12	386.4
Colombia	74.75	73.45	69.82
Costa Rica	3.99	3.9	3.69
Ecuador	15.22	14.95	14.63
Guatemala	7.53	7.14	6.65
Guyana	18.39	18.23	18.16
Honduras	7.44	7.19	6.73
Nicaragua	6.27	5.98	4.91
Panama	4.6	4.44	4.01
Peru	74.31	73.79	73.04
Suriname	14.01	13.95	13.88
Venezuela	51.22	50.33	47.07
Tropical Latin America	769.08	743.37	703.84
Cameroon	20.32	20.21	19.88
Congo	23.88	23.66	23.43
Democratic Republic Congo	153.23	152.2	147.93
Equatorial Guinea	2.59	2.56	2.54
Gabon	23.38	22.92	22.99
Liberia	7.46	7.27	7.23
Madagascar	8.93	8.55	7.58
Sierra Leone	3.79	3.7	3.53
Tropical Africa	243.58	241.06	235.12
Bangladesh	2.03	1.99	1.88
Brunei Darussalam	0.52	0.52	0.51
Cambodia	7.81	7.5	6.32
Indonesia	154.82	148.29	139.87
Laos	19.22	18.79	18.14
Malaysia	30.12	28.81	27.18
Myanmar	40.12	39.29	37.5
Papua New Guinea	41.81	41.21	40.54
Philippines	16.86	16.11	14.46
Sri Lanka	2.91	2.8	2.45
Thailand	17.81	17.16	15.46
Vietnam	16.39	15.79	14.07
Tropical Asia	350.43	338.24	318.37
Pan-Tropics	1363.08	1322.68	1257.33

During the 1990-2000 period, the annual net change across all the countries was $-4 \times 10^6 \text{ ha}\cdot\text{yr}^{-1}$; the gross rate of loss was $4.9 \times 10^6 \text{ ha}\cdot\text{yr}^{-1}$, and the gross rate of gain was $0.9 \times 10^6 \text{ ha}\cdot\text{yr}^{-1}$. During the 2000-2010 period, the rate of loss was $7.8 \times 10^6 \text{ ha}\cdot\text{yr}^{-1}$, and the rate of gain was $1.3 \times 10^6 \text{ ha}\cdot\text{yr}^{-1}$, resulting in a $-6.5 \times 10^6 \text{ ha}\cdot\text{yr}^{-1}$ net rate of change. My estimates indicate a dramatic 62% ($2.5 \times 10^6 \text{ ha}\cdot\text{yr}^{-1}$) acceleration of net forest loss from the 1990s to the 2000s. Forest area change rates by continent and country in each period area shown in Table 3-3.

Table 3-3 Changes in forest area (1,000 ha·yr⁻¹) from Landsat-based estimates versus FRA reports (FAO 2010) for 1990-2000 and 2000-2010 in tropical Latin America, Asia, and Africa. Negative sign indicates a net loss.

	This Study		FRA (UNFAO 2010) ²	
	1990-2000	2000-2010	1990-2000	2000-2010
Belize	-8	-7	-10	-10
Bolivia	-191	-298.5	-270	-289.5
Brazil	-1,936	-2,571	-2,890	-2,642
Colombia	-130	-363	-101	-101
Costa Rica	-9	-21	-19	23
Ecuador	-27	-33	-198	-198
Guatemala	-39	-49	-54	-55
Guyana	-16	-6.5	0	0
Honduras	-25	-46.5	-174	-120
Nicaragua	-29	-107.5	-70	-70
Panama	-15	-43.5	-42	-12
Peru	-52	-75	-94	-122
Suriname	-5	-7.5	0	-2
Venezuela	-89	-326.5	-288	-288
Tropical Latin America	-2,570	-3,954	-4,210	-3,887
Cameroon	-11	-33.5	-220	-220
Congo	-22	-22.5	-17	-14.5
Democratic Republic Congo	-104	-426.5	-311	-311
Equatorial Guinea	-3	-2	-12	-12
Gabon	-46	7	0	0
Liberia	-19	-3.5	-30	-30
Madagascar	-38	-97	-57	-57
Sierra Leone	-9	-16.5	-20	-20
Tropical Africa	-251	-594	-667	-664.5
Bangladesh	-4	-11	-3	-3
Brunei Darussalam	0	-1	-2	-2
Cambodia	-31	-117	-140	-145
Indonesia	-653	-842	-1,914	-497.5
Laos	-43	-65	-78	-78
Malaysia	-130	-163.5	-79	-113.5
Myanmar	-83	-179.5	-435	-309.5
Papua New Guinea	-60	-66.5	-139	-140.5
Philippines	-75	-165.5	55	55
Sri Lanka	-12	-34.5	-27	-22.5
Thailand	-66	-170	-55	-3
Vietnam	-60	-172	236	207
Tropical Asia	-1,218	-1,988	-2,581	-1,052.5
Pan-Tropics	-4,040	-6,535	-7,458	-5,604

This acceleration of net forest loss from the 1990s to the 2000s is corroborated by the Landsat-based estimates for 1990-2000, 2000-2005, and 2005-2010 adjusted by error matrices (Figure 3-1). Max and min in the figure indicates the range of net forest change estimates adjusted by standard error, which are calculated from global error matrices.

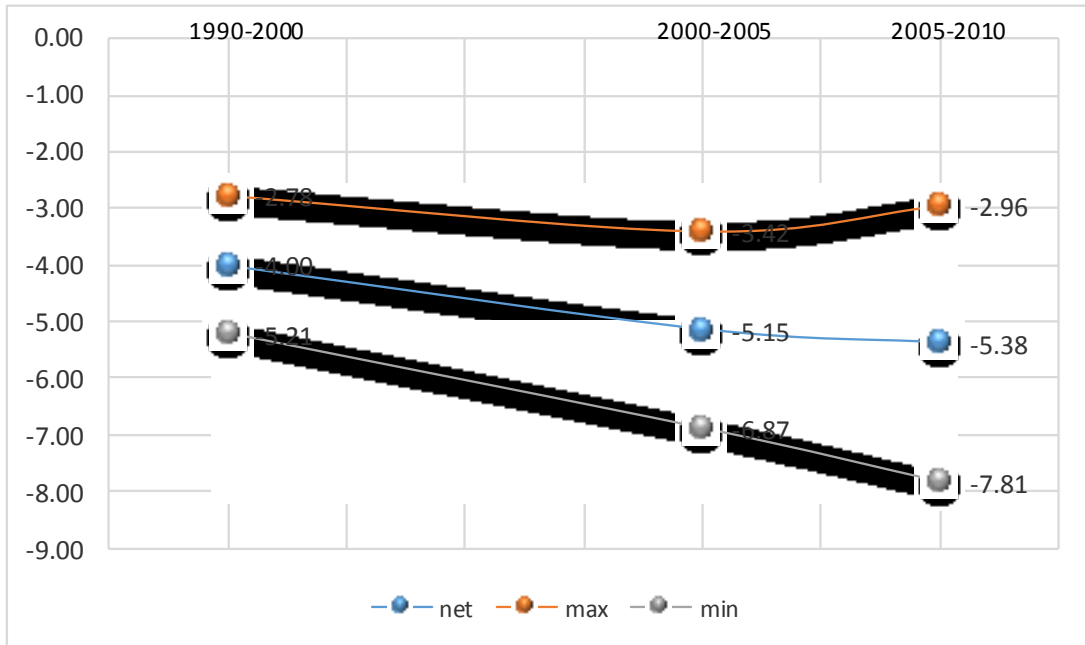


Figure 3-1 Sum of net forest area change ($10^6 \text{ ha}\cdot\text{yr}^{-1}$) over the humid tropics from Landsat-based estimates for 1990-2000, 2000-2005, and 2005-2010 adjusted by error matrices. Max and min indicates the range of net forest change estimates adjusted by standard error. Standard errors are calculated from global error matrices.

Table 3-4 Net forest area change (10^6 ha·yr⁻¹) over each tropical country from Landsat-based estimates for 1990-2000, 2000-2005, and 2005-2010 adjusted by error matrices. Max and min indicates the range of net forest change estimates adjusted by standard error. Standard errors are calculated from global error matrices.

Country	1990-2000			2000-2005			2005-2010		
	Net	max	min	Net	max	min	Net change	max	min
Bangladesh	0.00	0.01	-0.01	0.00	0.01	-0.02	-0.02	0.00	-0.03
Belize	-0.01	-0.01	-0.01	0.00	0.00	0.00	-0.01	0.00	-0.01
Bolivia	-0.20	-0.15	-0.26	-0.17	-0.09	-0.25	-0.32	-0.21	-0.43
Brazil	-1.96	-1.54	-2.39	-2.29	-1.65	-2.93	-2.44	-1.58	-3.30
Brunei	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Darussalam									
Cambodia	-0.03	-0.02	-0.04	-0.11	-0.10	-0.12	-0.11	-0.09	-0.13
Cameroon	0.00	0.02	-0.03	-0.02	0.02	-0.05	-0.02	0.03	-0.06
Colombia	-0.10	-0.04	-0.16	-0.18	-0.09	-0.26	-0.42	-0.29	-0.54
Congo	-0.02	0.00	-0.04	0.00	0.02	-0.03	-0.01	0.03	-0.05
Costa Rica	-0.01	0.00	-0.01	-0.01	-0.01	-0.01	-0.02	-0.01	-0.02
DRC	0.01	0.14	-0.12	-0.22	-0.05	-0.40	-0.46	-0.21	-0.72
Ecuador	-0.02	0.00	-0.03	-0.03	-0.01	-0.05	-0.01	0.02	-0.04
Equatorial Guinea	0.00	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	-0.01
Gabon	-0.05	-0.03	-0.07	0.00	0.03	-0.02	0.04	0.07	0.00
Guatemala	-0.04	-0.03	-0.04	-0.03	-0.02	-0.04	-0.04	-0.03	-0.05
Guyana	-0.02	0.00	-0.03	0.00	0.02	-0.02	0.01	0.03	-0.02
Honduras	-0.02	-0.02	-0.03	-0.02	-0.01	-0.03	-0.04	-0.03	-0.06
Indonesia	-0.82	-0.70	-0.94	-0.89	-0.73	-1.05	-0.19	0.04	-0.42
Laos	-0.04	-0.03	-0.05	-0.05	-0.03	-0.07	-0.04	-0.01	-0.07
Liberia	-0.02	-0.01	-0.02	0.00	0.01	-0.01	0.00	0.02	-0.01
Madagascar	-0.03	0.00	-0.06	-0.03	0.03	-0.09	-0.13	-0.06	-0.20
Malaysia	-0.15	-0.13	-0.18	-0.18	-0.15	-0.21	0.01	0.05	-0.04
Myanmar	-0.08	-0.04	-0.11	-0.11	-0.06	-0.16	-0.16	-0.09	-0.23
Nicaragua	-0.02	-0.01	-0.02	-0.05	-0.04	-0.06	-0.14	-0.12	-0.15
Panama	-0.01	-0.01	-0.02	-0.02	-0.02	-0.03	-0.04	-0.03	-0.05
Papua New Guinea	-0.06	-0.03	-0.10	-0.08	-0.04	-0.12	0.00	0.06	-0.07
Peru	-0.05	0.01	-0.12	-0.07	0.03	-0.17	-0.02	0.12	-0.16
Philippines	-0.06	-0.05	-0.08	-0.16	-0.14	-0.18	-0.10	-0.07	-0.13
Sierra Leone	0.00	0.00	-0.01	0.00	0.00	-0.01	-0.02	-0.01	-0.02
Sri Lanka	0.00	0.00	-0.01	-0.02	-0.01	-0.02	-0.04	-0.03	-0.05
Suriname	-0.01	0.01	-0.02	-0.01	0.00	-0.02	0.00	0.02	-0.02
Thailand	-0.05	-0.02	-0.07	-0.18	-0.13	-0.22	-0.08	-0.02	-0.13
Venezuela	-0.06	-0.01	-0.11	-0.14	-0.07	-0.21	-0.41	-0.32	-0.50

Vietnam	-0.05	-0.04	-0.07	-0.08	-0.06	-0.11	-0.17	-0.14	-0.20
Sum	-4.00	-2.78	-5.21	-5.15	-3.42	-6.87	-5.38	-2.96	-7.81

Net changes in forest area ($10^6 \text{ ha}\cdot\text{yr}^{-1}$) from Landsat based estimates for 1990-2000, 2000-2005, and 2005-2010 in tropical countries are adjusted by error matrices from the global accuracy assessment (Kim et al., 2014, Min et al. in review). For 2005-2010 periods, error matrices for 1990-2000 are used (Fig 3-4). Area estimates for net change are adjusted by the ratio between the estimated proportion of classes based on the reference classification and the estimated proportion of classes based on the map area in the global error matrices. Error range including maximum and minimum amount of net forest area change ($10^6 \text{ ha}\cdot\text{yr}^{-1}$) over each country from Landsat based estimates for each period are calculated by standard error for each forest cover change class. Standard errors are calculated from the global error matrices (Kim et al., 2014, Min et al, in review) using the methods by Olofsson et al (2014). The accuracy of error ranges may be affected by the size of country since it is based on the global scale estimates.

