EVALUATING UNCERTAINTY IN TROPICAL FOREST LOSS BETWEEN 1990 AND 2010: AN INTER-COMPARISON OF DIFFERENT DATA SETS

by

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ABSTRACT

Tropical forests are a lynchpin for environmental and social services, but are undergoing rapid deforestation. Despite the urgency of this issue, and despite rapid technological advances in monitoring tropical deforestation, and the existence of multiple studies of tropical forest loss over the last two decades, there is little certainty on the rates of tropical forest loss. We intercompared available pan-tropical forest change studies over the 1990-2010 period to examine: 1) differences in tropical forest loss during the 1990s, 2) differences in tropical forest loss in the 2000s, 3) differences in the rate of change of tropical forest loss from the 1990s to the 2000s, and 4) how these pan-tropical estimates compare to independent country/regional-level estimates of tropical forest loss. On balance, we conclude that tropical forest loss is decelerating between those decades. We also find that country reports from the Forest Resources Assessment of the Food and Agriculture Organization appear to be the least reliable; that satellite-based data appear the most reliable despite some persistent differences; and that there is higher agreement between forest loss estimates in Latin America. Our study improves current understanding of tropical forest loss in order to better inform policies to reduce deforestation, and in order to improve future tropical forest change analyses.

LAY SUMMARY

Tropical forests provide important environmental and social services, but are undergoing rapid deforestation. Despite the urgency of this issue, and despite increasing efforts to stop tropical forest loss, little is known about how much tropical forest is being lost. We compared the available studies on all tropical forest loss over the 1990-2010 period. The data suggests that tropical forest loss has decelerated from the first to the second decade. Further, the country reports from the Forest Resources Assessment of the Food and Agriculture Organization appear to be the least reliable and that satellite-based data appear the most reliable despite some persistent differences. Finally, we find that there is a regional bias higher agreement between forest loss estimates in Latin America. Our study improves current understanding of tropical forest loss in order to better inform policies to reduce deforestation, and in order to improve future tropical forest change analyses.

PREFACE

Navin Ramankutty, my research supervisor, helped to conceptualize each research question and its associated methodology. The members of my committee, Dr. Nicholas Coops and Dr. Milind Kandlikar helped shape and narrow these questions. While preliminary research and the majority of data acquisition was completed by myself, Dr. Ramankutty facilitated key data set acquisition from Dr. Frédéric Achard. Analysis and interpretation of data was completed jointly by myself and Dr. Ramankutty, with instrumental feedback on approaches to data aggregation from Dr. Achard, help with data visualization from colleague Dr. Zia Mehrabi, and help with formatting and final edits from colleague Larissa Jarvis. The graphics and text comprising this thesis was completed by me. Dr. Ramankutty has reviewed the material as presented in this text.

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CBD ITTO	Convention on Biological Diversity’s Initiative for Tropical Forest Biodiversity
DRC	Democratic Republic of the Congo
FAO	Food and Agriculture Organization of the United Nations
FRA	Forest Resources Assessment
PNG	Papua New Guinea
RSS	Remote Sensing Survey
UN-REDD	United Nations Program for Reducing Emissions from Deforestation and Forest Degradation

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1. Introduction:

Globally, forests provide environmental services critical to human existence. Forests are a critical ecological lynchpin, mitigating climate change by providing carbon storage (Dixon 1994), supporting areas of concentrated biodiversity (Gibson et al. 2014), preventing soil erosion (Mohammad and Adam 2010), and increasing water quality (Fiquepron, Garcia and Stenger 2013). Forests also provide social services as a key source of environmental income for the rural poor, in the form of both direct forest products for construction and fuel, indirect products in the form of forest-supported wildlife and plants, as well as payments for forest-based environmental services (Angelsen et al. 2014)

Of all forest biomes, tropical forests are uniquely able to provide substantial quantities of these benefits. Tropical forest ecosystem services are estimated to be worth twice the dollar value of temperate forests (Costanza et al. 2014), sustaining the most biodiverse terrestrial ecosystems on Earth (Montagnini and Jordan 2005). They account for around 25% of stored terrestrial carbon, and provide 33% of the world's terrestrial net primary production of plants through carbon fixation (Bonan 2008). Trees in tropical forests regulate water flow by retaining and releasing water in dry seasons, and by supporting water-retaining "cloud forests"[1]. These forests also act as water filtration systems by regulating flow, removing or biochemically transforming contaminants, and reducing soil erosion (Calder and Aylward 2006). Finally, tropical forests contribute to soil fertility by increasing the availability of organic matter and supporting microbial activity (Don, Schumacher and Freibauer 2011, Dinesh et al. 2003). Tropical forests do all this on less than 5% of global land area (Bonan 2008).

Yet, despite tropical forests' pivotal ecological and social roles, they are being steadily converted to other uses, including cropland, pasture, mining, and urban areas (Hosonuma et al. 2012). Of these, the major driver of forest loss is agriculture; that is, countries with higher economic

[1] However, the science is mixed on whether or not tropical forests in general act as a net "pump" or net "sponge" of water (Brandon 2014).

returns to agriculture are more likely to clear their forests (Busch and Ferretti-Gallon 2017). This is particularly true for tropical countries, whose agriculture is expanding and is predicted to continue to do so (Laurance, Sayer and Cassman 2014).

To prevent further loss of tropical forests, international policy interventions are critical. To this end, major international efforts to mitigate deforestation are already in place, including United Nations Program for Reducing Emissions from Deforestation and Forest Degradation (UN-REDD), the Convention on Biological Diversity's Initiative for Tropical Forest Biodiversity (CBD ITTO), and a constellation of other bilateral and multilateral efforts between governments, international governing bodies, and many international conservation organizations (Leplay and Thoyer 2011).

But have these policies worked? There seems to be good evidence that some policies have worked, for example, the Soy Moratorium in the Brazilian Amazon seems to have successfully slowed down Brazilian deforestation (Gibbs et al. 2015). But there is uncertainty as to whether or not past efforts to address tropical forest loss have been successful across the board. The confusion is apparent in recent policy analyses arguing that, over the last two decades, tropical deforestation has decelerated (Boucher 2015), accelerated (Busch 2015), and more recently that we simply do not know (Hance 2016). This uncertainty has major policy implications. If forest loss has decelerated, it gives policy makers an opportunity to identify and support successful forest loss mitigation policies (e.g., the Soy Moratorium), as well as the opportunity to redirect resources to other competing issues. Alternatively, accelerated forest loss may imply ineffective policies (e.g., although policies work in Brazil, deforestation has leaked to other regions; van Marle et al. 2016), and has implications for climate change and biodiversity targets. In this case, decision-makers would need to improve or change policy approaches. It is clear that resolving uncertainty in tropical forest loss estimates by improved global forest monitoring is necessary for evaluating the success of our measures to protect this valued biome.

Similar to the policy community, the media is likewise confused as to how tropical forests are changing. A quick news search on overall forest trends renders mixed reports on forest loss rates. Some news articles reported that forest loss is decelerating.

"Rate of global forest loss halved, says UN" (Guardian 2015)

"Worldwide deforestation has more than halved since 1990, but..." (Richard 2015)

While others reported that forest loss is accelerating

"Satellite data suggest that forest loss accelerated in the past 20 years" (Tollefson 2015)

"Tropical forests may be vanishing even faster than previously thought" (Mooney 2016)

"Satellite data suggests forest loss is accelerating" (Plantz 2015)

The incongruity in our knowledge of trends in tropical forest loss in the public media and policy realms directly reflects incongruity in the science on forest loss assessments. Over the last two decades multiple studies have been published analyzing tropical forest loss on a country-by-country basis. As explained below, the results of these studies present contradictory trends on deforestation. For instance, the Food and Agriculture Organization of the United Nations (FAO) has collected and published national estimates of deforestation since 1948. In the 1980s it introduced the Forest Resources Assessment (FRA), a more technical approach to understanding forest area change. These assessments collect information on the state of national forests and publish them in reports produced by the countries themselves. By the 1990s, these assessments were being regularly published every five years (FAO 2017), introducing new forest change estimates and revising previous estimates. In 2010, the FRA reported that, between 1990 and 2010, countries with tropical forests experienced a deceleration in forest loss (Table 1). This was encouraging for all governments and organizations that had been instrumental in forest loss mitigation policies over the same time period. The most recent report, FRA 2015, showed an even slightly greater decrease in deforestation (FRA's evolution and content will be further discussed later in the paper).

In 2015, a study from the University of Maryland performed another analysis of forest loss using satellite data, also at a country-level but for tropical forests, specifically. They reported tropical forest change between 1990 and 2010 for thirty-four tropical countries, and systematically found that each one had undergone a marked *increase* in the rate of deforestation over the same two decades (Kim, Sexton and Townshend 2015). They concluded that rates of forest loss had increased by 65% over the last two decades, radically contradicting FRA's estimates that the same thirty-four countries experienced reduced rates of deforestation by 25%.

At first glance, the differences in these two studies may be attributed to their different methods of data collection and analysis. While FRA depends on reported estimates, Kim et al.'s 2015 analysis (hereafter referred to as Kim) was based on data from satellite imagery. The methodology and quality of nationally reported FRA data vary from country to country. Some countries have better institutional capacity for monitoring their forests. For instance, Brazil has established its own National Institute for Space Research (INPE), facilitating the nation-wide Project Brazilian Amazonian Forest Monitoring by Satellites (PRODES), which is a robust forest area assessment and monitoring tool using satellite data established in 1988 (INPE 2011). Meanwhile, countries with fewer resources and/or lower institutional capacity to conduct such high quality surveys, like the Democratic Republic of the Congo (DRC), tend to base their assessments on older data, partial inventories, or expert estimates. While these differences in data quality are acknowledged in the FRA reports themselves through a tiered system, issues with low quality data are a disproportionate challenge for tropical countries. The majority (over 75%) of tropical forests national reports are based on lower quality estimates (Tiers 1 and 2), compared with temperate and boreal country reports that are predominantly based on the highest quality (Tier 3) estimates (90 and 100%, respectively) (Figure 1). Thus one might conclude that the differences between FRA and Kim may be attributed to the poor quality of FRA data, and therefore that Kim's estimate is superior.