Among the continents, tropical Latin America showed the largest acceleration of annual net forest area loss from the 1990s to the 2000s. The trend was dominated by Brazil, where net forest area loss accelerated by 33%. Tropical Asia showed the second largest acceleration of net loss from the 1990s to the 2000s (Figure 3-2), with similar trends across the individual countries of Indonesia, Malaysia, Cambodia, Thailand and the Philippines. Tropical Africa showed the least amount of annual net forest area loss, whereas it showed the largest increasing rate. The steady increase of

net forest loss in this area is mainly dominated by Democratic Republic of Congo and Madagascar.

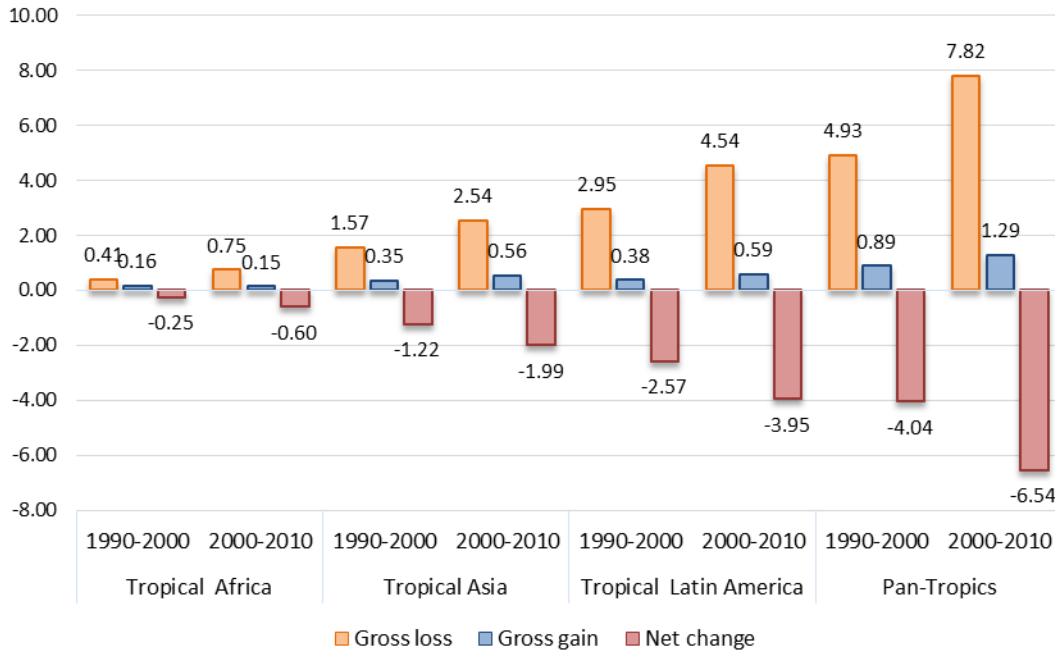


Figure 3-2 Gross losses and gains and net changes in tropical forest area ($10^6 \text{ha} \cdot \text{yr}^{-1}$), by continent from 1990-2000 and 2000-2010.

Figure 3-3 depicts the acceleration or deceleration of annual net forest-area change from the 1990s to the 2000s as a percentage of each country's land area.

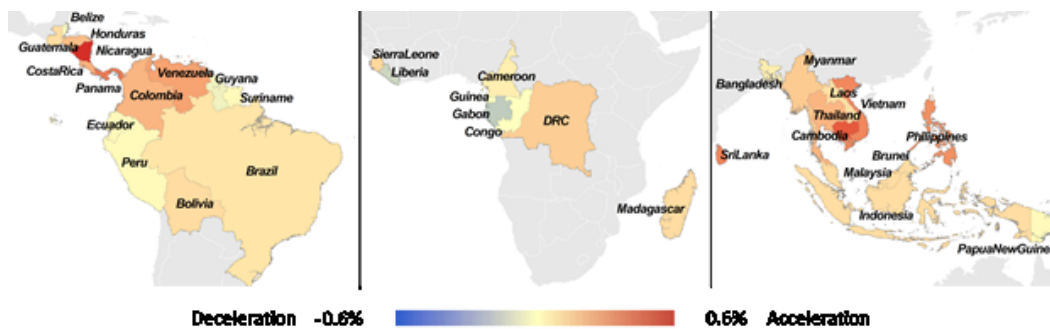


Figure 3-3 Acceleration and deceleration of net forest loss for the humid tropics between 1990–2000 and 2000–2010 periods. The values represent the difference in annual net forest area loss between the periods as a percent of land area.

Overall, this shows an acceleration of forest loss from the 1990s to the 2000s, which was due to the imbalance of strong acceleration in forest loss and small acceleration in forest gains (Table 3-4).

Table 3-5 Forest loss and gain (1,000 ha·yr⁻¹) by countries for 1990-2000, 2000-2005 and 2005-2010.

Country	1990- 2000 Loss	1990- 2000 Gain	2000- 2005 Loss	2000- 2005 Gain	2005- 2010 Loss	2005- 2010 Gain
Bangladesh	6.80	2.58	8.20	2.07	22.16	6.01
Belize	7.94	0.37	9.24	2.52	9.11	2.34
Bolivia	214.86	23.99	304.27	45.43	380.60	42.24
Brazil	2191.39	255.59	3001.27	281.01	2787.45	365.45
Brunei						
Darussalam	1.04	1.05	1.29	0.19	0.99	0.40
Cambodia	38.33	7.32	141.71	10.33	107.17	4.34
Cameroon	20.66	9.80	37.91	4.09	48.02	15.42
Colombia	170.41	40.88	324.68	44.08	498.87	54.00
Congo	26.10	3.71	41.34	20.41	39.88	16.09
Costa Rica	10.81	1.39	24.81	3.10	26.19	6.41
Democratic Republic Congo	227.97	124.40	388.50	47.21	600.46	88.35
Ecuador	31.24	4.53	70.58	18.84	55.06	41.45
Equatorial Guinea	3.10	0.45	2.29	2.30	5.37	1.11
Gabon	49.53	3.39	39.88	29.73	13.07	36.86
Guatemala	43.68	4.89	47.54	2.20	59.10	6.48
Guyana	18.23	2.04	18.16	10.52	14.03	9.23
Honduras	26.95	1.65	41.96	3.41	61.19	7.14
Indonesia	789.11	135.99	1384.35	190.19	808.61	319.47
Laos	61.24	18.06	88.92	18.80	95.09	34.97

Liberia	19.13	0.17	3.35	0.62	4.64	0.43
Madagascar	54.48	16.72	88.60	19.83	141.28	16.77
Malaysia	174.84	44.35	304.51	36.02	144.40	85.40
Myanmar	127.61	44.19	213.81	48.08	254.41	61.24
Nicaragua	31.04	1.68	102.80	19.30	142.84	12.30
Panama	16.83	1.61	46.49	4.13	54.66	9.39
Papua New Guinea	64.98	4.73	149.89	31.39	64.96	49.89
Peru	67.08	15.44	133.18	23.82	84.69	43.99
Philippines	87.57	12.59	224.85	16.26	169.48	47.44
Sierra Leone	9.55	0.83	10.17	0.59	25.44	2.07
Sri Lanka	13.97	2.31	30.73	2.15	49.72	9.60
Suriname	6.41	1.21	16.11	2.90	8.53	6.73
Thailand	90.78	25.26	244.44	19.08	151.81	37.17
Venezuela	109.59	20.79	288.52	43.94	461.29	53.38
Vietnam	113.03	52.67	183.37	34.76	234.62	39.29
Total	4926.27	886.62	8017.75	1039.31	7625.20	1532.85

Separate estimates of forest-cover change statistics for 2000-2005 and 2005-2010 (Table 3-5) reveal a small deceleration of 7.5% ($0.9 \times 10^6 \text{ ha}\cdot\text{yr}^{-1}$) in net forest loss in the later periods, due to the imbalance between small deceleration in forest loss and accelerated forest gain. The deceleration of net forest loss between 2000-2005 and 2005-2010 was mainly driven by Brazil and tropical Asian countries.

Table 3-6 Gross losses and gains and net changes in tropical forest area (10^6 ha·yr⁻¹), by continent for 2000-2005 and 2005-2010.

	Tropical Latin America		Tropical Africa		Tropical Asia		Pan-Tropics	
	2000-2005	2005-2010	2000-2005	2005-2010	2000-2005	2005-2010	2000-2005	2005-2010
Gross loss	4.43	4.64	0.61	0.88	2.98	2.1	8.02	7.63
Gross gain	0.51	0.66	0.12	0.18	0.41	0.7	1.04	1.53
Net change	-3.92	-3.98	-0.49	-0.7	-2.57	-1.41	-6.98	-6.09

These national and continental trends confirm other satellite-based studies. Ernst et al. (2013) showed a 100% acceleration of net forest loss in the Democratic Republic Congo and an 89% acceleration in the Congo Basin from the 1990s to the 2000s, driven by increased population density, small-scale agriculture, fuel-wood collection, and forest accessibility. Eva et al. (2012) corroborated the trends I observed in Tropical Latin America and Brazil, showing 25% and 23 % acceleration of net forest loss between the 1990s to the 2000s, changes which DeFries et al. (2013) attributed to forest clearing for cattle pasture and soybean cultivation. Stibig et al. (2014) showed a 124% acceleration in forest loss in continental Southeast Asia in the 1990-2000 period. Rapid growth of agribusinesses (cattle ranching, soybean farming, and plantation agriculture) after declination of smallholder farmer-driven deforestation has been identified as a major driver of acceleration of net deforestation in this area (Rudel et al. 2009). The post-2000, national estimates of forest change were significantly correlated with those of Hansen et al. (2013) ($r^2 > 0.95$), who also found an overall acceleration of tropical forest loss after 2000, with an exception of

Brazil. The Brazilian exception was explained by enforcement of policy, interventions in soy and beef supply chains, and expansion of protected areas (Nepstad et al., 2014). Accelerated annual loss in Tropical Africa and Asia observed in this study was also identified by Hansen et al. (2013). The estimates from this study complement sample-based estimates for the 1990s (e.g. Ernst et al. 2013; Eva et al. 2012; Stibig et al. 2014; Achard et al. 2014) and the estimates limited to the post 2000 period (e.g. Hansen et al. 2013).