Figure 1. Proportion of forest area by climatic domain in 2015 reported at different tiers

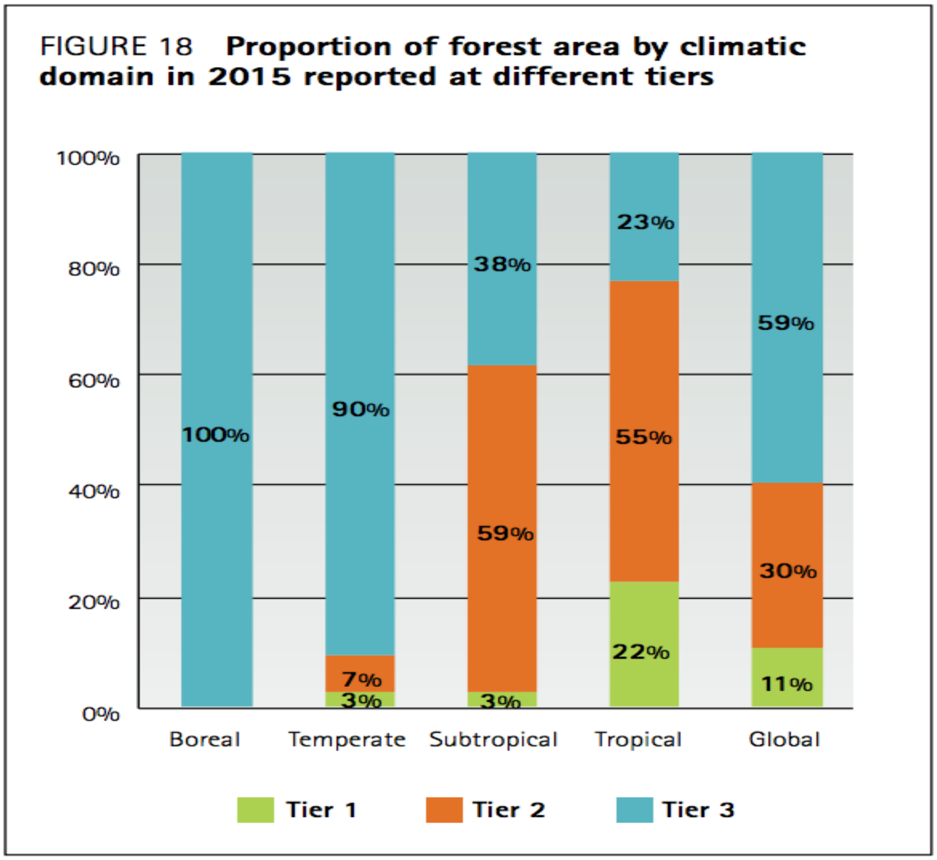


Figure 1 displays the amount of forest area reported by different tiers for each climatic region. The quality is ranked in ascending order: Tier 1 is the lowest quality based on expert estimate, Tier 2 describes low intensity or incomplete surveys and older data, while Tier 3 is the highest quality boasting high reliability, based on recent sources with a national scope.
Source: (FAO 2016)

Kim's study was conducted through analysis of satellite imagery. Satellite imagery has been used to analyse forest cover change globally since the early 1980s (Heller 1985). As the technology has become increasingly affordable and available to researchers, satellite imagery has been increasingly used to understand trends in forest change (Busch and Ferretti-Gallon 2017). Kim analyzed historical satellite imagery to estimate the trends in forest loss from 1990-2010.

To some, remote sensing represents a cleaner, objective, and more consistent approach to forest change estimates (Goetz and Dubayah 2011, Mayaux et al. 2005, Asner 2009). This is also acknowledged by the FRA, who performed a complimentary regional forest loss Remote Sensing

Survey (RSS) to verify their trends based on nationally reported data (Table 1). In recognizing that "the quantity and quality of data available for reporting varies widely on a country-by country basis", the FRA endeavoured to strengthen reporting by comparing the assessments to a study that uses satellite remote sensing "to obtain systematic information on the distribution and changes in forest cover and forest land use… at regional, ecozone and global levels" (FAO 2010b, p.1). While the RSS reported a third as much deceleration as the FRA survey, the trend was consistent: the rate of deforestation in tropical countries decelerated from the first decade to the second. Given that RSS, a satellite-based estimate, contradicts Kim, we have to revisit our conclusion that Kim is superior to FRA simply because it is satellite-based.

Table 1. Data on change in tropical forest loss from the 1990s to 2000s

Study	Period of time	Method	# Countries	Annual forest change, 1990-2000 (ha/year)	Annual forest change, 2000-2010 (ha/year)	Change in forest change
FRA FAO * 2010	1990-2010	Country report	34	-7455	-5601.8	**-25%**
FRA FAO 2015	1990-2010	Country report	34	-6775.7	-4905.9	**-28%**
FRA RSS 2010*	1990-2010	Remote Sensing	Pan-tropic	-7000	-6000	**-14%**
Kim et al, 2015	1990-2010	Remote Sensing	34	-4038	-6537	**62%**

*FRA FAO 2010 is an older report included in Kim's analysis, but for our purposes we used the updated 2015 report .
**The RSS study is pan-tropical, and aggregated at a regional/biome-level, and therefore not included in our analysis.

These contradicting claims about tropical deforestation underscore a fundamental uncertainty in trends of one of the most important global biomes. Each study claims reasonable validity in methods and results; and therefore no single study can be said to be objectively superior to the others without comparative analysis. While all four studies agree that tropical forests are decreasing in area, a crucial question remains unanswered: is tropical forest loss slowing down or not?

To investigate these differences further, we intercompared available data sets of tropical forest loss at the national-level to examine where the data sets differ and why, with the hope that such an analysis might bring new insights on tropical forest loss, and an improved basis for future analyses.

There currently exist multiple studies on tropical forest loss covering the two time periods:

- Annual forest change at the national-level for 15-34 tropical nations for both 1990-2000 and 2000-2010 (n=3)
- Annual forest change at the national-level for 15-34 tropical nations for only 2000-2010 (n=4)
- Independent country and regional-level estimates of annual forest change for both 1990-2000, 2000-2010, as well as 2000-2010 (n=13)

This study aims to intercompare these data sets to address the following four questions:

1. *How do different data sets of tropical forest loss in the 1990s compare?*
2. *How do different data sets of tropical forest loss in the 2000s compare?*
3. *Has tropical forest loss slowed down or accelerated during 1990-2010?*
4. *How do these pan-tropical forest estimates compare to other independent country/regional-level estimates of tropical forest loss?*

2. Methodology

All data examined in this paper were gathered through a review of available literature, including contacting an author for data in one case where it was not reported in the original publication. Our study was conducted in four separate streams of analysis. First, we examined existing pan-tropical data sets with information on forest loss for 1990-2000. Next, we examined existing pan-tropical data sets with information on forest loss from 2000-2010. In the third analysis we examined those data sets with information for both 1990-2000 and 2000-2010, with the aim of evaluating whether tropical forest loss is slowing down or not. In the fourth analysis, we compared the results to independent country/regional (non-pan-tropical) analyses where available; this last analysis helped provide new insights for understanding the differences between data sets for these particular countries, and ultimately postulate accurate trends in forest loss.

2.1 Selection Criteria

Analyses 1-3 were similar in scope and used the same selection criteria, which were as follows: 1) the study must be a pan-tropical analysis; 2) the estimates must report net forest loss; 3) data need to be reported or available at the country level of aggregation, as that was the unit of our analysis; 4) the study must present annual average forest change over the 1990-2000 decade for analysis 1, over the most recent decade (2000-2010) for analysis 2, and for both decades (1990-2000 and 2000-2010) in the case of analysis; 5) statistically robust estimates of forest loss were required from studies aggregating their own pan tropical data (one study used a sampling approach and had too few samples for some of the smaller countries); therefore data need not cover all tropical forest nations exhaustively, but the data set must be regionally representative covering the continents of Latin America, Africa and Asia.

For analysis 4, we broadened the selection criteria to include a greater number of studies in order to independently verify trends concluded in the first three analyses. The selection criteria were as follows: 1) the study must be an analysis of net or gross forest loss, with either quantitative or qualitative information; 2) the study period must overlap with the two decades of focus (1990-2000, and 2000-2010); 3) data can be reported at the country or regional level of aggregation in order to help ascertain broad patterns of change; 4) the independent national data set should overlap with at least one country represented by the pan-tropical data sets, while independent regional estimates should represent trends in either Africa, Latin America, or Southeast Asia and can include countries not included in the pan-tropical data sets.

Table 2. Inclusion criteria for each analysis

	Subject	Time period	Unit of analysis	Data set Scope
Analysis 1	Net Deforestation	1990-2000	Country	Regional, representative of tropics
Analysis 2	Net Deforestation	2000-2010	Country	Regional, representative of tropics
Analysis 3	Change in Net Deforestation	1990-2000 and 2000-2010	Country	Regional, representative of tropics
Analysis 4	Forest Loss	1990-2000 and 2000-2010	Country/ Region	National / regional , overlapping with countries examined in the previous analyses; and regional including countries not examined in the previous analyses

For all analyses, we reviewed the included studies' methodologies and definitions, compared outcomes in terms of estimated forest loss, and posited reasons for differences. We then discuss our findings in terms of the trends they support, where the differences in data sets occur, and why they occur.

2.2 Description of available data sets

2.2.1 Forest Resources Assessment (FRA)

As explained above, FRA reports are made at 10 year, and more recently 5 year, increments. They are based on the FAO mandate stating that "The Organization shall collect, analyse, interpret, and disseminate information relating to nutrition, food, and agriculture." Agriculture here includes forestry and primary forest products (Keenan et al. 2015). As previously described, statistics for these reports are based off of the submission of national data by governments. Methods for data collection vary by country and have changed over time. However, each country uses a common framework, relying on National Correspondents to submit the information. The definition of forest within this framework is broadly described as "forest and other wooded areas." As of the 2000 FRA report, all countries have been asked to use a more specific definition of forest, describing "land of at least 0.5 ha, with a tree canopy cover of more than 10%, which are not primarily under agricultural or urban land use" (Lund 2002). Note that this definition can include un-forested land (un-stocked due to clear-cutting as part of forest management practice or natural disasters) as well as plantation trees (rubberwood, Christmas tree plantations, bamboo and palms) (FAO 2015). The countries are required to report the area of forest, rate of forest expansion, and rate of forest loss. The calibre of data varies by methods of collection, and is denoted by tiers of quality, as previously described. When new FRA reports become available, they update forest area and loss numbers not only for the most recent time increment, but the report also revises all numbers previously published. This means, for instance, that total numbers in the 1990s published in the 2000 report are different for the same decade in the 2010 report

Kim compared their satellite-based estimates to the FRA 2010 study. However, an updated FRA report (FRA 2015) has been published since then, and we used this latest report to provide an updated comparison (hereafter FRA 2015 is simply referred to as FRA). As established in Table 1, the latest FRA corroborates the main findings of the earlier FRA 2010, and actually found even greater deceleration of forest loss over 1990-2010 (FAO 2010a, FAO 2016)

While an FRA satellite review of forest area exists (FAO RSS), the data set provides only regional (continental) and biome-level estimates; there were not enough remote sensing samples to derive country-level estimates (D'Annunzio, Lindquist and MacDicken 2010). The RSS report was therefore omitted from our analysis.

2.2.2 Kim et al. (2015)

Kim's estimates relied on satellite imagery, specifically Landsat images to collect observations for 1990, 2000, 2005, and 2010. The definition of forest cover used was parcels greater than 1 hectare in area and comprising pixels with more than 30% tree cover (Kim et al. 2015). The data provides full coverage of the Earth's terrestrial surface, therefore the study is considered to be a wall-to-wall analysis of forest for each epoch under consideration.

A challenge to satellite imagery analysis is cloud cover impeding observation of land cover and land cover change. Kim's 2015 paper did not address how they dealt with cloud pixels, however another paper by the same authors on forest change in the 1990s suggests they may have used pixels covering the same area from years other than the target year to infer the presence or absence of forest for that year (Kim, Sexton and Noojipady, et al. 2014).