Table 3-6 Recent satellite-based estimates of biome-level forest change (1,000 ha·yr¹) in the 1990s and 2000s.

	<i>Area</i>	<i>1990s</i>	<i>2000s</i>	<i>Δrate</i>	<i>Method</i>	<i>Data</i>
FAO, JRC (2012)	Tropics	-5,648	-9,111	61.3%	Sampling	Landsat
FAO, JRC (2014)	Tropics	-6,000	-7,000	16.7%	Sampling	Landsat
Achard (2002)	Humid Tropics	-5,800	-		Sampling	AVHRR
Achard (2014)	Tropics	-6,050	-5,930	-2%	Sampling	Landsat
	Humid Tropics	-3,960	-3,170	-20%	Sampling	Landsat
defries (2002)	Tropics	-5,563	-	-	Wall-to-wall	AVHRR
Hansen (2008,2010)	Humid tropics	-	-5,400 (gross loss)	-	Sampling	Landsat
Hansen (2013)	Tropics	-	-7,100	-	Wall-to-wall	Landsat
	Humid tropics (34 countries)	-	-5,500		Wall-to-wall	Landsat
This study	Humid tropics (34 countries)	-4,040	-6,535	61.8%	Wall-to-wall	Landsat

Table 3-6 shows the difference between satellite-based estimates of forest change in each time period from studies at tropical biome level. Estimates of forest change differ among satellite-based studies. The major sources of difference include differences in the definition of forest, resolution of input data, classification accuracy,

and sensitivity of algorithms to detect change. Sample-based estimates vary widely, especially in estimating differences in rates of change over time. Due to similarities in spatial and temporal scale, Hansen et al. (2013) provide the only estimates directly comparable to this study. The estimates of this study for the 34 countries show strong correlation to those of Hansen et al. (2013), but are consistently higher (Table 3-7) due in large part to different sensitivities to forest gain.

Table 3-7 Comparison between this study and Hansen et al (2013).

<i>COUNTRY</i>	<i>HANSEN</i>	<i>THIS STUDY</i>	<i>COUNTRY</i>	<i>HANSEN</i>	<i>THIS STUDY</i>
BANGLADESH	-4	-11	Indonesia	-735	-842
BELIZE	-9	-7	Laos	-73	-65
BOLIVIA	-234	-299	Liberia	-24	-3
BRAZIL	-2370	-2571	Madagascar	-88	-97
BRUNEI DARUSSALAM	-1	-1	Malaysia	-179	-164
CAMBODIA	-96	-117	Myanmar	-98	-179
CAMEROON	-35	-33	Nicaragua	-63	-107
COLOMBIA	-164	-363	Panama	-20	-44
CONGO	-375	-22	Papua New Guinea	-34	-67
COSTA RICA	-11	-21	Peru	-111	-75
DEMOCRATIC REPUBLIC CONGO	-375	-427	Philippines	-29	-165
ECUADOR	-35	-33	Sierra Leone	-13	-16
EQUATORIAL GUINEA	-3	-2	Sri Lanka	-6	-34

GABON	-13	7	Suriname	-5	-8
GUATEMALA	-65	-49	Thailand	-59	-170
GUYANA	-7	-6	Venezuela	-92	-326
HONDURAS	-36	-46	Vietnam	-55	-172
			Sum	-5516	-6535

Large differences are evident between the FRA 2010 report and this study's estimates of forest area and change. The long-term results of this study contradict the FAO (2010) report of a 25% reduction in the rate of forest loss. Also contrary to the results of this study, 16 out of 34 countries in the FRA main report were estimated to have a constant net rate of forest change through the 1990-2000 and 2000-2010 periods (FAO, 2010). The discrepancies are likely due to differences in survey methods and definition of forest. The FRA 2010 reports forest area defined by 'forest use', and it compiles country-level estimates from national reports, which have been criticized for inaccuracy and inconsistency (Mayaux et al. 1998; DeFries et al. 2002; Hansen et al. 2008; Grainger 2008; Hansen et al. 2013; Achard et al. 2014). The differences is likely partly due to changes in the area of commodity forest plantations, which are included in most current satellite estimates as forest cover but are variably reported as "forest" in the FRA report. It is possible that the slow rate of forest gain make biases toward increased net deforestation especially in boreal areas where the regrowth is relatively slow. Biases toward increase in net deforestation based on the low detectability of forest gain in the remote sensing based estimates can be compared with the net change in forest area adjusted by the ground observation by FAO-FRA.

Errors from backward and forward projection based on previous FRA reports may also contribute to overestimated net forest loss for the 1990s, thus resulted in muting the effect of acceleration of forest loss during the 2000s (Grainger 2008). The difference might arise partly from a statistical bias from the satellite data gaps from clouds, especially for countries such as Indonesia (gap ~ 30 %). This may be resolved as other satellite images become available.

These findings highlight the importance of a consistent definition and method to track forest-area changes. These findings provide a consistent, spatially explicit basis for the inference of the drivers of forest cover change in various geographical and socio-economical contexts, especially where the relationship between long-term trends in forest cover change and its drivers are hindered by inaccurate estimates of forest cover change resulting from semantic and methodological inconsistencies.

3.4 Conclusions

This study applied a series of forest-cover maps based on satellite imagery and a consistent, biophysical definition of forest cover to estimate the area and change of humid tropical forests in 34 countries from 1990 to 2010. The results of this study indicate a 62% acceleration of net forest loss over the humid tropics, from 4.04×10^6 ha·yr⁻¹ during the 1990s to 6.54×10^6 ha·yr⁻¹ in the 2000s—mainly driven by strong acceleration in gross forest loss in tropical Latin America. Second, this study identified a 7.2 % deceleration in net forest loss, from 6.98×10^6 ha·yr⁻¹ in the early 2000s to 6.09×10^6 ha·yr⁻¹ in the late 2000s, due to accelerated forest gains in tropical Asia and decelerated forest losses in Brazil. Although slower than on other

continents, gross forest-cover changes in tropical Africa, dominated by changes in the Democratic Republic of Congo and Madagascar, resulted in net losses that accelerated steadily from 1990 to 2010. The estimates of this study reveal an acceleration of net deforestation from the 1990s to the 2000s across the humid tropics. Gross and net forest-cover losses rose from the 1990s to a peak in the early 2000s and then decelerated slightly from 2005 to 2010. This acceleration contradicts commonly accepted assertions of deceleration (e.g. Anon. 2014).

Chapter 4 Effectiveness of Protected Areas in the Pan-Tropics and International Aid for Conservation³

4.1 Introduction

In 2010, the Convention on Biological Diversity (CBD) adopted a revised strategic plan for biodiversity for 2011-2020 including the Aichi Biodiversity Targets. One of the targets is to reduce the rate of loss of all natural habitats including forest by 2020 (www.cbd.int/sp/targets). However, recent studies have shown acceleration and high sustained rates of tropical deforestation since 2000 (Hansen et al. 2013; Kim et al. 2015)(Hansen et al., 2013; Kim et al., 2015). To meet the proposed targets of conservation plans like the Aichi Biodiversity Targets, evaluation of the effectiveness of previous and current efforts to reduce tropical deforestation is essential. Within this context, assessment of the effectiveness of PAs throughout the tropics is vital as PAs are central to climate and biodiversity policies (DeFries et al. 2005; Joppa et al. 2008; Pimm et al. 2001). Previous efforts have been made to evaluate the effectiveness of PAs over various spatial and temporal extents (Andam et al. 2008; DeFries et al. 2005; Huang, Kim, et al. 2009; Joppa et al. 2008; Joppa & Pfaff 2011; Laurance et al. 2012; Schmitt et al. 2009), evaluating the cost-effectiveness of these PAs (Kindermann et al. 2008; Soares-Filho et al. 2010), exploring the links between the value of PAs and surrounding socio-economic drivers of tropical deforestation (Nolte

³ The presented material is under review : D. H. Kim, A. Anand, J. O. Sexton, P. Noojipady, A. Zazueta, B. Soares-Filho, M. E. Kelly, C. M. DiMiceli, S. Channan, J. R. Townshend (*in review*) Effectiveness of Protected Areas in the Pan-Tropics and International Aid for Conservation, Science Advances.

et al. 2013), while others have examined the management effectiveness of PAs for limited times and spatial extents (Hockings et al. 2004).

Satellite based remotely sensed data have been used to evaluate the effectiveness of PAs in reducing deforestation because of their spatio-temporal consistency and its capability of complementing ground-based observations including filling of data gaps and solving compatibility issues (Curran et al. 2004; DeFries et al. 2005; Gaveau et al. 2009)(Curran, et al., 2004; Defries et al., 2005; Gaveau et al, 2009). Spatially explicit information on pan-tropical forest cover change at Landsat resolutions has not previously been available beyond satellite analysis in selected locations (Achard et al. 2002; DeFries et al. 2005). Lack of comprehensive long-term spatial data has precluded pan-tropical scale analysis on the effectiveness of PAs in terms of their regulating factors.

Long term, large-scale forest cover change at 30-m resolution has been recently made available (Kim et al. 2014; Townshend et al. 2012). Based on this information, this study aims to, 1) estimate avoided deforestation by PAs in each tropical country during the 2000s, 2) estimate effects of international aid received by each country on avoided deforestation by PAs in each country and 3) analyze the relationships between the socio-economic variables and increases in deforestation, avoided deforestation by PAs and effects of international aid of each country.

4.2 Methods

4.2.1 Forest change data

Landsat based forest cover change data between 1990, 2000, and 2010 (Kim et al. 2014; Channan et al. 2015; Sexton et al. 2013) were used to derive net forest cover change in 34 tropical countries that comprise over 80 % of forest area in the tropics (Kim et al. 2015), and dominates the forest area of the humid tropics. These data were derived from 5,444 surface reflectance images collected for the 1990, 2000, and 2010 epochs from the GLS collection of Landsat images (Channan et al. 2015; Feng et al. 2013; Gutman et al. 2008; Masek et al. 2006) supplemented by many additional images (Channan et al. 2015). Forest cover was defined as parcels > 1 ha in area and comprising pixels with > 30% tree cover (Belward 1996; FAO 2002; UNFCCC 2002) and with the International Geosphere-Biosphere Programme's (IGBP) classes of forest (> 60 % tree cover) and woody savannas (> 30 % tree cover) combined.

4.2.2 Socio-economic data

Previous studies have shown the significant impact of population growth, increased agricultural production and agricultural trade on tropical deforestation (DeFries et al. 2010,2013; Rudel 2007). In this study, this study used various sources of demographic, economic and agricultural statistics to examine the relationships with increased rates of deforestation between the 1990s and 2000s, and with effectiveness of PAs (Table 4-1).

Table 4-1 Socio-economic variables and data sources for regression analysis.

Data	Sources
Agricultural production	FAO, 2012
Export of agricultural product	FAO, 2012
Trade of agricultural product	FAO, 2012
Urban population	FAO, 2012
Rural population	FAO, 2012
Gross domestic product	World Bank, 2015
Rule of law	World Bank, 2013
Control of corruption	World Bank, 2013
Monitoring capacity	Romijin et al (44)
International aid	AidData (27)

Although the forest change data used in this analysis is of comparatively high spatial resolution, there is not enough socio-economic data at this resolution for the tropics. This limits the scale of this study to a country level. At this coarse scale, the relationships between individual PAs and geophysical factors (e.g. terrain characteristics, distance to edge) were not taken into account.