2.2.3 Achard et al. (2014)

Achard et al. (2014) [hereafter Achard] is the most recent study to have estimated forest loss from 1990-2010. We contacted the author for the as-of-yet unpublished country-level data. Achard's method is generally the same as Kim. Achard uses the same Landsat imagery as Kim to estimate forest loss over the same time period. The definition of forest is the same, using a consistent percentage threshold for the same unit of observation (pixels with greater than 30% forest cover). However, whereas Kim was a wall-to-wall analysis, Achard used a sampling method, discussed in further detail later. As Table 3 (below) indicates, the number of countries investigated by Achard is not an exhaustive list of tropical countries. Because the study used a sampling approach, the only countries included in our analysis were those sufficiently large to provide statistically defensible results on forest loss. Achard's approach to overcome the challenge of cloudy pixels differs from Kim. Because Achard used a sampling approach, they were able to find and use cloud-free scenes for the analysis, and they further used a local average surrounding the cloudy areas to act as surrogate results (Achard et al. 2014).

2.2.4 Hansen et al. (2013)

Hansen et al (2013) [hereafter Hansen] has data on forest change for only the last decade, 2000-2010, therefore this study was used only for the second analysis. The study measured forest area change for all biomes globally from 2000-2012. Like Kim and Achard, Hansen used satellite observations from Landsat at a spatial resolution of 30 meters. Like Kim, Hansen used a wall-to-wall analysis, using all available observations to estimate net forest area change. Similar to Kim, cloud covered images for the time period were managed by finding a cloud-free image from the closest year with cloud-free data for the first and last years of the time period examined. Since this paper was published, the authors have released estimates up until 2014 (Hansen et al. 2013).

2.2.5 Independent Country Analyses

Studies for the fourth analysis were included if they presented national or regional forest change results for at least one of the countries included in our analysis, over one or both decades. We found 13 studies, whose results are primarily based on satellite analyses. Of these, 11 were national, and 2 covered regional forest change (Central Africa and Southeast Asia).

While there are only a handful of studies at a pan-tropical-scale that covered forest change from the 90s-00s, there were more studies that looked at change at more local levels. We found studies that analyzed country forest estimates over the last decade (2000-2010), as well as studies covering the change from the 90s to the 00s. There weren't as many independent analyses covering 1990-2000, likely due to less availability of data as compared to 2000-2010, therefore an independent analysis for the first decade was omitted.

Of the studies covering the 2000s, we chose countries with large forest areas and those with high levels of disagreement between studies. According to the latest estimates of forest carbon, Brazil, Indonesia and the DRC, account for 26%, 7% and 6% of the tropical total, respectively (Saatchi et al. 2011). We found four studies for Brazil, three studies for Indonesia, and two studies for the DRC that looked at net forest loss for 2000-2010. We then chose Laos and Malaysia as they each are challenged with high levels of disagreement in the last decade, where estimates range from accelerated forest loss to net forest area gain. We found one independent study for both countries, quantifying forest loss in Malaysia, and qualitatively describing forest loss in Laos.

Of the studies that analyzed forest change from the 1990s-2000s, we found three covering each region: one estimating Brazil's forest change; one estimating forest change in Central Africa, and finally one looking at countries in Southeast Asia

Table 3. List of countries by included study

Tropical Region	Kim	FRA	Hansen	Achard	Independent
	All Tropics	*All Tropics*	*All Tropics*	*Selected Tropics*	*Country/Regional Level*
Latin America	Belize	X	X		
Latin America	Bolivia	X	X	X	
Latin America	Brazil	X	X	X	X
Latin America	Colombia	X	X	X	
Latin America	Costa Rica	X	X		
Latin America	Ecuador	X	X	X	
Latin America	Guatemala	X	X		
Latin America	Guyana	X	X		
Latin America	Honduras	X	X		
Latin America	Nicaragua	X	X		
Latin America	Panama	X	X		
Latin America	Peru	X	X	X	
Latin America	Suriname	X	X		
Latin America	Venezuela	X	X	X	
Africa	Cameroon	X	X	X	
Africa	Congo	X	X		
Africa	DRC	X	X	X	X
Africa	Equatorial Guinea	X	X		
Africa	Gabon	X	X		X
Africa	Liberia	X	X		
Africa	Madagascar	X	X	X	
Africa	Sierra Leone	X	X		
Asia	Bangladesh	X	X		
Asia	Brunei Darussalam	X	X		
Asia	Cambodia	X	X	X	
Asia	Indonesia	X	X	X	X
Asia	Laos	X	X	X	X
Asia	Malaysia	X	X	X	
Asia	Myanmar	X	X	X	

Tropical Region	Kim	FRA	Hansen	Achard	Independent
	All Tropics	*All Tropics*	*All Tropics*	*Selected Tropics*	*Country/Regional Level*
Asia	Papua New Guinea	X	X	X	
Asia	Philippines	X	X		
Asia	Sri Lanka	X	X		
Asia	Thailand	X	X		
Asia	Vietnam	X	X		

Not included in the table are regional studies for Central Africa and Southeast Asia, component countries of these regional analyses are listed in text below.

The number of countries used in our analysis was determined by how many countries overlapped across all four studies (Table 3), leaving us with 15 countries. In our analysis, we look at differences in agreement by region. While there is a smaller sample of countries in Africa (n=3) as compared to Latin America and Southeast Asia (n=6, each), the countries in Africa represent the majority[2] of African tropical forests, and therefore are included in regional comparisons.

2.3 Description of metrics used to analyze differences between data sets

There are numerous metrics to quantify data similarity (Ding et al. 2008), we chose three measures that best suited our data: a Simple Ratio, Euclidean Distance, and Distance from the Mean.

We compare two studies using the Simple Ratio $\frac{A}{B}$, where the numerator is always smaller than the denominator, and agreement is measured as the value closest to 1.

The second metric was a Euclidean Distance metric, included to verify the conclusions of the first metric. Euclidean Distance is a popular method used to measure dissimilarity

[2] Based on forest extent number given in the included studies, the three African countries represent between 75 to 88% of Tropical Africa.

(Shirkhorshidi, Aghabozorgi and Teh Ying 2015), in which the distance between two values in a group of values is compared to the other distances in the group and normalized. The metric is calculated as follows $\sqrt{(A-B)^2} \big/ \sqrt{(A-B)^2+(A-C)^2+(B-C)^2}$, where A and B are two data sets being compared, while A, B, and C are all the data sets being intercompared. The metric ranges from 0 to 1, and shows higher agreement when the value is closest to 0. A similar formula was used in the case of four data sets being intercompared, where the denominator would have six terms instead of three.

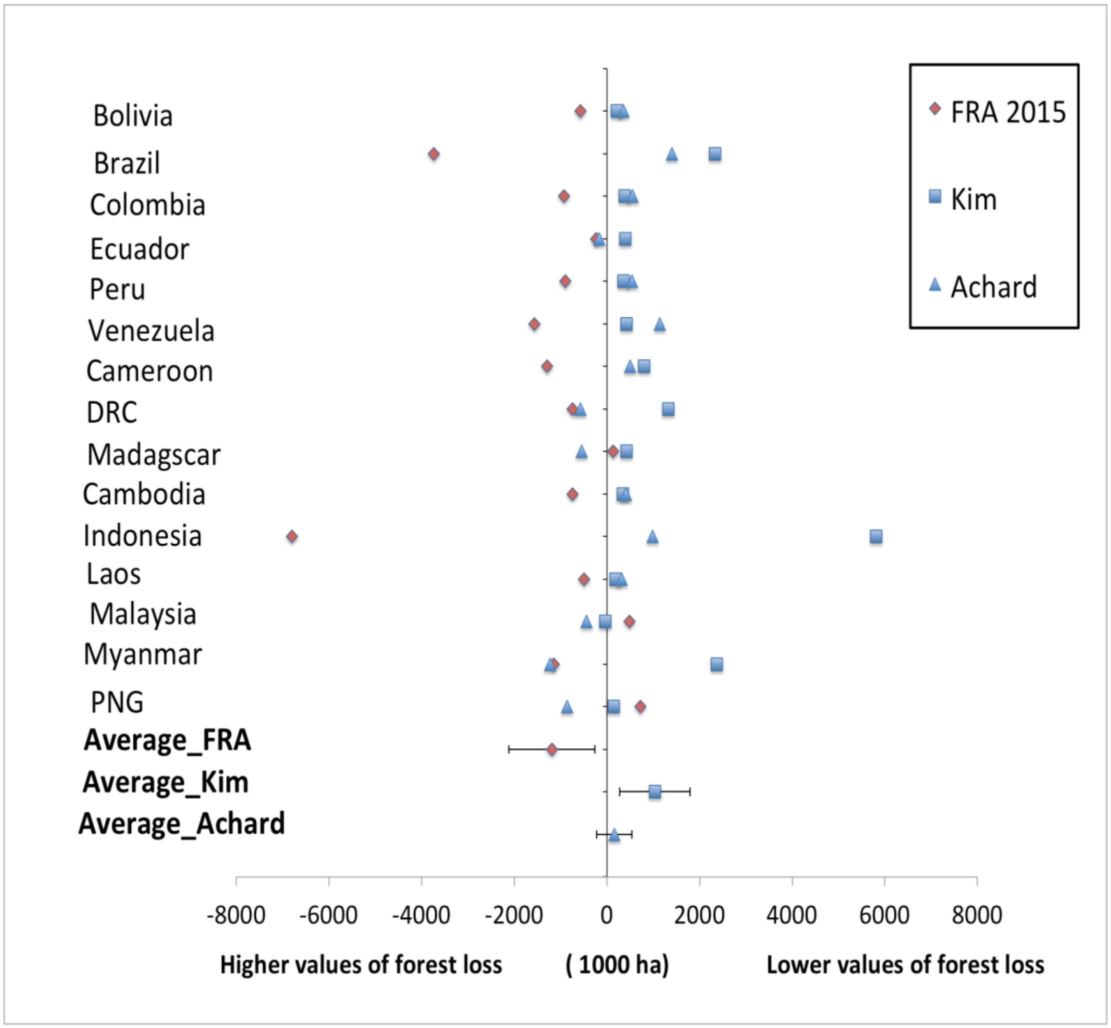
The first two metrics evaluate the difference between pairs of data sets, but says nothing about the quality of each individual data set. As there is no standard against which to compare these data sets, we estimated the percentage difference between each data set and the mean (Distance from the Mean), calculated as $\left(\left(A-\bar{x}\right)/\bar{x}\right)*100$ where A is the data set being evaluated and $\bar{x}$ is the mean of all data sets.

By using these three measures, we were able to better understand the relative differences between all data sets, and ultimately identify which data sets varied least and which varied most from general consensus.

3. Results

FRA's forest loss estimates for the 1990s are much higher than the mean, while Kim's estimates are lower, and Achard's estimates are closer to the mean (Figure 2). Aside from Brazil, there is greater disagreement between estimates for countries in Southeast Asia (the bottom six countries).

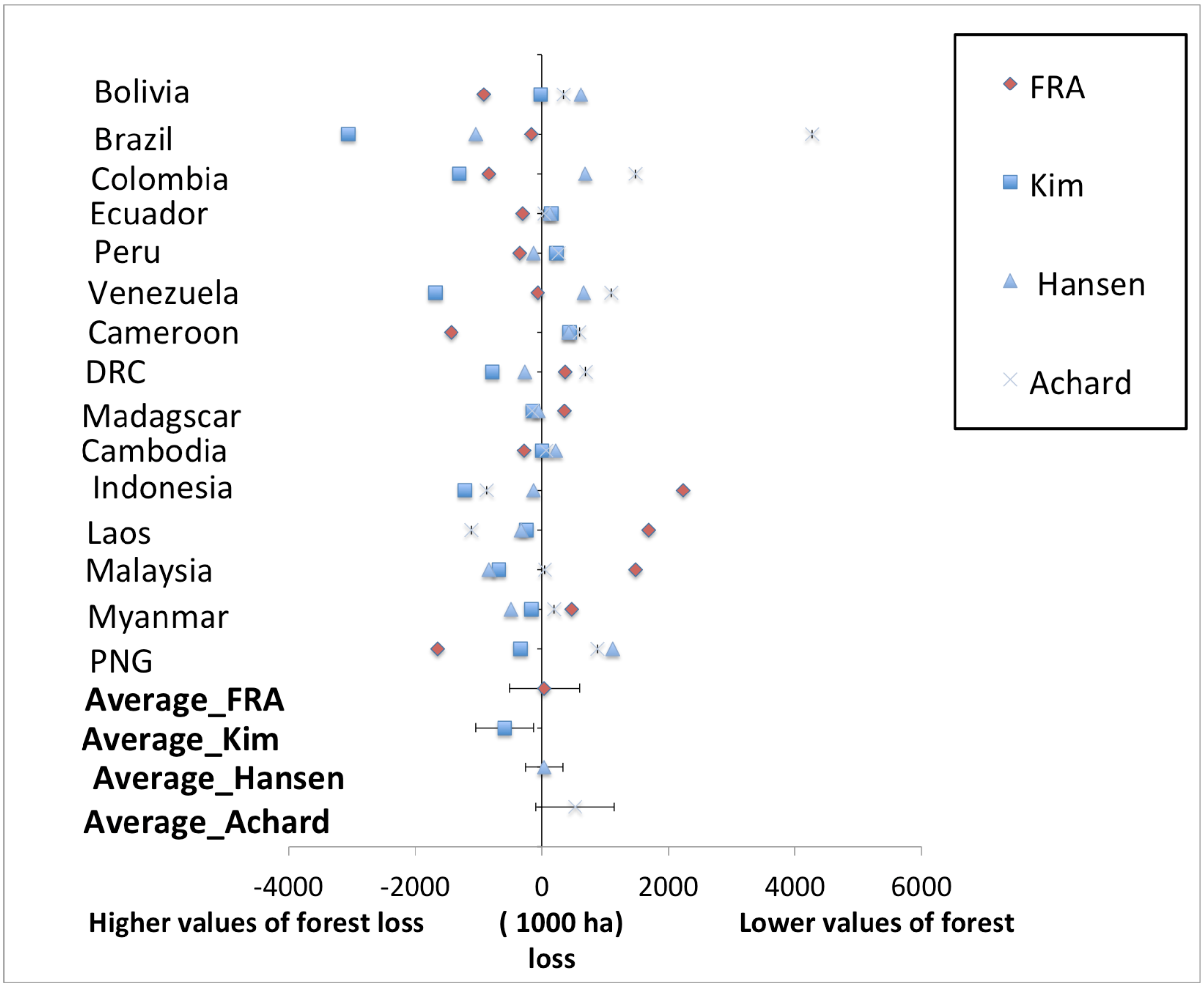
Figure 2. Forest loss estimates for 1990-2000 (values relative to the mean)



Different study estimates of forest loss in the 1990s are expressed as their difference relative to the mean of all estimates per country. Satellite-based estimates and country-report estimates (FRA) are represented by blue and red markers, respectively.

During the 2000s, there appears to be less disagreement between forest loss estimates, as error bars for the average study estimates overlap more with each other (Figure 3). While Kim estimated lower forest loss in the 1990s, their study had some of the highest deforestation values in the 2000s, especially in Brazil. Also, there is higher agreement between forest loss estimates across all studies in the second decade compared to the first (error bars in Figure 3 overlap more than they do in Figure 2).

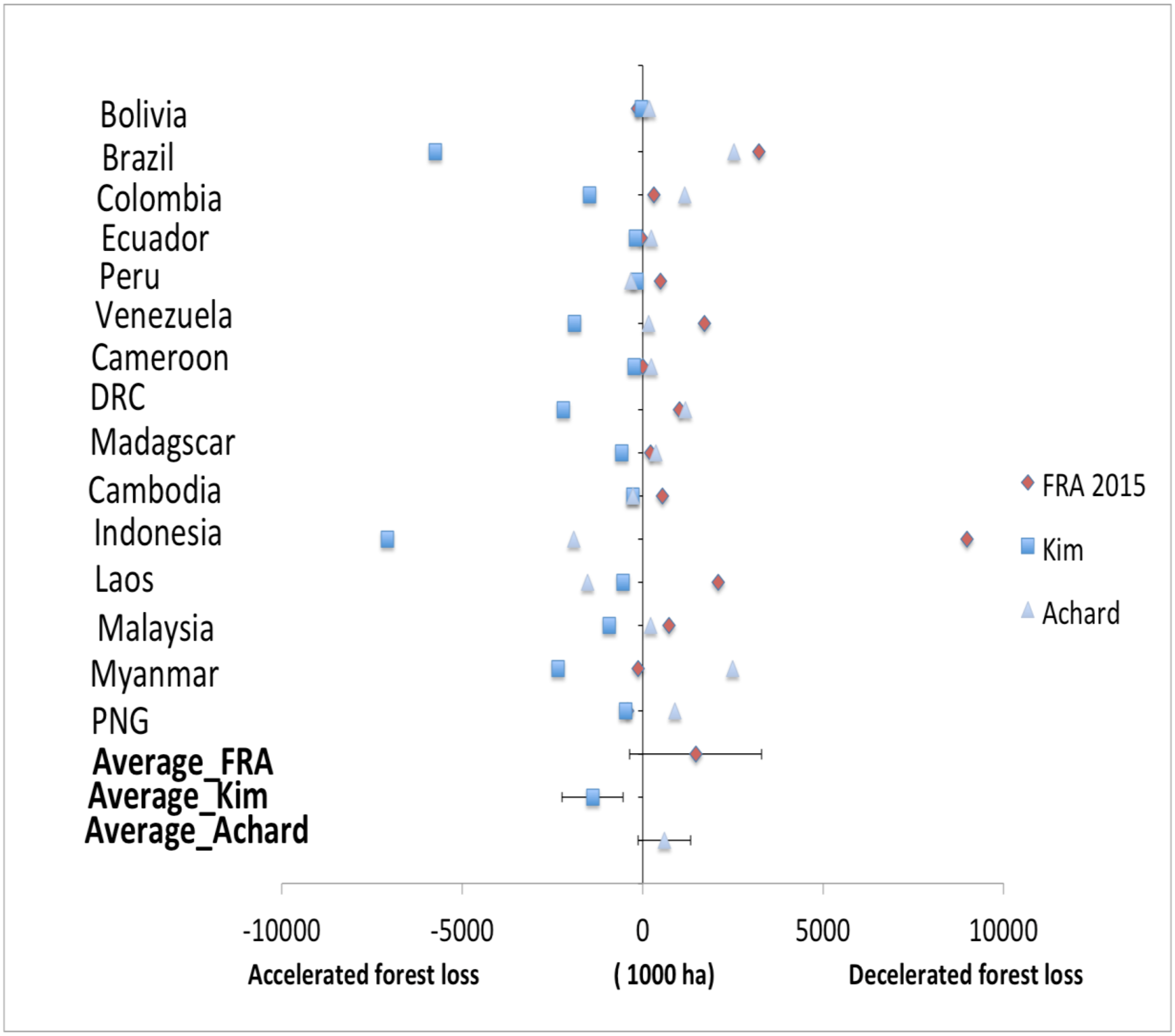
Figure 3. Forest loss estimates for 2000-2010 (values relative to the mean)



Different study estimates of forest loss in the 2000s are expressed as their difference relative to the mean of all estimates per country. Satellite-based estimates and country-report estimates (FRA) are represented by blue and red markers, respectively.

In terms of change in forest loss rates between the two decades, FRA shows a deceleration of forest loss for most countries, while Kim estimated an acceleration for every country (Figure 4). Achard's estimates show acceleration in some countries and deceleration in others.

Figure 4 . Change in forest loss from the 1990s to 2000s (values relative to the mean)



Different estimates of change in forest loss between the 1990s and the 2000s expressed as their difference relative to the mean of all estimates per country. Satellite-based estimates and country-report estimates (FRA) are represented by blue and red markers, respectively.

3.1 Comparing data sets of tropical forest loss over the first decade: 1990-2000

In general, Kim has lower estimates of forest loss in the 1990s, while FRA has significantly higher estimates (-35,780 and -69,103 thousand ha, respectively) (Table 4). Kim's lower estimates compared to the other studies are especially evident in Brazil and Indonesia. These countries are also where FRA estimates higher forest loss. In general, in the 1990s, FRA nearly always had the highest estimate of forest loss (in 11/15 cases).

Table 4. Forest loss from 1990-2000 (1000 ha/decade)

Region	Country	FRA	Kim	Achard
Latin America	**Bolivia**	-2704	-1910	-1768
	Brazil	-25431	-19360	-20295
	Colombia	-2619	-1300	-1138
	Ecuador	-902	-270	-831
	Peru	-1774	-520	-337
	Venezuela	-2875	-890	-167
Africa	**Cameroon**	-2200	-110	-413
	DRC	-3114	-1040	-2941
	Madagascar	-669	-380	-1343
Southeast Asia	**Cambodia**	-1398	-310	-249
	Indonesia	-19136	-6530	-11356
	Laos	-1119	-430	-307
	Malaysia	-785	-1300	-1715
	Myanmar	-4350	-830	-4439
	PNG	-27	-600	-1608
	TOTAL	**-69103**	**-35780**	**-48907**

The minimum and maximum values for each country and totals are represented by green and red shading, respectively.

The differences between data sets are sometimes immense (Tables 5, 6). FRA's estimate for Cameroon is 20 times that of Kim's, and FRA's estimate for Venezuela is 17 times Achard's. However, FRA's estimates are not always larger. In fact, the largest difference between studies is in PNG, where Achard estimates almost 60 times more loss than FRA's. Achard and Kim have the best agreement for forest loss in the 1990s, with the closest agreement in 9/15 countries, and having the worst disagreement in only 2 countries (Madagascar and Myanmar) (Tables 5-7). FRA and Kim agree the least with (Tables 5, 6, 7).

Table 5. Difference between forest loss estimates in the 1990s (1000 ha/decade)

Region	Country	FRA - Kim	FRA - Achard	Kim - Achard	Country Average
Latin America	Bolivia	794	936	142	**624**
	Brazil	6071	5136	935	**4047**
	Colombia	1319	1481	162	**987**
	Ecuador	632	71	561	**421**
	Peru	1254	1437	183	**958**
	Venezuela	1985	2708	723	**1805**
Africa	Cameroon	2090	1787	303	**1393**
	DRC	2074	173	1901	**1383**
	Madagascar	289	674	963	**642**
Southeast Asia	Cambodia	1088	1149	61	**766**
	Indonesia	12606	7780	4826	**8404**
	Laos	689	812	123	**541**
	Malaysia	515	930	415	**620**
	Myanmar	3520	89	3609	**2406**
	PNG	573	1581	1008	**1054**
	Pan-tropical	**2367**	**1783**	**1061**	
	Latin America	2009	1962	451	**1474**
	Africa	1484	878	1056	**1139**
	Southeast Asia	3165	2057	1674	**2299**

Country estimates are color-coded and scaled to show greatest difference between studies (red), and least difference between studies (green). The mean of differences between study estimates for each country are shown in the last column, with the three largest and smallest country averages represented by red and green shading, respectively; regional averages of these are shown and similarly presented in the last three rows. Pan-tropical mean of the differences between each pair of studies are also shown.