National scale data from United Nations Food and Agriculture Organization (FAO) were used to derive demographic and agricultural statistics (FAO 2012)(FAO, 2012). The Worldwide Governance Index (WGI) (World Bank 2013) reports governance indicators for countries over the period 1996-2013. This study used two indicators, the ‘Rule of law’, which is a measure of the ability to enforce the law and

‘control of corruption’, which measures perceptions of the extent to which public power is exercised for private gain. Global aid data for the period 1990- 2010 was obtained from AidData Version 3 database (Tierney et al. 2011). The database contains records of development projects from more than 90 bilateral and multilateral donors, and constitutes a detailed source of project-level information on international aid (Tierney et al. 2011). This study used the real value of currency (in US dollars) to account for changes in the value of currency over time. The project data extracted from AidData includes data from all the sectors (Miller et al. 2013). This study excluded the sectors less relevant for biodiversity and natural resource management such as reproductive health care and secondary education. Averages for the 1990s and the 2000s were calculated from each data set and the differences are used as independent variables for regression analysis.

4.2.3 Forest cover change rate inside and outside PAs

The forest cover change maps for each of the 3,888 designated PAs and their surrounding areas in 34 tropical countries (IUCN 2010) are extracted from the Landsat-based forest cover change data. The protected areas in this study are defined by information of PAs in IUCN data. Although IUCN data have different categories of PAs by its management status, in this study I do not analyze PAs separately by their categories since the scope of this study is to estimate overall effectiveness of PAs by each country. However, this study provides a framework for individual PA based analysis.

To maintain environmental similarity among PAs (Mas 2005; Peres & Terborgh 1995), The surrounding areas are derived using a 10 km buffer distance

from the PA boundaries. This study derived the annual gross forest loss, gross forest gain and net forest change rates within each PA and its surrounding area from the forest change maps. The forest loss rate are then calculated t by dividing the area of forest loss by area of forest within PAs or surrounding areas. Each GLS epoch spans a range of years focused on the nominal year (Gutman et al. 2008), so the forest/nonforest layer in each year was accompanied by the year of image acquisition to estimate changes over time as rates.

4.2.4 Estimation of Avoided Deforestation by PAs

Measuring the amount of avoided deforestation by PAs is not straightforward because it cannot be directly measured (Andam et al, 2008). Broadly, two different approaches have been in use to estimate avoided deforestation. The first set of approaches, compare differences in forest change rate between the inside and outside of PAs (Curran et al., 2004; Defries et al., 2005; Nepstad et al., 2006; Joppa et al., 2008). These, however, have been criticized for their inability to account for the spillover effect from PAs to the adjacent areas outside of PAs and for selection bias due to un-randomized selection of PAs and inherently different deforestation probability between the inside and outside of PAs (Stern et al. 2001). Second, there are statistical matching approaches to match the difference of deforestation probability between samples inside and outside PAs (Andam et al., 2008; Joppa et al., 2011). The statistical matching of samples is robust, but hard to implement due to high computational cost and difficulties in finding statistically significant matches, especially when the PA network covers large continuous tracts of land (Soares-Filho, 2010), and some important factors which contribute to the deforestation probability

such as policies (e.g. concession) can be overlooked. To avoid selection bias and computational difficulties associated with previously mentioned methods, the Difference-In-Difference (DID) estimator was used to measure avoided deforestation in the 2000s compared to the 1990s for PAs in the pan-tropics. This method has a relatively strong inferential ability as it eliminates selection biases by attempting to mimic an experimental research design using observational data (Card & Krueger 1995; Abadie 2005).

The impact of a treatment on an outcome Y_i , annual forest change rate of each protected area and surrounding area was modeled by the following equation:

$$Y_i = \alpha + \beta T_i + \gamma t_i + \delta(T_i \cdot t_i) + \varepsilon_i \quad (1)$$

Where, T is the treatment status, t is the time period before and after the treatment, the coefficients given by the Greek letters α , β , γ , δ are all unknown parameters and ε_i is a random, unobserved "error" term. Since the socio economic data scaled at individual protected area level are not generally available, those socio economic variables are not included in the equation (1). Since the forest cover change data used in this study are for periods of 1990-2000 and 2000-2010, we measure collective effects from PAs between the decades in each country.

In the DID estimator, the effect of treatment (avoided deforestation), δ_{DID} , is defined as the difference in average outcome in the treatment group T before and after treatment minus the difference in average outcome in the control group C before and after treatment and expressed as:

$$\delta = \bar{Y}_1^T - \bar{Y}_0^T - (\bar{Y}_1^C - \bar{Y}_0^C) \quad (2)$$

Where, the treatment group is PAs and the control group is surrounding areas before and after the year 2000 (Figure. 4-1).

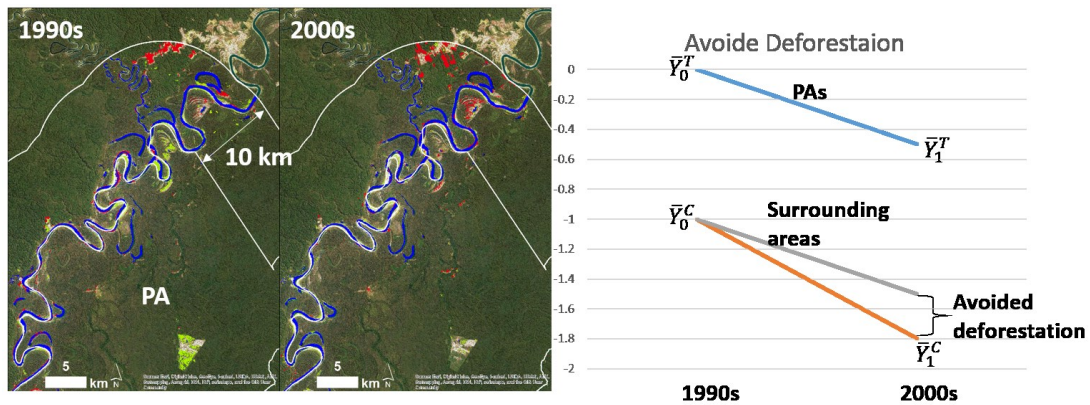


Figure 4-1 Avoided deforestation estimates for a designated protected area in Brazil (Peneri/Tacquiri Indigenous Area designated in 2000); red pixels represent forest loss, green pixels represent forest gain. Y axis represents the net forest cover change rate, while x axis represents time periods. Avoided deforestation (DID) is calculated by taking differences between difference in forest loss rate in the treatment group T before and after treatment and the difference in forest loss rate in the control group C over time.

This study applied this method to a) the 3,888 PAs and surrounding areas designated prior to 2010 to determine the accumulated effect during the 2000s, and b) to the subset of 1,253 PAs established between 2000 -2010 to estimate the effect of newly established PAs.

4.2.5 Spillover effect

Spillover effect refers to displacement of forest loss from one place to a neighboring area due to the establishment of PA. If PAs displaced deforestation to immediate surrounding areas through spillover effect, deforestation rate inside immediate surrounding areas will be higher than in the wider landscape (Ewers & Rodrigues 2008; Gaveau et al. 2009). Based on these assumptions, potential spillover (leakage) effect was measured by comparing avoided deforestation estimates using surrounding areas of different distances (10km and 25km).

4.2.6 Statistical Analysis

To ensure the robustness of DID method, this study tested 1) Ordinary least squares (OLS) regression analysis between treatment, time period, and estimated avoided deforestation as expressed in equation (1); 2) paired t-test between the difference in forest loss rates in PAs and the difference in forest loss rates in the surrounding areas to determine significance of the effect of PAs before and after 2000. Effects of PAs are graphically presented with changes in frequency distributions. Variables for the regression analysis were selected based on variation inflation factor, which account for collinearity (DeFries et al. 2010). All independent variables were log transformed. I used a minimum node size of three, for both regression trees and random forest analysis to minimize residual deviance. R packages CAR and TREE are used for the collinearity check and regression tree analysis respectively.

4.3 Results.

Paired t-test results between the difference in forest loss rates in PAs and the difference in forest loss rates in the surrounding areas confirms the hypothesis that two groups show a significant difference before and after the designation of PAs with the value of 6.6 (Table 4-2).

Table 4-2 Results of paired t-test.

Paired t-test
t = 6.6452, df = 3337, p-value = 3.523e-11
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval: 0.2439623 0.4481797

sample estimates: mean of the differences 0.346071

Ordinary Least Square (OLS) regression analysis of the PA effect evaluation model (equation 1) shows a r^2 value of 0.28 with p-value < 0.001 between gross forest loss rate within PAs and avoided deforestation by PAs over time (Table 4-3). The avoided deforestation, the value of the coefficient for the treatment over time δ (equation 1) was 0.35 (%/yr) with a standard error of 0.092 with a p value < 0.001.

Table 4-3 Statistics of Ordinary Least Square (OLS) regression analysis for avoided deforestation by country and individual PA.

By country				
Independent variables	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-0.39885	0.06	-6.020	1.62e-08 ***
Period	-0.39489	0.09370	-4.215	4.61e-05 ***
Treatment	0.23511	0.09370	2.509	0.0133 *
Treatment·Period	0.27194	0.13250	2.052	0.0421 *

* P < 0.01 ** P < 0.001 *** P < 0.0001, independent variables are log transformed

Residual standard error: 0.3863 on 132 degrees of freedom, Multiple R-squared: 0.2781, Adjusted R-squared: 0.2617

F-statistic: 16.95 on 3 and 132 DF, p-value: 2.257e-09

By individual PA				
Independent variables	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-0.91003	0.04603	-19.772	< 2e-16 ***
Period	-1.41258	0.04603	-21.702	< 2e-16 ***

Treatment	0.32492	0.06509	4.992	6.06e-07 ***
Treatment·Period	0.34607	0.09205	3.759	0.000171 ***

* P < 0.01 ** P < 0.001 *** P < 0.0001, independent variables are log transformed

Residual standard error: 2.659 on 13348 degrees of freedom, Multiple R-squared: 0.0603, Adjusted R-squared: 0.06009

F-statistic: 285.5 on 3 and 13348 DF, p-value: < 2.2e-16

Effects of PAs are graphically presented in Figure 4-2 with changes in frequency distributions before and after 2000. The figure suggests that at t1 (pre-2000), the forest loss rate was high inside PA area and at t2 (post-2000) loss was lower confirming the positive effects of PAs in the tropics in reducing deforestation.

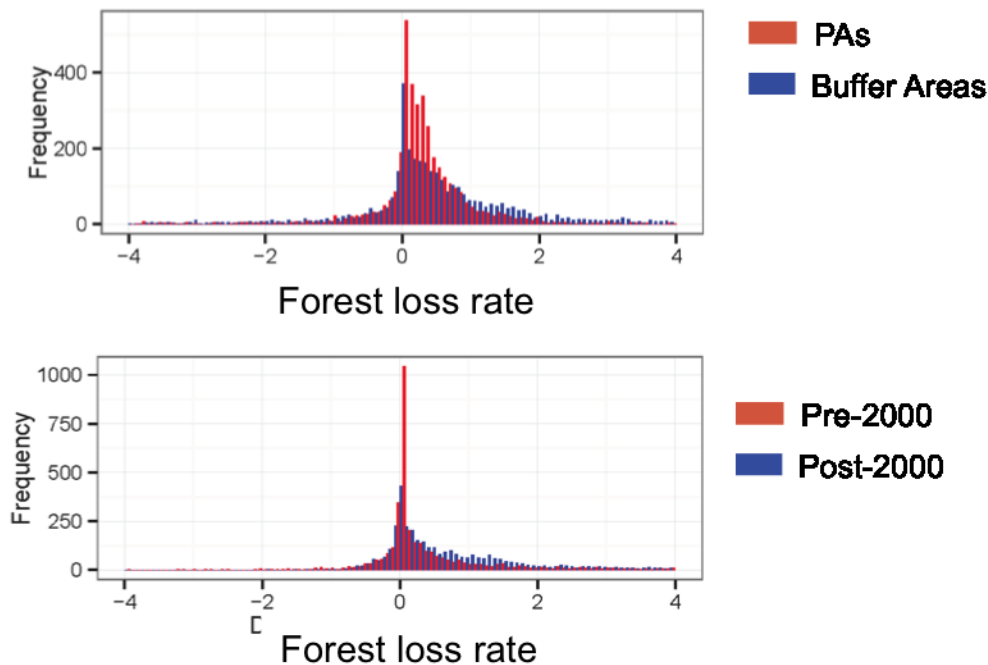


Figure 4-2 Frequency distribution of the difference in forest loss rates between the interior of protected areas and the surrounding 10 km buffers in the 1990s (t1) (Blue) and the 2000s (t2) (Red). The figure suggests that at t1, the forest loss rate was high inside PA area (before 2000) and at t2 loss was lower.

4.3.1 Avoided Deforestation by Protected Areas

Table 4-2 Summary of the avoided deforestation estimates by countries and continents. Acceleration of deforestation is indicated by percent increase in net deforestation rate from the 1990s to the 2000s (3), Avoided deforestation as presented in percent of conserved forest relative to remaining forest in PAs and total area of conserved forest. All estimates are on an annual basis. Negative effect means forest loss rates within PAs exceeded the forest loss rates in surrounding areas.

Country	Acceleration of deforestation (%)	Avoided deforestation (%)	Avoided deforestation (km ²)	Area of PAs (km ²)	Forest area in PAs (%)	No. of PAs
Cameroon	20.6	1.39	341.1	46,414	53	35
Congo	0.0	-0.23	-24.2	22,624	46	13
Democratic Republic Congo	31.2	-0.09	-77.4	219,677	41	31
Equatorial Guinea	-2.0	-0.32	-10.7	3,602	93	6
Gabon	-11.5	0.01	1.5	16,677	97	8
Liberia	-8.2	-0.17	-1.5	1,687	53	2
Madagascar	15.6	0.69	57.5	15,322	55	42
Sierra Leone	8.9	0.03	0.3	2,955	38	31
Africa Total	6.8	0.18	286.5	328,957	47	168
Bangladesh	16.3	0.17	0.5	490	56	19
Brunei Darussalam	0.0	-0.90	-3.8	448	94	18
Cambodia	27.8	0.49	61.7	24,779	51	24
Indonesia	2.9	0.22	100.8	95,981	49	152
Laos	5.1	0.49	67.6	17,095	80	12
Malaysia	2.5	0.21	38.4	19,330	96	122
Myanmar	11.5	0.88	64.5	15,201	48	29
Papua New Guinea	1.1	-0.19	-5.1	3,849	69	27
Philippines	12.0	-0.05	-9.0	26,890	64	165
Sri Lanka	19.5	-0.05	-3.0	11,860	46	210
Thailand	15.9	0.76	357.1	61,541	76	117
Vietnam	18.5	0.06	4.7	18,295	43	65
Asia Total	11.1	0.38	674.4	295,758	61	960
Belize	-1.1	-0.06	-2.2	4,353	86	63
Bolivia	5.6	0.92	661.1	98,585	73	42
Brazil	3.3	0.34	5087.0	1,852,181	82	1,321

Colombia	18.0	0.89	582.9	169,960	38	593
Costa Rica	12.0	0.23	10.8	5,424	86	79
Ecuador	2.2	0.76	119.8	22,467	70	20
Guatemala	2.6	0.27	42.7	18,053	86	225
Guyana	-6.2	0.01	0.6	10,426	41	3
Honduras	8.3	0.02	1.6	11,733	56	62
Nicaragua	26.5	0.68	9.4	4,597	30	61
Panama	18.8	0.76	27.3	4,610	78	13
Peru	4.5	0.51	997.0	308,599	64	185
Suriname	4.4	0.05	14.2	29,041	99	7
Venezuela	26.7	-0.39	-162.2	80,919	51	85
Latin America	9.0	0.38	7389.8	2,620,949	75	2,759
Total						
Grand Total	6.2	0.35	8350.6	3,245,663	71	3,887

The results demonstrate an overall $83,500 \pm 21,200 \text{ km}^2$ of avoided deforestation by the PAs during the 2000s throughout the tropics, which equals 3.5 % of all forest area within PAs in the study area (Table 4-4). Among the continents, Latin America showed the largest estimates of avoided deforestation during the 2000s ($73,900 \text{ km}^2$). In Latin America, Brazil showed the largest avoided deforestation ($50,870 \text{ km}^2$), followed by Peru ($9,970 \text{ km}^2$), and Bolivia ($6,611 \text{ km}^2$) for the same time- period. Venezuela was found to have the largest negative effect ($-1,622 \text{ km}^2$) among Latin American countries. Negative effect means forest loss rates within PAs exceeded the forest loss rates in surrounding areas. Tropical Asia showed the second largest estimates of avoided deforestation of $6,744 \text{ km}^2$, with the largest amount in Thailand followed by Indonesia. Tropical Africa has the lowest estimates, except Cameroon, which showed the largest estimate of $3,411 \text{ km}^2$. In terms of the percentage of avoided deforestation against the entire forest area in PAs, Africa

showed the lowest estimates of 1.8 % while Latin America and Asia showed similar estimates of 3.8 %.

Table 4-3 Estimates of Avoided deforestation by time of establishment of PAs. Numbers in parenthesis represent estimates using median forest loss rate.

Year of establishment	Avoided deforestation		Mean forest loss rate within PAs		Mean forest loss rate within BZs	
	(%)	(km ²)	Before 2000	After 2000	Before 2000	After 2000
Prior to 2010	3.46 (4.1)	83,500	0.59 (0.09)	1.65 (0.17)	0.91 (0.46)	2.32 (0.94)
1990-2000	3.42 (4.6)	22,800	0.5 (0.01)	1.66 (0.02)	0.86 (0.46)	2.32 (1)
2000-2010	4.47 (5)	47,650	0.5 (0.02)	1.52 (0.04)	0.897 (0.35)	2.37 (0.87)

The comparison between estimates for the entire set of PAs and for the PAs established after 2000 showed that PAs established post 2000 had a somewhat higher rate of avoided deforestation at 0.5% annually compared to 0.4 % for entire set of PAs (Table 4-5). The area of avoided deforestation by PAs established during the 2000s was about 60% of estimated avoided deforestation by all PAs in the study area. Estimates of avoided deforestation based on the median value of forest loss exhibited similar results.

Changes in mean and median forest loss within PAs and the surrounding areas before and after 2000 demonstrate the positive effects of PAs on reducing deforestation (Table 4-4). Similar to the results of OLS regression analysis of the DID

estimator, the results of the paired t-Test showed significant ($p < 0.0001$, $t = 6.2$) effects of PAs, as a change in frequency distribution (Figure 4-2).

4.3.2 Spillover effect

This study compared the estimates of avoided deforestation for each country based on surrounding areas with a 10 km buffer distance and surrounding areas with a 25 km buffer distance. The comparison showed a linear relationship ($P < 0.0001$, $R^2 = 0.95$, coefficient = 0.81, intercept = 0.0084) between the two estimates. Also, the 10 km buffer showed slightly higher estimates of avoided deforestation than the 25 km buffer confirming the assumption that deforestation rate inside immediate surrounding areas (10 km buffer) will be higher than in the wider landscape (25 km buffer) due to the spillover effect (Figure 4-3).

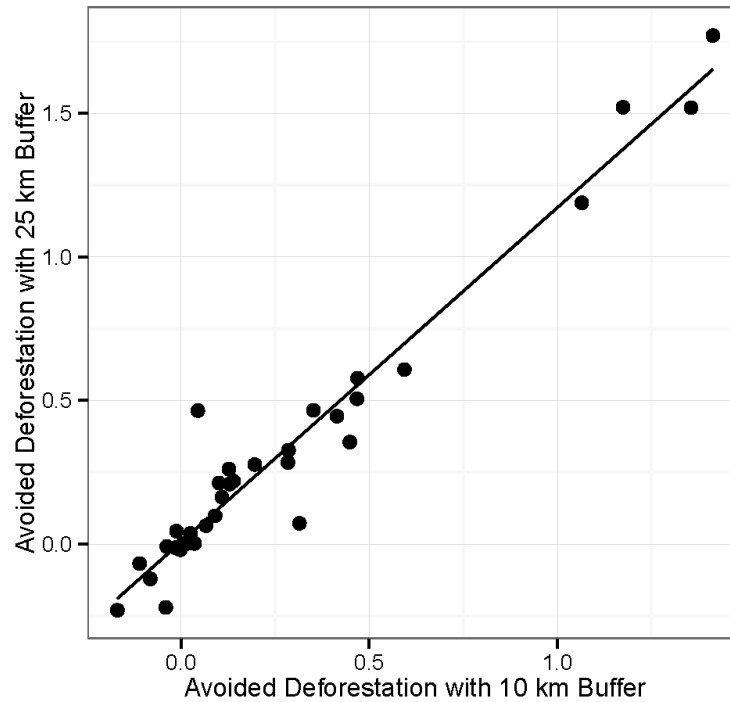


Figure 4-3 Comparison between estimates of avoided deforestation by each country using a 10 km buffer zone and a 25 km buffer zone. Median forest loss rate of PAs and surrounding areas at different distances are used in this comparison.

4.3.3 Effectiveness of international aid for conservation

34 countries received a total international aid for conservation of 42 billion USD during 1990s and 62 billion USD during 2000s, with a net increase of 46% (20 billion U.S Dollars) between two periods (figure 4). Among continents, Tropical Asian countries were the largest recipients, receiving 62% of all funds during the 2000s, followed by Latin American countries (28 %). Among the countries, Indonesia received the largest amount of aid, 18% of all funds received by 34 tropical countries, followed by Vietnam (12%) and the Philippines (9%) for the same period (AidData, 2015). The effect of international aid (avoided deforestation/international aid) was

highest in Latin America with 4.3 m²/USD, led by Brazil, while tropical Asian countries showed the lowest average effect of international aid of 0.17 m²/USD. Among the countries, Brazil showed the absolute highest cost-effect of 21 m²/USD. The blue line in Figure 4 indicates the average effect of international aid on all 34 countries, and only 9 out of 34 countries were found to have higher effects of international aid than average (Figure 4-4).