Finally, we find that Kim and Achard are closer to the mean of all data sets than FRA (Table 8). Overall, FRA seems to have the greatest discrepancy in forest loss estimates for the 1990s compared to the other data sets, having low agreement with Kim and Achard in 13 of the 15 countries (5 and 8 times, respectively, according to both distance measures between study pairs – Simple Ratio and Euclidean Distance).

The discrepancies between data sets are greatest in Southeast Asia and least in Africa in absolute terms (Table 5), with Indonesia, Brazil, and Myanmar being the worst. In terms of relative loss, discrepancies are least in Latin America, and worst in Africa followed closely by Southeast Asia (Table 6 and 8). The worst disagreements in relative terms are in PNG, Cameroon, and Venezuela.

Table 6. Simple ratio index (1990-2000)

Region	Country	FRA/Kim	FRA/Achard	Kim/Achard	Average
Latin America	Bolivia	0.71	0.65	0.93	**0.76**
	Brazil	0.76	0.80	0.95	**0.84**
	Colombia	0.50	0.43	0.88	**0.60**
	Ecuador	0.30	0.92	0.32	**0.52**
	Peru	0.29	0.19	0.65	**0.38**
	Venezuela	0.31	0.06	0.19	**0.19**
Africa	Cameroon	0.05	0.19	0.27	**0.17**
	DRC	0.33	0.94	0.35	**0.54**
	Madagascar	0.57	0.50	0.28	**0.45**
Southeast Asia	Cambodia	0.22	0.18	0.80	**0.40**
	Indonesia	0.34	0.59	0.58	**0.50**
	Laos	0.38	0.27	0.71	**0.46**
	Malaysia	0.60	0.46	0.76	**0.61**
	Myanmar	0.19	0.98	0.19	**0.45**
	PNG	0.05	0.02	0.37	**0.14**
	Pan-tropical	**0.37**	**0.48**	**0.55**	
	Latin America	0.48	0.51	0.65	**0.55**
	Africa	0.32	0.54	0.30	**0.39**
	S.E. Asia	0.30	0.42	0.57	**0.43**

This measure compares the differences between studies' forest loss estimates from 1990-2000 as a ratio between the two, where the denominator is always the higher estimate of the two studies, and therefore better agreement is closer to 1. Measures are color-coded and scaled to show the greatest difference between studies (red), and least difference between studies (green). The mean of measures are shown in the last column, with the three overall largest and smallest country averages represented by red and green cells, respectively. Pan-tropical and regional mean of the ratios are also shown.

Table 7. Euclidean Distance measure (1990-2000)

Region	Country	FRA/ Kim	FRA/ Achard	Kim/ Achard
Latin America	Bolivia	0.64	0.76	0.11
	Brazil	0.76	0.64	0.12
	Colombia	0.66	0.74	0.08
	Ecuador	0.75	0.08	0.66
	Peru	0.65	0.75	0.10
	Venezuela	0.58	0.79	0.21
Africa	Cameroon	0.76	0.65	0.11
	DRC	0.74	0.06	0.67
	Madagascar	0.24	0.56	0.80
Southeast Asia	Cambodia	0.69	0.73	0.04
	Indonesia	0.81	0.50	0.31
	Laos	0.64	0.76	0.11
	Malaysia	0.45	0.81	0.36
	Myanmar	0.70	0.02	0.72
	PNG	0.29	0.81	0.51
	Pan-tropical	**0.62**	**0.58**	**0.33**
	Latin America	**0.67**	**0.63**	**0.21**
	Africa	**0.58**	**0.42**	**0.53**
	Southeast Asia	**0.60**	**0.60**	**0.34**

This measure uses Euclidian Distance, or the square root of sum of squares (see section 2.3 for details) to compare the difference between pairs of studies' forest loss estimates relative to the average distance between all studies. This is simply another way to show the differences in Table 5, but where better agreement measures are closer to 0. Color shading follows the same logic as before.

Table 8. Distance from the mean - 1990-2000 (%)

Region	Country	FRA	Kim	Achard	Average
Latin America	Bolivia	27.11	10.22	16.89	**18.07**
	Brazil	17.22	10.76	6.45	**11.48**
	Colombia	55.37	22.88	32.49	**36.91**
	Ecuador	35.10	59.56	24.46	**39.71**
	Peru	102.28	40.71	61.57	**68.19**
	Venezuela	119.35	32.10	87.26	**79.57**
Africa	Cameroon	142.38	87.88	54.50	**94.92**
	DRC	31.67	56.03	24.36	**37.35**
	Madagascar	16.10	52.34	68.44	**45.62**
Southeast Asia	Cambodia	114.31	52.48	61.83	76.21
	Indonesia	55.06	47.09	7.98	36.71
	Laos	80.87	30.50	50.38	53.92
	Malaysia	38.03	2.63	35.39	25.35
	Myanmar	35.67	74.11	38.44	49.41
	PNG	96.38	19.46	115.84	77.23
	Pan-tropical	**64.46**	**39.92**	**45.75**	
	Latin America	59.4	29.4	38.2	**44.39**
	Africa	63.4	65.4	49.1	**64.40**
	S.E. Asia	70.1	37.7	51.6	**53.88**

This measure shows the percentage difference between each forest loss estimate and the mean of all estimates (as visualized in Figure 2). Averages and color shading follows the same logic as before.

3.2 Comparing data sets of tropical forest loss over the second decade: 2000-2010

The three satellite data sets agree relatively well with each other on forest loss in the 2000-2010 period compared to FRA, which is the outlier (Tables 9-12). Hansen and Kim have the closest agreement, while FRA agrees the worst with all other data sets. Comparing the estimates to the mean (Table 13), Hansen has the best agreement, followed by Kim (averaging 29% and 39% from the mean), while FRA is in significant disagreement (~80% from the mean).

In absolute terms, there is most disagreement in Latin America and least in Africa (Table 10). Disagreement is greatest in Brazil (as in the 1990s), followed by Indonesia and Colombia. In relative terms, however, discrepancies are *least* in Latin America (much *higher* agreement in Brazil in relative terms vs absolute), and highest in Southeast Asia (Table 11). The disagreements in relative terms shifts to countries in South East Asia: particularly Laos, Malaysia and PNG.

Table 9. Forest change from 2000-2010 (1000ha/decade)

Region	Country	FRA	Kim	Achard	Hansen
Latin America	**Bolivia**	-3882	-2985	-2619	-2344
	Brazil	-22816	-25710	-18379	-23701
	Colombia	-3163	-3630	-842	-1640
	Ecuador	-787	-330	-446	-352
	Peru	-1336	-750	-716	-1115
	Venezuela	-1646	-3265	-483	-921
Africa	**Cameroon**	-2200	-335	-175	-347
	DRC	-3114	-4265	-2792	-3753
	Madagascar	-470	-970	-985	-884
Southeast Asia	**Cambodia**	-1452	-1170	-1107	-958
	Indonesia	-4977	-8420	-8083	-7346
	Laos	1290	-650	-1517	-725
	Malaysia	533	-1635	-904	-1790
	Myanmar	-3095	-1795	-569	-984
	PNG	-27	-665	-304	-336
	TOTAL	-47142	-56575	-39921	-47195

The minimum and maximum values for each country and totals are represented by green and red shading, respectively.

Table 10. Difference in absolute values of forest loss estimates in the 2000s (1000 ha/decade)

Region	Country	FRA/ Kim	FRA/ Achard	FRA/ Hansen	Kim/ Achard	Kim/ Hansen	Achard/ Hansen	Average
Latin America	**Bolivia**	897	1263	1538	366	641	275	**830**
	Brazil	2894	4437	885	7331	2009	5322	**3813**
	Colombia	467	2321	1523	2788	1990	798	**1648**
	Ecuador	457	341	435	116	22	94	**244**
	Peru	586	620	221	34	365	399	**371**
	Venezuela	1619	1163	725	2782	2344	438	**1512**
Africa	**Cameroon**	1865	2025	1853	160	12	172	**1015**
	DRC	1151	322	639	1473	512	961	**843**
	Madagascar	500	515	414	15	86	101	**272**
Southeast Asia	**Cambodia**	282	345	494	63	212	149	**257**
	Indonesia	3443	3106	2369	337	1074	737	**1844**
	Laos	1940	2807	2015	867	75	792	**1416**
	Malaysia	2168	1437	2323	731	155	886	**1283**
	Myanmar	1300	2526	2111	1226	811	415	**1398**
	PNG	638	277	309	361	329	32	**324**
	Pantropical	**1347**	**1567**	**1190**	**1243**	**709**	**771**	
	Latin America	1153	1691	888	2236	1228	1221	**1403**
	Africa	1172	954	969	549	203	411	**710**
	S.E. Asia	1629	1750	1603	598	443	502	**1087**

Country estimates are color-coded and scaled to show greatest difference between studies (red), and least difference between studies (green). The mean of differences between study estimates for each country are shown in the last column, with the three largest and smallest country averages represented by red and green shading, respectively; regional averages of these are shown and similarly presented in the last three rows. Pan-tropical mean of the differences between each pair of studies are also shown.

Table 11. Simple ratio index (2000-2010)

Region	Country	FRA/ Kim	FRA/ Achard	FRA/ Hansen	Kim/ Achard	Kim/ Hansen	Achard/ Hansen	Average
Latin America	Bolivia	0.77	0.67	0.60	0.88	0.79	0.90	**0.77**
	Brazil	0.89	0.81	0.96	0.71	0.92	0.78	**0.84**
	Colombia	0.87	0.27	0.52	0.23	0.45	0.51	**0.48**
	Ecuador	0.42	0.57	0.45	0.74	0.94	0.79	**0.65**
	Peru	0.56	0.54	0.83	0.95	0.67	0.64	**0.70**
	Venezuela	0.50	0.29	0.56	0.15	0.28	0.52	**0.39**
Africa	Cameroon	0.15	0.08	0.16	0.52	0.97	0.50	**0.40**
	DRC	0.73	0.90	0.83	0.65	0.88	0.74	**0.79**
	Madagascar	0.48	0.48	0.53	0.98	0.91	0.90	**0.71**
Southeast Asia	Cambodia	0.81	0.76	0.66	0.95	0.82	0.87	**0.81**
	Indonesia	0.59	0.62	0.68	0.96	0.87	0.91	**0.77**
	Laos	-1.98	-0.85	-1.78	0.43	0.90	0.48	**-0.47**
	Malaysia	-0.33	-0.59	-0.30	0.55	0.91	0.51	**0.13**
	Myanmar	0.58	0.18	0.32	0.32	0.55	0.58	**0.42**
	PNG	0.04	0.09	0.08	0.46	0.50	0.91	**0.35**
	Pan-tropical	**0.34**	**0.32**	**0.34**	**0.63**	**0.76**	**0.70**	
	Latin America	0.67	0.52	0.65	0.61	0.68	0.69	**0.64**
	Africa	0.46	0.48	0.51	0.72	0.92	0.72	**0.63**
	S.E. Asia	-0.05	0.04	-0.06	0.61	0.76	0.71	**0.33**

This measure compares the differences between studies' forest loss estimates from 2000-2010 as a ratio between the two, where the denominator is always the higher estimate of the two studies, and therefore better agreement is closer to 1. Measures are color-coded and scaled to show the greatest difference between studies (red), and least difference between studies (green). The mean of measures is shown in the last column, with the three overall largest and smallest country averages represented by red and green cells, respectively. Pan-tropical and regional means of the ratios are also shown.

Table 12. Euclidean Distance measure (2000-2010)

Region	Country	FRA/ Kim	FRA/ Achard	FRA/ Hansen	Kim/ Achard	Kim/ Hansen	Achard/ Hansen
Latin America	Bolivia	0.39	0.54	0.66	0.16	0.28	0.12
	Brazil	0.27	0.41	0.08	0.68	0.19	0.50
	Colombia	0.10	0.52	0.34	0.62	0.44	0.18
	Ecuador	0.62	0.47	0.59	0.16	0.03	0.13
	Peru	0.57	0.60	0.21	0.03	0.35	0.39
	Venezuela	0.38	0.27	0.17	0.66	0.55	0.10
Africa	Cameroon	0.56	0.61	0.56	0.05	0.00	0.05
	DRC	0.51	0.14	0.28	0.65	0.22	0.42
	Madagascar	0.60	0.61	0.49	0.02	0.10	0.12
Southeast Asia	Cambodia	0.39	0.48	0.69	0.09	0.30	0.21
	Indonesia	0.64	0.58	0.44	0.06	0.20	0.14
	Laos	0.47	0.68	0.49	0.21	0.02	0.19
	Malaysia	0.59	0.39	0.63	0.20	0.04	0.24
	Myanmar	0.34	0.66	0.55	0.32	0.21	0.11
	PNG	0.71	0.31	0.34	0.40	0.36	0.04
	Pan-tropical	0.48	0.48	0.44	0.29	0.22	0.19
	Latin America	0.39	0.47	0.34	0.38	0.31	0.23
	Africa	0.55	0.45	0.44	0.24	0.11	0.20
	S.E. Asia	0.52	0.52	0.52	0.21	0.19	0.15

This measure uses the Euclidian Distance, or square root of sum of squares (see section 2.3 for details) to compare the difference between pairs of studies' forest loss estimates relative to the average distance between all studies. This is simply another way to show the differences in Table 10, but where better agreement measures are closer to 0. Color shading follows the same logic as before.

Table 13. Distance from the mean - 2000-2010 (%)

Region	Country	FRA	Kim	Achard	Hansen	Average
Latin America	Bolivia	31.26	0.93	11.45	20.74	**16.09**
	Brazil	0.73	13.50	18.86	4.63	**9.43**
	Colombia	36.41	56.55	63.69	29.28	**46.48**
	Ecuador	64.42	31.06	6.82	26.55	**32.21**
	Peru	36.44	23.41	26.88	13.85	**25.14**
	Venezuela	4.27	106.82	69.40	41.68	**55.54**
Africa	Cameroon	187.86	56.17	77.10	54.59	**93.93**
	DRC	10.54	22.52	19.79	7.82	**15.17**
	Madagascar	43.19	17.26	19.07	6.86	**21.59**
Southeast Asia	Cambodia	23.91	0.15	5.53	18.22	**11.96**
	Indonesia	30.94	16.84	12.16	1.93	**15.47**
	Laos	422.01	62.25	278.68	81.08	**211.01**
	Malaysia	156.16	72.29	4.74	88.62	**80.45**
	Myanmar	92.14	11.44	64.68	38.91	**51.79**
	PNG	91.89	99.74	8.69	0.84	**50.29**
	Pan-tropical	**82.14**	**39.39**	**45.84**	**29.04**	
	Latin America	28.92	38.71	32.85	22.79	**30.82**
	Africa	80.53	31.98	38.66	23.09	**43.56**
	S.E. Asia	136.18	43.79	62.41	38.27	**70.16**

This measure shows the percentage difference between each forest loss estimate and the mean of all estimates (as visualized in Figure 3). Averages and color shading follows the same logic as before.

3.3 Comparing data sets of change in deforestation rates from the 1990s to the 2000s

Kim estimated an increase in forest loss for all 15 countries, while FRA and Achard mostly estimated decreases in forest loss or a forest transition (deforestation in 1990s but increases in forest area in the 2000s) between the two decades (Tables 14 and 15). In absolute terms, FRA estimated as much forest loss reduction between the two decades as Kim estimated forest loss increase (a reduction of 22 and an increase of 21 M ha/decade, respectively). Contradicting Kim's satellite study, Achard also estimates a decrease in forest loss from the 1990s to the 2000s, but of much lower magnitude than FRA (9 M ha/decade). Note that FRA describes a forest transition for both Laos and Malaysia (net forest area increase for Laos relative to 1990 estimates), and no change in forest loss for Cameroon, DRC and PNG.

Table 14. Forest change per decade by study - 1990-2000 and 2000-2010 (1000 ha/ decade)

		Forest change per decade (1000 ha)						Difference in forest change between decades		
		FRA 2015	**FRA 2015**	**Kim**	**Kim**	**Achard**	**Achard**	**FRA**	**Kim**	**Achard**
		1990-2000	***2000-2010***	***1990-2000***	***2000-2010***	***1990-2000***	***2000-2010***	-1178	-1075	-851
Latin America	**Bolivia**	-2704	-3882	-1910	-2985	-1768	-2619	2615	-6350	1916
	Brazil	-25431	-22816	-19360	-25710	-20295	-18379	-544	-2330	296
	Colombia	-2619	-3163	-1300	-3630	-1138	-842	115	-60	385
	Ecuador	-902	-787	-270	-330	-831	-446	438	-230	-379
	Peru	-1774	-1336	-520	-750	-337	-716	1229	-2375	-316
	Venezuela	-2875	-1646	-890	-3265	-167	483	0	-225	238
Africa	**Cameroon**	-2200	-2200	-110	-335	-413	-175	0	-3225	149
	DRC	-3114	-3114	-1040	-4265	-2941	-2792	199	-590	358
	Madagascar	-669	-470	-380	-970	-1343	-985	-54	-860	-858
South East Asia	**Cambodia**	-1398	-1452	-310	-1170	-249	-1107	14159	-1890	3273
	Indonesia	-19136	-4977	-6530	-8420	-11356	-8083	2409	-220	-1210
	Laos	-1119	1290	-430	-650	-307	-1517	1318	-335	811
	Malaysia	-785	533	-1300	-1635	-1715	-904	1255	-965	3870
	PNG	-27	-27	-600	-665	-1608	-304	0	-65	1304
	Myanmar	-4350	-3095	-830	-1795	-4439	-569	**21961**	**-20795**	**8986**

Table 15. Ratio of forest loss in 2000s to forest loss in 1990s

Region	Country	FRA	Kim	Achard
Latin America	Bolivia	1.44	1.56	1.48
	Brazil	0.90	1.33	0.91
	Colombia	1.21	2.79	0.74
	Ecuador	0.87	1.22	0.54
	Peru	0.75	1.44	2.12
	Venezuela	0.57	3.67	2.89
Africa	Cameroon	1.00	3.05	0.42
	DRC	1.00	4.10	0.95
	Madagascar	0.70	2.55	0.73
Southeast Asia	Cambodia	1.04	3.77	4.45
	Indonesia	0.26	1.29	0.71
	Laos	-1.15	1.51	4.94
	Malaysia	-0.68	1.26	0.53
	Myanmar	0.71	2.16	0.13
	PNG	1.00	1.11	0.19
	Pan-tropical	**0.68**	**1.58**	**0.82**

Values greater than 1 indicate increased deforestation, values of 1 indicate no change in deforestation rate, values less than 1 indicate decreased deforestation, and negative values indicate forest transition (i.e., forest loss in the 1990s but net forest area increase in the 2000s).

3.4 Comparing pan-tropical estimates to independent analyses

3.4.1 Intercomparing data sets of forest loss during 2000-2010

We compared the pan-tropical estimates of forest loss for the 2000s to independent estimates for five different countries (Table 17). We next present a more in-depth narrative of forest loss in the 2000s for each country.

Table 16. Comparison of forest loss estimates in the 2000s between pan-tropical studies and independent national studies (1000 ha/decade)

Country	FRA	Kim	Achard	Hansen	Ind. 1	Ind. 2	Ind. 3
Brazil	-22,816	-25,710	-18,379	-23,701	-16,900[1]	-12,500[2]	-16,930[3]
Indonesia	-4,977	-8,420	-8,083	-7,346	-8,828[4]	-4,549[5]	-8,000[6]
DRC	-3,114	-4,265	-2,792	-3,753	-3,669[7]		
Laos	1,290	-650	-1,517	-725	N/A*		
Malaysia	533	-1,635	-904	-1,790	-2,281[8]		

* Studies for these countries presented qualitative analysis of forest loss trends for the period of concern.
Independent study citations: Brazil: 1) Souza et al. 2013, 2) Song et al. 2015, and 3) Tyukavina et al. 2017; Indonesia: 4) Miettinen et al. 2011, 5) Margono et al. 2014, 6) Stibig et al. 2014; DRC: 7) Potapov et al. 2012 Malaysia: 8) Miettinen et al. 2011

Brazil

Brazil is home to the Amazon Rainforest, which boasts one of the highest concentrations of biodiversity (Brooks et al. 2002), vast carbon storage (Nepstad et al. 2009) and is a resource for medicinal plants (Mans , da Rocha and Schwartsmann 2000). From the mid 1990s to the mid 2000s, Brazil was known as the “world leader in tropical deforestation”, inciting worldwide focus and calls for forest loss mitigation (Nepstad et al. 2009, p. 1350). The drivers of deforestation in Brazil are widely attributed to conversion for agriculture, specifically for soy and pasture. The heightened awareness of the value of their forests and its purported rate of destruction motivated the Brazilian government to take measures to mitigate its deforestation in the mid 2000s. These measures included a moratorium on conversion of forests to soy, as well as the establishment of a monitoring unit overseeing implementation of these policies. The international spotlight encouraged the Brazilian government to implement innovative policies, enforce sanctions, and set up forest monitoring institutions. These efforts included the initiation of the Amazon Fund in 2006 to support heightened utilization of Brazil’s satellite-monitoring system (PRODES), its real-time satellite-based deforestation alert system (DETER), and the deforestation monitoring task force (IBAMA) (Nepstad et al. 2009).

All pan-tropical studies we examined estimate an all-together average of 22 million hectares of forest loss for the decade 2000-2010 in Brazil. The variation between different estimates is relatively low, indicating good agreement on forest loss for that decade. These estimates are somewhat corroborated by site-specific studies estimating forest loss in the Brazilian Amazon. There are no independent studies available for country-wide net forest loss in Brazil, rather forest loss for the Brazilian Amazon, Catinga, and Cerrado are estimated separately - likely due to specific interest in drivers and implications for those sites. We examined studies estimating Brazilian Amazon forest loss as it is generally accepted that the large majority of Brazil's forests are situated in the Amazon (Ratter, Ribeiro and Bridgewater 1997). The three studies estimating Brazilian Amazon forest loss for 2000-2010 are Souza et al. 2013 (hereafter Souza), Song et al. 2015 (hereafter Song), and Tyukavina et al. 2017 (hereafter Tyukavina), who estimate 16.9, 12.5, and 16.9 million ha of loss per decade, respectively. While all three studies are satellite-based, slight differences in output are due to different methods of image aggregation and classification. Song's lower estimates stands in contrast to the other two estimates likely because the study uses MODIS images with coarser spatial resolution (250m vs Landsat's 30 m). Souza and Tyukavina use Landsat images, but where Souza separates primary from secondary and planted forests, Tyukavina does not, likely explaining the latter's higher forest area loss estimates. (Souza et al. 2013, Song et al. 2015, Tyukavina et al. 2017).