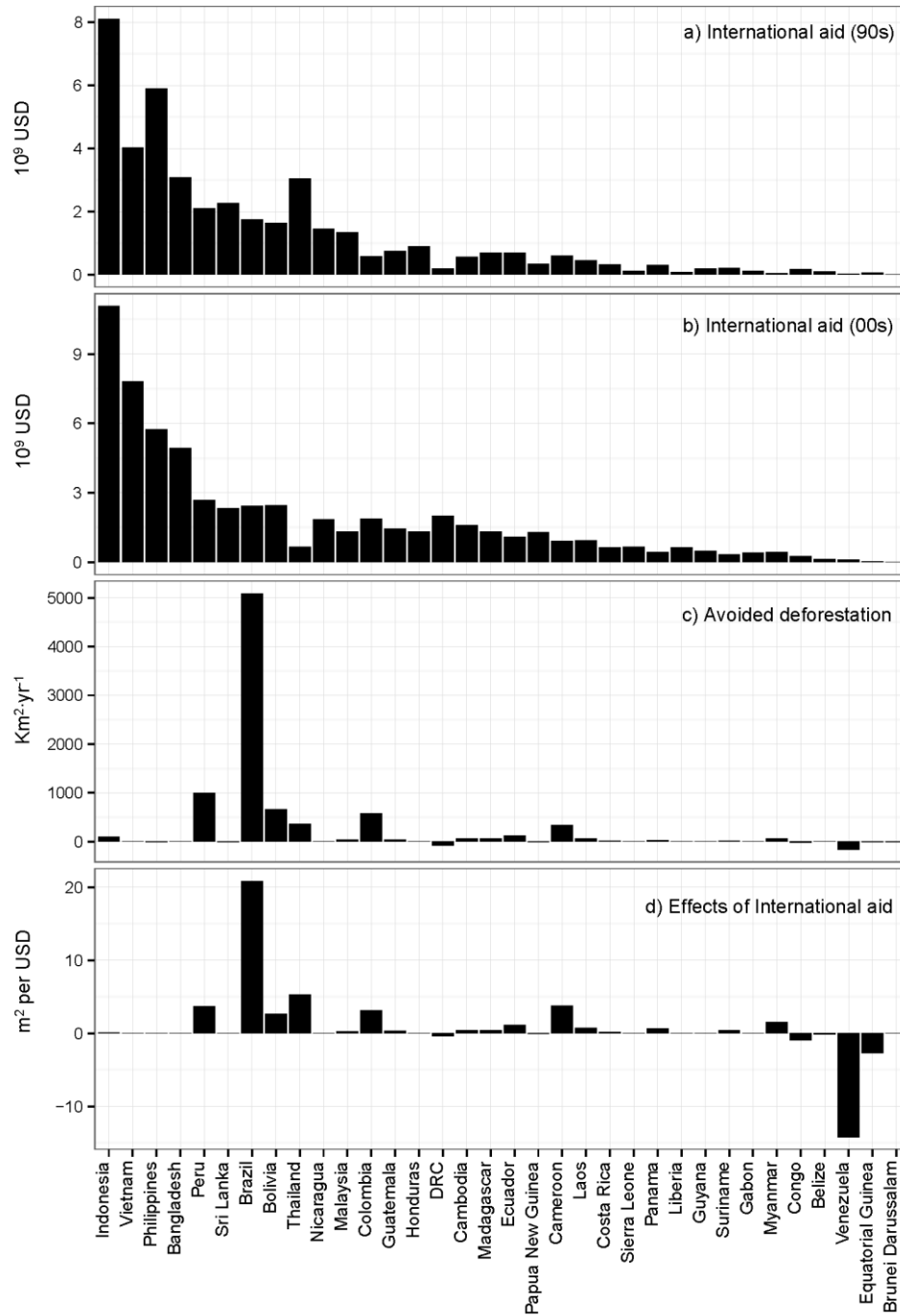


Figure 4-4 The amount of international funds committed to each tropical country in the 1990s (a) and the 2000s (b), the amount of funds are converted to a nominal value of US dollar. Avoided deforestation by each country (c). Effects of International aid (Contribution of international aid per unit of avoided deforestation) for 34 tropical countries (d).

4.3.4 Regression analysis

Table 4-6 summarizes the results of regression analysis based on multiple linear regression and regression tree analysis. Multiple linear regressions showed mild to moderate correlations

Table 4-4 Results of regression analysis based on different techniques including multiple linear regression, regression tree algorithm.

Independent variables	Multiple linear regression	R ²	P	Regression Tree
Difference of annual forest loss rate between the 1990s and the 2000s	GDP growth*** Difference of annual agricultural production growth rate between the 1990s and the 2000s ** urban population growth**	0.44	< 0.001	GDP growth, urban population growth
Avoided deforestation	Difference of annual forest loss rate between the 1990s and the 2000s ***	0.32	< 0.05	Difference of annual forest loss rate between the 1990s and the 2000s
Effectiveness of international aid	Agricultural production growth *, Rule of law*, monitoring**	0.25	< 0.05	Rule of law
* P < 0.01 ** P < 0.001 *** P < 0.0001				
independent variables are log transformed				

($0.2 < r^2 < 0.5$) and significant associations ($P < 0.05$) between independent variables and driving forces. The regression tree algorithm is used complementarily to seek a non-parametric relationship between each variable.

Multiple regression analysis between the difference of annual forest loss rate between the 1990s and the 2000s and potential driving forces showed an overall moderate correlation ($r^2 = 0.44$) and significant association ($p < 0.001$). There is a significant ($P < 0.01$) positive association between difference of annual forest loss rate between the 1990s and the 2000s and difference of annual agricultural production growth rate between the 1990s and the 2000s. A highly significant ($p < 0.001$), negative association exists between differences of annual forest loss rate between the 1990s and the 2000s and difference of annual GDP growth rate between the 1990s and the 2000s. There is a significant ($p < 0.01$) negative association between the difference of annual forest loss rate between the 1990s and the 2000s and the difference of urban population increase rate between the 1990s and the 2000s. The difference of annual GDP growth rate was the first split in the regression tree, which means that GDP growth is the most powerful discriminator between countries. Multiple regression analysis indicated a mild correlation ($r^2 = 0.32$) between the amount of avoided deforestation by PAs and the difference of annual forest loss rate between the 1990s and 2000s (Table 4-6). Both multiple regression analysis and regression tree analysis showed that annual forest loss rate between the 1990s and 2000s was significantly associated with avoided deforestation by PAs.

The contribution of international aid per unit of avoided deforestation shows mild correlation ($r^2 = 0.25$) with difference of annual agricultural production growth

rate between the 1990s and the 2000s, rule of law and monitoring capacity (Table 4-6). Regression tree analysis shows that rule of law makes the first split and the next split is made by monitoring ability. This is especially demonstrated by 3 countries including Democratic Republic of Congo, Myanmar and Venezuela with the lowest effect of international aid and the lowest value of rule of law, which is an indicator of the ability to enforce the law.

4.4 Discussion

The results of the estimated avoided deforestation and effects of international aid by countries 1) pinpoint where the conservation activity and resources distribution are effectively practiced, 2) helps establish the link to socio-economic factors and their significance and underlying implications.

County based estimates of avoided deforestation by PAs and effects of international aid showed a various pattern throughout the Tropics. Notably, two largest sources of tropical deforestation during the 2000s, Brazil ($2.2 \text{ Mha}\cdot\text{yr}^{-1}$) and Indonesia ($0.8 \text{ Mha}\cdot\text{yr}^{-1}$), showed a sharp contrast (Kim et al. 2015). Brazil showed about 50 times higher estimates of avoided deforestation compared to Indonesia while Indonesia has received about 5 times more international aid (11 billion US Dollars) compared to Brazil (2.4 billion US Dollars) resulting in 50 times lower estimates of effects of international aid ($0.5 \text{ m}^2/\text{USD}$) compared to Brazil ($22 \text{ m}^2/\text{USD}$). Relatively high rates of avoided deforestation from PAs in Brazil emphasize the important role of Brazil in tropical forest conservation. Positive avoided deforestation effects of PAs in Brazil were also reported by previous studies (Nolte et al. 2013; Soares-Filho et al.

2010). PAs in Brazil established since 2000 showed reduced deforestation of 2,794 km² annually which is corroborated by an annual 2,500 km² of avoided deforestation between 2004 and 2006 reported by Soares-Filho et al. (2010).

Previously, Defries et al. (2010) have demonstrated that agricultural export and urban population growth were the most dominant drivers of tropical forest loss between 2000 and 2005. To analyze the relationships between increased deforestation and the effectiveness of tropical forest conservation efforts, this study performed a regression analysis between factors which reflect socio-economic changes between the 1990s and the 2000s. The results show a highly significant, negative association ($p < 0.0001$) with increased deforestation rate and difference of annual GDP growth rate between the 1990s and the 2000s, which suggests that countries with fewer resources for economic development during the 2000s were under higher pressure to deforest (Alvarez-Berríos & Mitchell Aide 2015; Geist & Lambin 2001; Rudel & Roper 1997). The significant association between the difference of agricultural product growth rate and increased forest loss rate, between the 1990s and the 2000s suggests that agricultural intensification, evidenced in Mato Grosso in Brazil (Gibbs et al. 2015) may not be prevalent throughout the tropics (DeFries et al. 2013). The pronounced positive association ($p < 0.0001$) exhibited by the regression analysis between estimated avoided deforestation from PAs and increase in deforestation rate between the 1990s and the 2000s in each country (Table 2) suggests that protected areas have been effectively established where deforestation is accelerating. Latin American countries showed higher rates of avoided deforestation compared to the increased forest loss rate although it cannot be ascertained if it is due to proper

allocation of PAs, or that PAs in Latin American countries are more effectively managed. The results presented in this paper also demonstrate the possibilities of satellite-based forest loss monitoring to supplement and enhance the process of allocation of conservation efforts and resources. A highly significant association of the effect of international aid with the rule of law emphasizes the importance of good governance in enhancing the effectiveness of international aid. This finding is consistent with studies (Miller et al. 2013) that illustrate that aid agencies have a preference for countries with ‘good governance’.

The avoided deforestation from PAs is estimated with Landsat based, spatially explicit long-term forest change data and the DID estimator. The approach of this study offers an alternative way to handle the commonly criticized selection bias and spillover problems (Andam et al. 2008; Stern et al. 2001).

The 10 km buffer was estimated to be better in avoiding deforestation than the 25km buffer from PAs (Figure 4-3). This could be due to a modest spillover effect (Gaveau et al. 2009), and areas closer to PA boundaries might be inaccessible, isolated (DeFries et al. 2005) or even better protected due to buffer zone conservation initiatives (Alers 2007). However, since the overall differences between the two estimates using different buffer distances were marginal at the country level, and they show a near-linear relationship ($p < 0.0001$, $R^2 > 0.92$), this study used estimates of avoided deforestation with a 10 km buffer distance for the regression analysis. The overall positive effect of PAs in reducing deforestation throughout the tropics corroborates with previous studies (Andam et al. 2008; Gaveau et al. 2009; Joppa & Pfaff 2010; Nagendra 2008; Nelson & Chomitz 2011; Oliveira et al. 2007). However,

unlike many previous studies, the results of this study provide a consistent, long-term estimate throughout the pan-tropics.

On average, PAs established after 2000 showed a greater avoided deforestation than PAs established before 2000. Nevertheless, old established PAs were still effective, just not as much as recently established ones (Nelson & Chomitz 2011). Table 4-5 shows the mean deforestation rate in PAs and surrounding areas designated during 1990-2000 and 2000-2010. The lower deforestation rates in recent PAs and the higher rates in the recent surrounding areas after 2000 shows that, the greater avoided deforestation of recent PAs are not because of its remoteness. Congo, Belize, the Philippines and Sri Lanka showed positive avoided deforestation from PAs established since 2000, while estimates including all PAs established before 2000 showed negative effects in these countries, suggesting the old established PAs in those countries are experiencing higher rate of deforestation.

Although the estimates of avoided deforestation and the regression analysis were statistically robust, this study has some limitations. First, the estimates of forest cover change do not distinguish between primary and managed forests, thus leaving a potential for confusion between loss of natural forest and harvest. Second, the coarse spatial scale of socio-economic data limited the regression analysis to the country scale that in turn prevented the regression analysis between individual PAs and their geophysical factors. Third, Brazil's success in reducing deforestation is an exceptional case made possible under a special political landscape (Gibbs et al. 2015; Nolte et al. 2013), which is difficult to generalize to other tropical countries. Finally, for the estimates of the effect of international aid, I only considered the contribution

of international monetary aid. Other domestic sources of funds (e.g. Amazon Region Protected Areas Program of Brazil) and different aspects of conservation (e.g. biodiversity) or political environment, which vary by country and over time were not accounted for in this study. Also, the processes of international aid delivery were not considered in this study. For example, Norwegian funds are committed to Indonesia under the condition that they meet specific conservation goals. Further analysis is needed to estimate the effects of differences in the distribution of funds.

4.5 Conclusion

The results of this study showed an overall positive effect of pan-tropical PAs on reducing deforestation during the 2000s. The overall positive effect of PAs in reducing deforestation throughout the tropics corroborates with previous studies (Andam et al. 2008; Gaveau et al. 2009; Joppa & Pfaff 2010; Nagendra 2008; Nelson & Chomitz 2011; Oliveira et al. 2007). However, unlike many previous studies, the results of this study provide a consistent, long-term estimate throughout the pan-tropics. The results of the estimated avoided deforestation and effects of international aid by countries pinpoint where the conservation activity and resources distribution are effectively practiced and helps establish the link to socio-economic factors and their significance and underlying implications. The analysis of this study showed that, the increase in deforestation rate between the last two decades were positively and significantly associated with increases in GDP growth rate, agricultural production growth, and urban population growth; PAs that were established in areas with high deforestation rates were relatively more effective; the effectiveness of international aid can be suppressed by weak governance and lack of forest change monitoring

capacity in each country. These patterns and links underscore the challenges that policy instruments face and also provide a launch pad for alternative strategies for future conservation policies and initiatives. Nevertheless, with robust empirical approach and future availability of data on socio-economic drivers, the protection of critical ecosystem services in a coupled human-natural system can be better understood.

Chapter 5 Conclusion

5.1 Summary

The three individual studies in this dissertation develop the methods to estimate pan-tropical/global forest cover change, using Landsat data, analyze the long-term trends in pan-tropical deforestation, and combine the remote sensing based estimates of pan-tropical forest cover change with econometrics, to evaluate the effectiveness of the protected areas, and international aid, as outlined in section 1.5.

This final chapter summarizes the key findings from the dissertation, related to the initial questions (Section 5.2). Section 5.3 demonstrates the theoretical implication of this research, and Section 5.4 considers the political implication of these conclusions, for improving the monitoring and evaluation of tropical forest conservation activities. Finally, Section 5.4 suggest the avenues for future research, based on the conclusions from each chapter.

5.2 Dissertation Summaries and Conclusions Related to Priority Research Areas

The individual chapters in this dissertation address the issues, when assessing historical forest cover change in the global or pan-tropical scale, using Landsat data, and the issues that arise when evaluating the effectiveness of conservation efforts, to reduce pan-tropical deforestation. The main findings from each chapter are summarized in this section.

Chapter 2 demonstrates the feasibility of extending the global, Landsat-resolution forest cover mapping, and the change detection, back to 1990. A method is presented to retrieve the historical maps of forest cover, and change from 1990 to 2000, based on the archival Landsat images and reference data hind-cast from the more recent (i.e., post-2000) periods. The results of this retrospective classification, and change-detection algorithm, are presented in this chapter, including: (1) a global map of 1990 forest cover at 30 m resolution, and global extent with a correspondingly scaled layer, estimating the classification uncertainty and (2) a global map of forest-cover change between 1990 and 2000, also with a corresponding uncertainty layer.

The error estimates are based on the samples of independently collected reference data over the United States, and globally, are reported to assess the quality of the forest-cover, as well as the change estimates. Results of accuracy assessments are compared to those from the previous change-detection efforts, such as NLCD (Fry et al. 2009).

Chapter 3 analyzes a consistent series of forest cover change datasets, based on the satellite observations in 1990, 2000, and 2010 period, with application of the methods developed in this research (Kim et al. 2014; Sexton et al. 2013) to estimate the changes in tropical forest area at high (30-m) spatial resolution in 34 tropical countries from 1990 to 2010. The data enable a spatio-temporally comprehensive alternative to the FAO reports, and other sample-based satellite analyses throughout (e.g., Achard et al. 2014; FAO, JRC 2012), with the application of a consistent definition of forest.

Chapter 4 estimates the effectiveness of Protected Areas in the tropics, during the 2000s, based on long term, large-scale forest cover change, from the series of forest cover change datasets that are based on satellite observations in the 1990, 2000, and 2010 periods (Kim et al. 2014, 2015). This chapter also estimates the effect of international aid on avoided deforestation by the PAs, and analyzes the relationship between the socio-economic variables on the increase in deforestation, avoided deforestation by PAs, and the effects of international aid, to identify the factors most strongly associated with them.

The main conclusions from the dissertation, regarding the priority research areas outlined in Section 1.6, are summarized below:

- 1. How can historical global forest cover change from 1990 to 2000 be estimated using Landsat data?**

A world first, the global map of 1990 forest cover, and 1990 to 2000 forest-cover change, has been produced from the USGS archive of Landsat images, using training data hind-cast from the 2000 and 2005 GLS epochs.

Overall accuracies are reported for the US of 93% for the forest cover map in 1990, and 84% for 1990 to 2000 forest-cover change. The maps are of equal or greater accuracy than 1992-2001 retrofit change product of the 2001 NLCD, over the conterminous United States (Fry et al. 2009). Globally, the forest-cover change accuracy was 88 %. The method gained its strength from the use of stable pixels, with

consistent definition of forest over time, and, through the minimization of influence from training data uncertainty.

The maps depict the global distribution of gross gains and losses in the forest cover, as well as their net change. Whereas some regions (e.g., the Amazonian arc of deforestation, Indonesia) have been the perennial centers of forest loss, others (e.g., the southeastern United States and southern Sweden) have retained relatively rapid rates of both gains and losses from 1990 to 2000. While some regions (e.g. inland Southeast Asian countries) exhibited a rapid change of deforestation rates around 2000, most of Africa exhibited persistent and relatively slow rates of forest cover change, except for some regions (e.g. Democratic Republic of Congo).

2. What are the forest cover change trends in the tropics? Is tropical deforestation decelerating since 1990?

A series of forest-cover maps, based on satellite imagery, are applied, with a consistent, biophysical definition of forest cover, to estimate the area and change of pan-tropical forests in 34 countries, from 1990 to 2010. The results indicate a 62% acceleration of net forest loss over the humid tropics, from $4.04 \times 10^6 \text{ ha}\cdot\text{yr}^{-1}$ during the 1990s, to $6.54 \times 10^6 \text{ ha}\cdot\text{yr}^{-1}$ in the 2000s—mainly driven by the strong acceleration in gross forest loss in tropical Latin America. Second, a 7.2 % deceleration in net forest loss was identified, from $6.98 \times 10^6 \text{ ha}\cdot\text{yr}^{-1}$ in the early 2000s, to $6.09 \times 10^6 \text{ ha}\cdot\text{yr}^{-1}$ in the late 2000s, due to the accelerated forest gains in tropical Asia and decelerated forest losses in Brazil.

Although slower than on the other continents, the gross forest-cover changes in tropical Africa, dominated by the changes in the Democratic Republic of Congo and Madagascar, resulted in some net losses, which accelerated steadily from 1990 to 2010.

The estimates reveal an acceleration of net deforestation, from the 1990s to the 2000s, across the tropics. Gross and net forest-cover losses rose from the 1990s, to a peak in the early 2000s, and then decelerated slightly from 2005 to 2010. This acceleration contradicts the commonly accepted assertions of deceleration (e.g. Anon, 2014).

3. How effective are the conservation efforts, including designation of protected areas and international monetary aid, for biodiversity conservation to reduce tropical deforestation?

Long term, large-scale forest cover change from Landsat (30-m), which has been recently made available (Kim et al. 2014), are applied to calculate the deforestation rate during the 1990s and the 2000s. Avoided deforestation, by protected areas in the tropics during the 2000s, is estimated, using the forest cover change data, and an econometric method, called difference-in-difference.

The results demonstrate that the protected areas in the tropics avoided $83,500 \pm 21,200$ km² of deforestation during the 2000s. Brazil's PAs have the largest amount of avoided deforestation at a total of 50,000 km² among the 34 tropical countries. Brazil showed the highest estimates of the effects of international aid on the avoided deforestation of 22 m²/USD, which is about 50 times higher, when compared to

Indonesia (0.5 m²/USD). The results also show that the protected areas have been relatively more efficient in those countries, where the deforestation pressures were increasing, and where governance and forest change monitoring capacity can be important factors, to enhance the efficacy of international aid.

5.3 Theoretical Implications of Dissertation Conclusions

The first contribution of this dissertation is the provision of the world's first, global forest cover map of 1990, and the forest cover change map from 1990 to 2000 in the Landsat resolution (30 m). Maps of historical forest cover provide crucial baselines for satellite monitoring of the changes in Earth's forests. They are also necessary for understanding the social and ecological causes, and impacts of forest changes, and for assessing the effectiveness of conservation policies—most notably, for the REDD (Olander et al. 2008). Methodological advances are made, by the application of hind-cast approach, coupled with the use of globally available surface reflectance data, derived from the GLS data (Feng et al. 2013). This method demonstrated the feasibility to extend the spectral signatures through time and space, for the purpose of large-area mapping (Kim et al. 2014; Pax-Lenney et al. 2001; Sexton et al. 2013; Woodcock et al. 2001). Importantly, the application of consistent definition of forest and method, over time and space, enabled the pan-tropical/global scaled long-term analysis. The successful application of this concept and methods provided the opportunities to explore different temporal domains forward, and even further backward to 1970s, when the first Landsat satellite was launched.

The second contributing aspect of this research is that it advances the understanding of the trends in pan-tropical forest cover change, based on the data

produced from this dissertation. Chapter 4 presents the world-first, Landsat scale pan-tropical analysis, of changing deforestation rates between the 1990s and 2000s. The results from Chapter 4 demonstrated the overall opposite trends of tropical forest cover change, compared to the FAO estimates, showing 62 % of increase in forest loss between the decades. Besides the opposing estimates of the changes in forest cover change trends, this research is distinguished from the FRA, through 1), the enforcement of spatially and temporally consistent definition of forest, thus enabling a direct comparison between the estimates for different periods possible. 2), application of an easily replicable and consistent method on the entire study area, and 3), publicly available data sources and intermediate forest cover change product, used to calculate the forest cover change rate, which provides a basis for further geospatial analysis. Those characteristics are the essential basis for the inference of the drivers of forest cover change in various geographical and socio-economical contexts, especially where the relationship between long-term trends in forest cover change and its drivers are hindered by its inaccurate estimates, resulting from semantic and methodological inconsistencies.

The final contribution of this research is that it sets a link between the remote sensing-based observations, and the evaluation of conservation policies, by applying comprehensive, spatially explicit forest cover change data, to evaluate the efficacy of the policies and resource distribution. Methodological advances are made to overcome the issues, including selection bias, spillover effects, and the computational difficulties in the existing methods. The application of the developed methods demonstrates the feasibility of analysis, to identify the socio-economic factors, which

significantly affects the efficacy of conservation policies. The results of this study provide a comprehensive, pan-tropical scale evaluation of the effectiveness of conservation efforts, including protected areas and international aid, which were not affordable before this study.

5.4 Policy-Relevant Implications of the Dissertation Conclusions

Since 2005, the negotiations under the UNFCCC have emphasized the role of REDD+ in climate change mitigation. As the global interest in reducing deforestation grows, the increasing numbers of governments, corporate groups, and inter-governmental organizations have set the time-bounded targets for achieving “zero deforestation”. For example, in 2010, the CBD adopted a revised strategic plan for biodiversity for 2011-2020, including the Aichi Biodiversity Targets. One of the targets is to reduce the rate of loss of all natural habitats, including forest, by 2020.

Recent FAO-FRA in 2015, reported that the global deforestation rates have fallen to below half the rates at the 1990 level (FAO 2015). While the reports seemingly demonstrate the effects of the previously mentioned policies and plans, there has been a considerable amount of criticism on the FAO-FRA, which remains unresolved. These criticisms for the FAO-FRA come from the ambiguity in the definition of forest (DeFries et al. 2002; Grainger 2008; Matthews 2001), the inconsistent survey methods were largely dependent on the information gathered from country reports, and reporting the net deforestation over gross loss of forest, which adds the area of tree plantation as forest gain (Brown & Zarin 2013).