These results seem to be somewhat more conservative than pan-tropical estimates for the country. But again, this might be because these studies exclusively estimated forest loss for the Amazon. A study estimating non-Amazon Brazilian forest loss concluded that these areas experienced a combined loss of ~2.4 million hectares over the last decade (Beuchle et al. 2015). The addition of this estimate to the Amazonian estimates leaves the forest loss numbers of Souza and Tyukavina just under average estimates of the 2000-2010 pan-tropical analysis (~19 million ha per decade). This suggests that actual forest loss estimates are somewhat accurate for this country.

Indonesia

Like Brazil, Indonesia is one of the world's most forested countries, boasting high levels of biodiversity (Sodhi et al. 2010), acting as a critical carbon sink (Page, Rieley and Banks 2011), and providing important ecosystem services (UNORCID 2015).

During the last two decades, Indonesia has experienced a steady increase in deforestation, recently overtaking Brazil in its title as the world's leader in deforestation (Vidal 2014). This is likely due to the country's role as the world's top palm oil producer and exporter, converting much of its forests and peat swamps to palm oil plantations (Lee et al. 2014). More generally, the major drivers of deforestation in this country are due to large-scale conversion for industrial agriculture, small-scale conversion for local agriculture (mostly oil palm), and conversion for timber plantations (Busch et al. 2012), as well as mining (Lee et al. 2014).

There was somewhat more disagreement in 2000-2010 forest loss estimates for Indonesia than in Brazil. While, similar to Brazil, there was higher agreement between satellite-based studies, FRA's estimates disagreed more with the other studies. The lowest estimate was 5.0 million ha of forest loss over the decade (FRA), while the highest estimate was 8.4 million ha (Kim).

The independent country analyses available for 2000-2010 reported varying estimates of forest loss for the same period. We found three studies that estimated forest loss in Indonesia for the same time period. Miettinen et al. 2011 (hereafter Miettinen) estimate net forest loss of 8.8 million ha forest in Indonesia for that decade. Margono et al. 2014 (hereafter Margono) estimated gross primary forest loss for Indonesia from 2000-2012, and reported 4.5 million ha of loss over the decade. Finally, Stibig et al 2014 (hereafter Stibig) estimate net forest loss in Indonesia at 8.0 million ha forest loss for that decade. All studies are satellite-based, the former (Miettinen) using MODIS images, and the latter two using Landsat images. While Miettinen and Stibig estimate similar forest loss to those as the pantropical remote sensing data sets, Margono's estimates are more similar to those of the FRAs. It is difficult to really compare these studies. Margono estimates net primary forest loss, distinguishing these forests from secondary forests or plantations/regrowth (Margono et al. 2014). Meanwhile Miettinen and Stibig's definition of tree cover does not distinguish primary forests from other forested areas (Miettinen, Shi and Liew 2011, Stibig et al. 2014). In Brazil, there was better agreement between satellite-based estimates irrespective of whether they distinguished between secondary and primary forests or not. In contrast, the substantial differences between studies in Indonesia that used those different definitions suggests that forest cover estimates in Indonesia are highly sensitive to forest definitions and classifications.

DRC

Forests in the DRC make up the majority of the Congo Basin (57%). Like Indonesia and Brazil, the DRC is one of the largest forested countries in the world, and its forests are considered to be a reservoir of biodiversity and a vital regulator of global warming (Lushombo 2015). The country had experienced a marked increase in deforestation in the last half of the 2000s. This trend is largely attributed to political turmoil and population growth, which has increased the country's reliance on forested area for conversion to agriculture in order to cultivate coveted cash crops (Rudel 2013).

There is a high level of disagreement between the pantropical estimates of forest loss for the DRC during the 2000s. The lowest and highest estimates for this time period are 2.8 (Achard) and 4.3 million hectares for the decade (Kim et al), respectively. Furthermore, FRA's identical estimates of forest loss for the country across both time periods (3.1 million ha), as well as the lower Tier classification of data, suggests that the reported data for the two decades were based on a single estimate. This is potentially explained by political turmoil that obstructed the collection of national-scale ground truth data such as forest inventory information (Potapov et al. 2012). [3]

We found one study estimating change for all forests in the DRC. Potapov et al. (2012) (hereafter Potapov) estimate forest area change from 2000-2010 to be 3.7 million hectares for the country, which matches the average of all the pan-tropical estimates (~3.5 million ha per decade), and closely resembles Hansen's estimates (3.7 million ha per decade). This is unsurprising as both Potapov and Hansen use the same data (Landsat) and similar methods (forest definition and classification approaches). The slight differences between the two datasets are likely due to images chosen (Hansen's wall-to-wall approach, Potapov's images chosen for cloud-free qualities).

[3] Furthermore, the nature of the change in forest lost rates between both decades are not entirely clear as Potapov's analysis included an analysis of 1990-2000 and noted a significant 34% decadal increase of forest loss for the DRC in the 2000s (Potapov, et al. 2012), supporting Kim's analysis from 1990-2010 and contradicting Achard's.

It is, however, surprising that the FRA, which reports identical forest loss for the 1990s and 2000s (that we suggest is based on a single true estimate), remains closer to the average of all estimates than the satellite-based estimates of Achard and Kim. This may be pure chance rather than superior national reporting (the civil turmoil mentioned earlier presents a challenge to this). Overall, the difference between the lowest and highest estimates of forest loss for the decade remains significant (1.5 million ha per decade of discrepancy) for a country boasting highly valued and important forests.

The disagreement in forest loss for this country may be due to the type of forests specific to the DRC. Tropical African countries, like the DRC, include both humid tropical rainforest as well as dry woody forests, the latter being more difficult to spatially identify as "forest" (challenges of which are discussed further below). A study that estimated change in humid tropics for the *entire* region of Central Africa reported 1.9 million hectares of loss, almost half that reported by Potapov for just the DRC (Mayaux et al. 2013). This highlights the extent of dry woody forests in the tropical Africa, and the challenge it presents to spatial analysis for the region.

Lao PDR

Lao PDR is known for its abundant natural resources, however rates of deforestation have threatened to reduce the country's total forest area, contributing to global biodiversity losses, increasing climate change, and reduction of underground aquifer recharging (PDR 1999). Forest cover loss in Laos is believed to be due largely to conversion for farming (shifting cultivation), and logging (illegal and legal) (Lestrelin 2010).

There is large disagreement regarding forest loss in Lao PDR during 2000-2010. While Achard estimates a significant loss of 1.5 million ha per decade, FRA 2015 estimates an almost exact opposite net forest cover increase of 1.3 million ha. It should be noted here that in the previous FRA 2010 report, the country reported a net forest loss for the same period. While there are no independent quantitative analyses for the exact time period (2000-2010), one regional study contradicted FRA 2015, and described an increase in deforestation from the 1990s to 2000s along the Annamite mountain range (Stibig et al. 2014), a high biodiversity area covering a significant part of forested area in Laos (Robichaud et al. 2001). Conversely, another study from 2006-2012 described a net decrease in forest loss – however, any "contribution to the increase in forest cover is from plantations: mostly rubber" (Phompila et al. 2014). Other regional studies focused on forest transition in Southeast Asia support the state of unattained forest transition in Laos by 2010 (Youn et al. 2017, Liu et al. 2017). The drivers of change of natural forest to plantation forest in the country is likely the source of these major disagreements for the country.

Malaysia

Malaysia's forests have been an important source of biodiversity (Koh and Wilcove 2008) and carbon storage (Lasco 2002). The country has experienced deforestation initially from expansion of rubber in the mid 20th century, and more recently conversion to oil palm plantations (Miyamoto et al. 2014).

The pantropical forest loss estimates for Malaysia have very low agreement during 2000-2010, with agreement between only two studies (Kim and Hansen). Furthermore, one study (FRA) estimates forest transition for the country, with a net increase of 530,000 hectares during the decade.

We found one independent study reporting forest loss for 2000-2010, contradicting the FRA reported estimate of net forest area increase. Miettinen et al. 2011 estimated that Malaysia lost net 2.3 million ha per decade, an estimate that is even less conservative than the pan-tropical estimates included in our study. Interestingly, another independent analysis on Malaysia, based on FRA statistics, reinforces the narrative of net loss for the country (Li et al. 2017). This study notes that while afforestation had risen in this country, the trend either declined or remained stable as the proportion of exported forest products increased from 2000-2010. While the study came out the same year as the latest FRA report, it is not clear whether or not the FRA statistics used in Li et al. (2015) were based on 2015 or 2010 estimates. The FRA 2010 report for Malaysia estimated a net forest area loss for the same time period, contradicting increases reported in FRA 2015. Like Laos, disagreement in Malaysia is likely due to conversion to plantation forests (Miettinen et al. 2011).

3.4.2 Intercomparing data sets of change in forest loss from the 1990s to the 2000s

We found independent analyses of change in tropical forest loss from the 1990s to the 2000s covering all three major tropical regions (Table 18, Figure 5). PRODES estimates gross deforestation for Brazil, a country with the majority of forested area in Latin America. From the 1990s to the 2000s, there is a marked decrease in deforestation estimates. While PRODES does not offer net estimates, we can see that general trends suggest deforestation has decreased in the second decade. Independent studies of net forest loss for African rainforests[4] and Southeast Asia[5] tell a similar story (Table 18, Figure 5). All three studies' estimates are satellite- based. PRODES uses a combination of Landsat 7 and 8, CBERS-2, CBERS-2B, Resourcesat-1, and UK2-DMC (INPE 2010). The Central Africa study used MODIS data (Mayaux et al. 2013), while the Southeast Asia study used Landsat data (Stibig et al. 2014).