The results of this study clearly demonstrate how remote sensing-based estimates, with a consistent and biophysically defined definition of forest, can

demonstrate completely opposite trends of tropical deforestation. These results emphasize that, in order to achieve the goal of “zero deforestation”, much more efforts should be made, to accurately estimate the current status of tropical forest, and that allocation of efforts and resources for conservation should be based on accurate observations, to prevent any waste of valuable resources.

In 2010, there were about 4,000 designated PAs in the humid tropical countries, and about 62 billion US dollars of international aid was received by those countries, between 2000 and 2010, to promote the conservation of biodiversity. However, a comprehensive evaluation of the long-term effects of those efforts has been hardly achieved. The utilization of the consistent, spatially explicit long-term forest cover change data enabled the evaluation of the efficacy of policies and conservation efforts. The results of this study demonstrate the locations where the allocated resources are more efficiently used. The findings underscore the challenges that the policy instruments face, to efficiently distribute the existing resources, and also provide a launch pad for the alternative strategies for future conservation policies and initiatives.

5.5 Future Research Directions

A method to hind-cast the global scale forest cover change, back to 1990, using surface reflectance data from Landsat, is developed in this study. The successful application of the developed methods helped enable tracking the transition of Earth’s forest from 1990, and also provided a possibility to extend the observation backward to the 1970s, when the earliest Landsat archive was freely available. The

longer periods of observations are desirable, to better understand the changes made on the earth's surface, and their interactions with large scale changes, such as climate change.

For the successful application of the methods to the Landsat Multispectral Scanner (MSS) data, there are several challenges which needs to be overcome. First, the development and test of atmospheric correction algorithms for the Landsat MSS data are essential for the application of hind-cast approach, based on “stable pixels”. Recently, the adaptation of the LEDAPS (Masek et al. 2013) for the Landsat MSS data has been developed, and is being tested. However, rigorous evaluations of the results from the algorithm are required, before its operational applications. Second, even the Standard Terrain Correction (L1T) version of MSS show a large variability, in terms of geo-locational accuracy. Finally, the absence of the thermal band in MSS inhibit the use of cloud and water detection algorithm, that have been used in this study (Huang et al. 2010). A reliable method to delineate both cloud and water for MSS data should be developed and tested before their application on the hind-cast approach.

Enhancements of the results of this dissertation can be made, with supplemental imagery from various sources. Landsat global archive consolidation program (Repatriating program) (Loveland & Dwyer 2012) has increased the available numbers, and the extent of Landsat image (Figure 5-1, 5-2).

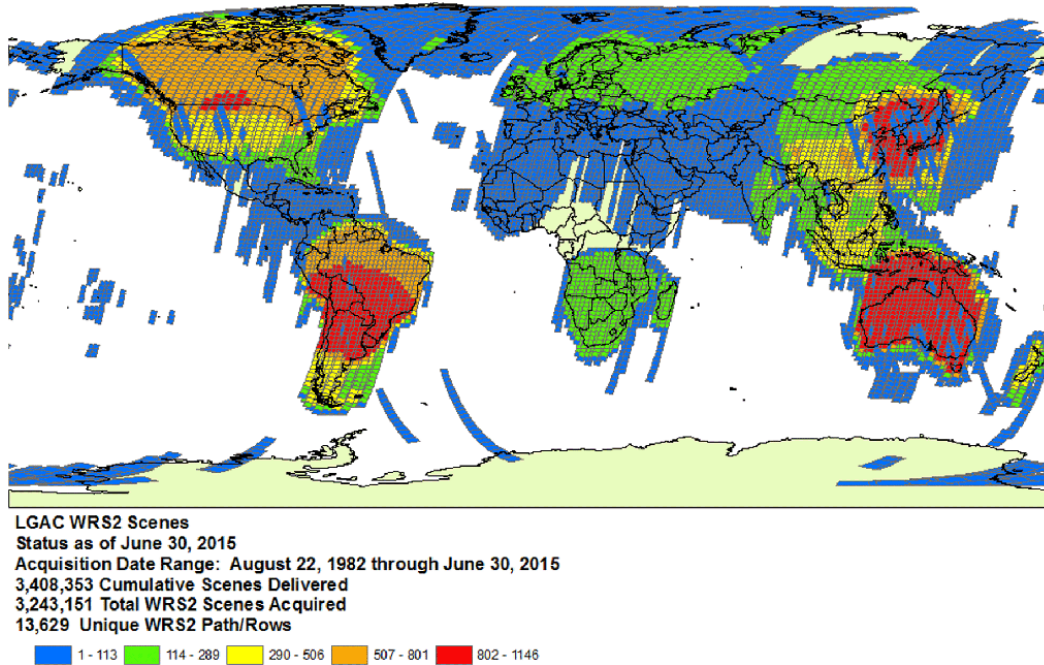


Figure 5-1 Numbers of Landsat TM image by WRS-II tile, consolidated from international archives by Landsat global archive consolidation program, on June 30, 2015 (http://landsat.usgs.gov/Landsat_Global_Archive_Consolidation.php).

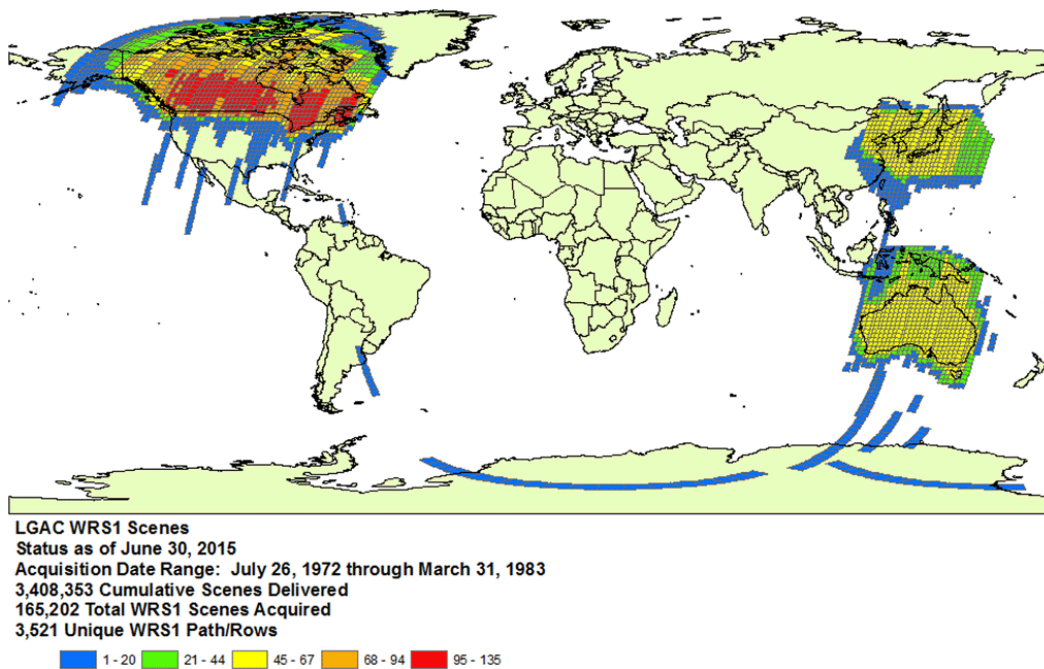


Figure 5-2 Numbers of Landsat MSS image by WRS-I tile, consolidated from international archives by Landsat global archive consolidation program, at June 30, 2015 (http://landsat.usgs.gov/Landsat_Global_Archive_Consolidation.php).

In addition, images such as Satellite Pour l'Observation de la Terre (SPOT) provides similar quality to Landsat TM. The USGS SPOT Historical archive provides North American coverage between 87 degrees north latitude and 10 degrees north latitude, acquired between 1986 and 1998. Each nominal scene covers a 60 by 60-km area. The USGS/Earth Resources Observation and Science (EROS) SPOT archive includes the following data volume: ~ 514,500 PAN scenes and ~ 281,700 Multi-spectral scenes. The acquisition years range from June 1986 to December 1998. All SPOT historical scenes are provided in L1T format, produced using Landsat GLS 2000 data as reference.

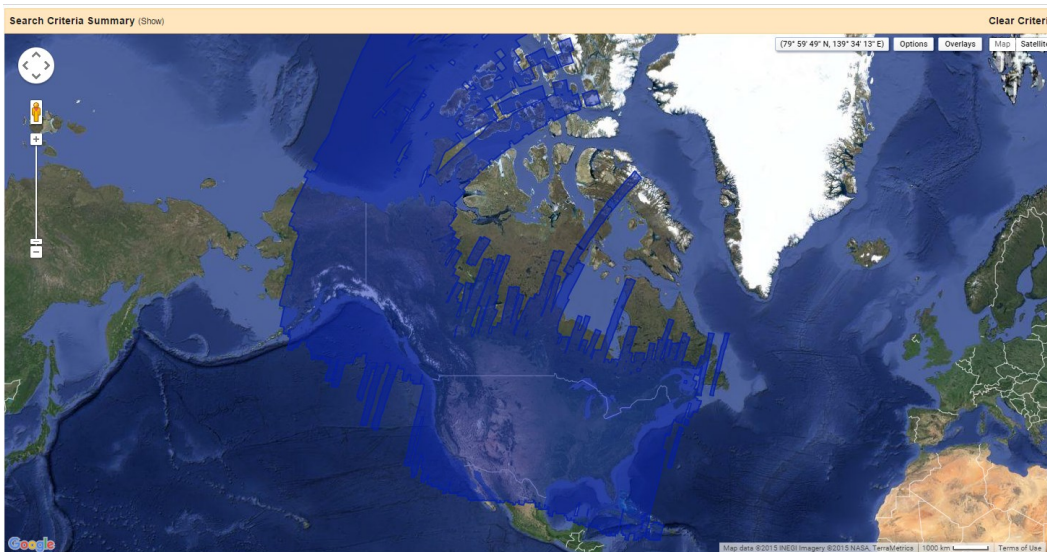


Figure 5-3 Spatial coverage of SPOT historical data in the USGS archive in blue tiles. SPOT historical data are available for download at no cost (https://lta.cr.usgs.gov/SPOT_Historical).

The Centre National d'Etudes Spatiales (CNES) recently announced the opening of their entire archive, which older than 5 years, to the public, by the end of 2015 (CNES, 2014). With the additional images, problems with cloud, gaps, and errors from the phenological mismatch can be significantly reduced. Other

improvements can be made, by using time series of Landsat data, such as Web Enabled Data (WELD). The development of WELD data for the 1990s is planned, and the data can be used to remove cloud contamination, and to address the forest phenology issues

(http://globalmonitoring.sdstate.edu/projects/weldglobal/gweld.html#prod_avail).

In this study, only 34 tropical countries were subject to the analysis on forest cover change rates, between the 1990s and the 2000s, and avoiding deforestation by protected areas. Since the processes are highly automated, the methods developed in this research can be applied to a global scale analysis. Critiques have been made of the remote sensing based studies of forest cover change, including this study, for not being able to distinguish between the loss of natural forest and the harvest of planted trees (Tropek et al. 2014). Efforts are being made to overcome such limitations, based on better algorithms and additional metrics from various supplementary data (Margono et al. 2014; Tyukavina et al. 2015). Also, the evaluation of effectiveness of PAs, and the international aid in the individual protected area level, can be done with a high quality socio-economic data, with detailed spatial scale. The lack of data, such as policy and their status of enforcement, could not be incorporated into the study, while, in many cases, it could be the most influential factor. More studies are required to develop such data, and the analysis will be based on the developments. Geotagged aid data is being developed, and some are already available (AidData, 2015). This enables the possibilities of tracking the effect of individual protected areas, through various methods.

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