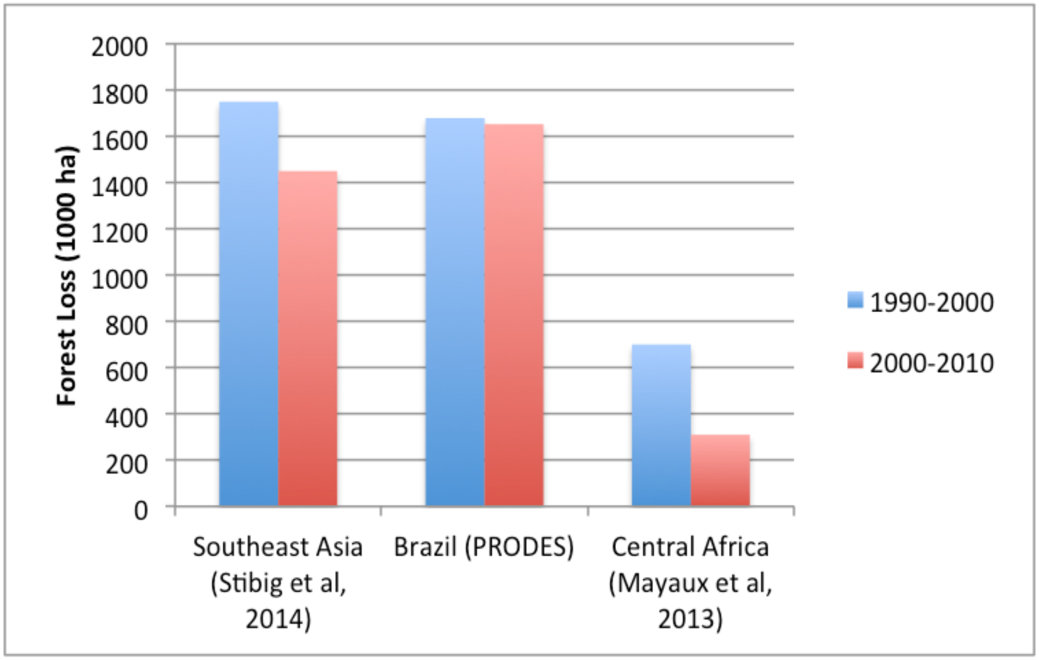
Table 15. Independent estimates of change in tropical forest change from the 1990s to 2000s

	Type of Forest Loss	1990-2000	2000-2010	% of Change
Brazil (PRODES)	Gross	-16792.3	-16530.9	-2%
Central Africa (Mayaux, 2013)	Net	-700.4	-310.2	-56%
Southeast Asia (Stibig et al, 2014)	Net	-17,500	-14,500	-17%

[4] Central Africa countries in this analysis include: DRC, Gabon, Congo, Cameroon, Central African Republic, Equatorial Guinea, Liberia, Nigeria, Cote d'Ivoire, Ghana, and Madagascar

[5] Southeast Asia countries in this analysis include: Cambodia, Laos, Myanmar, Thailand, Vietnam, Brunei, East Timor, Indonesia, Malaysia, and the Philippines

Figure 5. Independent estimates of change in tropical forest loss from the 1990s to 2000s



Southeast Asia and Brazil estimates are in annual numbers to scale numbers down for sake of visual comparison. Brazil numbers are gross, while other estimates are net.

It is commonly understood that the countries used in each study represent the majority of pan-tropical forest extent (Kim et al. 2015, FAO 2016, Hansen et al. 2013). Brazil represents ~50-65% of Tropical Latin America, countries included in Mayaux's analysis of Africa represent over 95% of Tropical Africa, and countries included in Stibig's analysis of Southeast Asia represent ~85-90% of Tropical Southeast Asia. Combined, all countries included in the respective analyses account for over 70% of pan-tropical forest extent. Therefore, these studies can be said to be representative of tropical forest trends in general.

However, while Brazil accounts for a majority of forest extent in Latin America, it ought to be noted that other studies have found opposite forest trends in the rest of South America. That is, while Brazil may have experienced decreased forest loss, observed increases in other countries may have partly offset this trend (van Marle et al. 2016). Conversely, while countries located within Central Africa may have generally experienced a significant reduction in forest loss rates, other studies report a significant jump in forest loss in the DRC (Potapov et al. 2012, Rudel 2013, Butsic et al. 2015).

4. Discussion

The balance of evidence suggests that deforestation has decreased from the 1990s to the 2000s. This is supported by our intercomparison of the pan-tropical studies, as well as other available regional estimates. The satellite estimates agree the best, with Achard in the least disagreement and FRA in most disagreement of all studies. While we cannot conclude from our analysis that Achard's estimates are of higher quality, it is suggestive. In contrast, for both the 1990s and 2000s, FRA is often the outlier.

Despite relative agreement between satellite-based studies, differences persist. Given Kim's departure from average estimates in the 1990s by estimating relatively much lower losses, and eventual agreement in the 2000s with the other satellite estimates, it appears that Kim may have underestimated forest loss in the first decade. This could explain why their study estimated accelerated deforestation from the 1990s to the 2000s. Ironically, the exact opposite was suggested of FRA by Kim: that FRA's deceleration in forest change was because of revisions to the definition of forest during the decade of the 2000s (Kim et al. 2015). However, we see a strong suggestion of underestimated forest loss in Kim as compared with the other satellite data sets during the 1990s. Furthermore, the assumption that FRA's revisions lead to underreporting of forest area loss in later decades (thus muting acceleration) is contradicted by the fact that, despite revisions of reported forest area, the slope of change in historical forest loss for different FRAs has remained remarkably similar (Grainger 2008).

Those countries that use satellite estimates for FRA reporting have the greatest agreement with other studies. As mentioned earlier, Brazil's FRA forest estimates are informed by satellite analyses, and their estimates agree most between studies and for each decade. High agreement for this country may be the result of 2 conditions: first that they have the institutional capacity to monitor their forests via satellite; second, that conversion in Brazil is largely to soy and pasture, and therefore less challenges in satellite analysis related to distinguishing forests from tree plantations.

Similarly, satellite-based estimates in Indonesia agree most between each other - except the results from the Margono study which, while satellite-based, agrees better with FRA. While

Margono et al's more conservative estimates can be explained by their narrow focus on "primary" forest, their approximation to FRA's estimates seems to be pure coincidence. Indonesia's FRA report presents results for forests as defined by FRA, without distinguishing between primary and secondary forests. The status of their data is Tier 1, which can either be based on National Inventory or Remote Sensing. The inconsistency of their results with other satellite-based studies suggests their FRA report relies more on the National Inventory estimates based on less consistent aggregation approaches. Further of note, that while one would expect satellite-based estimates for countries where forests are converted to tree plantations to underestimate forest loss, these satellite studies estimate *more* deforestation than national estimates. This suggests the National Inventories may be greatly underestimating deforestation. Estimates at the national level have long been a point of controversy; these discrepancies – similar to conclusions in our previous study – have been attributed to differences in definitions of forest, classification and data analysis methods (Intrarto, et al. 2012).

Where satellite estimates disagree, forest definitions are likely to be at issue. For instance, in the DRC not only do estimates disagree between FRA[6] and satellite-based studies, but there exist huge discrepancies between the satellite-based studies themselves. The DRC's forests are comprised of both dry and humid tropic forests. The identification of dry forests is subject to change based on definition of what a dry forest is (i.e. height criteria) (Grinand, et al. 2013). At issue here is that tropical dry forests are less distinct than tropical humid forests; they tend to grade into other vegetation types such as wet forests, savannas and woodlands (Miles, et al. 2006). Whether and how the studies distinguish between these types of forests likely determines forest loss estimates for countries with significant dry forest areas. Similarly, Malaysia experiences high disagreement between satellite estimates. This, too, may have to do with definitions. While Kim and Hansen agree most, with Achard agreeing to lesser extent, Miettinen et al's satellite-based estimates are twice as high. Their study distinguishes between forest and plantation/regrowth/degraded forests. This distinction between "forests" and "secondary forest" likely contributes to their higher estimate of forest loss. Similarly for Laos, satellite studies that include regrowth estimates, muting deforestation estimates for the country, acknowledge that

[6] It should be mentioned here that the FRA annual estimates for the country have been identical for each period of reporting (311.4 thousand hectares per year). These estimates are based on "expert" reports, suggesting that the country does not have access to better monitoring technology.

these regrowth estimates are based on including rubber plantations as forests. This confusion of what a forest is contributes to contradicting forest area and loss estimates.

Overall, there appears to be better agreement in Latin America. Based on the patterns of forest definition and agreement discussed above, this regional bias is likely due to the drivers of forest loss in each region, as well as type of vegetation. Latin America's forests are largely converted for soy and pasture, while Southeast Asia's forests are converted to plantation forests (rubber and oil palm) making deforestation more difficult to observe in Southeast Asia. In terms of vegetation type, the dry woody vegetation that exists in Africa often is often subject to disagreement on whether it constitutes forest, as well as challenges with detecting them from satellites, lending to overall disagreement in forest estimates for the region.

Through the course of this analysis we were able to answer the set of four questions articulated in the introduction. Overall, satellite estimates agree more in the 1990s, the additional satellite data set confirms this pattern of agreement in the 2000s, balance of evidence suggests that tropical forest loss has slowed down, and finally, our conclusion of overall deceleration of tropical forest loss from the 1990s to the 2000s is corroborated by other independent studies of tropical forest loss.

5. Conclusion

Tropical forests are a lynchpin for environmental and social services, however changes in their extent is poorly understood. The results presented here offer a first intercomparison of the latest data sets of tropical forest loss, to generate a better understanding of agreement and disagreement between studies using different approaches to measure forest loss in the same countries. The study highlights that the available quantitative data on tropical forest area change is variable and still uncertain in many countries.

This paper concurs with previous studies that find the FRA to be an unreliable source of forest cover data. FRA numbers have been used in thousands of documents to date. A 2007 study reviewed 2,000 scientific publications that cite FRA numbers and found 159 publications that made substantial contributions (Grainger 2007). An updated review would likely find many more important studies that are based on tenuous FRA numbers. Furthermore, inconsistent use of different FRA reports for a specific time period skews narratives for countries of focus. For example, Li's report published around the same time based on FRA numbers yielded extremely different narratives for Malaysia's forests, likely due to the reliance on FRA 2010 numbers. Similarly, Laos' FRA 2010 report contradicts forest transition claims of the later FRA 2015. FRA is a crucial conduit for international action and support in mitigating deforestation. However, based on our study, some changes to FRA's approach could augment its accuracy, including integrating satellite data to balance and check formal country reports, and identifying better and more consistent definitions of forest loss.

While our study finds that satellite studies appear to have better agreement, large discrepancies in reported numbers still exist. These disagreements are likely due to inconsistent definitions of forest, different approaches to data collection (sample vs wall-to-wall), different ways to deal with areas under cloud cover, difficulties distinguishing natural forest cover from tree crops and plantations, and difficulties distinguishing permanent anthropogenic forest loss from forest loss to fires, insects, and other natural disturbances. Agreement between satellite-based data can be improved by negotiating best practices: including shared definitions of forest, agreement on best approaches to data collection and analysis, and acknowledgement of regional land cover characteristics that present a challenge to observations of forest change (plantations, dry tropical forests, fires). Furthermore, new technologies for estimating forest cover are emerging. For instance Light Detection and Ranging technologies (LiDAR) is a remote sensing technique that uses laser to determine the height and structure of tree canopies (Drake, et al. 2002), which can be used to differentiate between the biodiverse-rich primary forests and secondary forests. More recently, advances in imaging spectroscopy has made it possible to remotely sense the chemistry of canopies and thus evaluate the species diversity of the vegetation (Asner, et al. 2017). These technologies could be invaluable for distinguishing plantation/regrowth from primary forests. However, for now they are expensive and available only at smaller scales (subnational levels).

Our study suggests that discrepancies in forest loss data will not be resolved until research coalesces on definitions and methods of data processing. However, even if this is achieved, the accuracy of the data - that is, how much forest area is actually being lost in the tropics – is not guaranteed. This partly explains the number of different approaches to tropical forest monitoring and the wide variety of results. It is unclear yet which is the best approach, and this will continue to be the case until monitoring technology evolves and capacity increases enough to present a clearer idea of tropical forest area change. Tropical forests are vital to environmental and social systems. Given the conclusions of country studies indicating rapid upticks in tropical deforestation rates (INPE 2016), particularly over the last five years, further collaboration on research in this area is urgently needed.

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