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WORKING PAPER

COMPARING GLOBAL AND NATIONAL APPROACHES TO ESTIMATING DEFORESTATION RATES IN REDD+ COUNTRIES

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EXECUTIVE SUMMARY

Highlights

- Forests have enormous potential to mitigate against climate change and could help the world reach the goals of the 2015 Paris Climate Agreement. Forests soak up CO_2 and deforestation releases it.
- An increasingly diverse menu of methods is being used by countries and international research organizations to monitor forests and estimate rates of deforestation. These multiple methods produce results of various quality, which is a barrier to cross-country comparisons and leads to confusion about which methods and results are most accurate, especially for countries claiming results-based payments for initiatives to halt deforestation.
- This working paper explains how much and why results differ between nationally reported deforestation estimates and the Global Forest Change (GFC) tree cover loss data of Hansen et al. (2013). Across all REDD+ countries, the GFC data represent an unbiased proxy for tropical deforestation and are produced for a fraction of the cost of what has been invested in national forest monitoring systems.[1]
- Opportunities to align, adapt, or customize global data for national forest monitoring and reporting may help reduce costs and improve the long-term sustainability and comparability of national systems, while maintaining desired levels of accuracy and national ownership.

CONTENTS

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Background

Forests are a critical component of any global strategy to mitigate climate change. Article 5 of the Paris Agreement under the United Nations Framework Convention on Climate Change (UNFCCC) encourages all Parties to make full use of forests for climate change mitigation, and explicitly calls for Parties to move forward with REDD+ implementation. REDD+[2] is the internationally agreed framework for incorporating forests into the emission reduction strategies of developing countries. Critically, REDD+ includes financial incentives in the form of "readiness" and "implementation" funding as well as "results-based" payments to countries.

How countries measure and report emission reductions is of critical importance to the success of REDD+. National forest monitoring systems must be widely perceived as credible by both domestic and international stakeholders to enable flow of results-based payments for REDD+. More broadly, robust forest monitoring systems are needed to accurately and consistently monitor progress toward the target of keeping global temperature rise below 2°C as set by the Paris Agreement.

The Problem: Too Many Numbers

Requirements of REDD+ reporting outlined under the 2013 Warsaw Framework have generated funds and interest in enhanced methods for deforestation monitoring. More than US$6 billion has been pledged toward REDD+ readiness activities, a portion of which includes the creation of baseline data and national forest monitoring systems. Investments to date have increased capacity for national reporting in developing countries.

A situation has arisen in which different data are being produced by different groups for different purposes, using different methods and time periods, and leading to divergent results. Because there is no consensus on deforestation monitoring methods, REDD+ countries are using a diverse range of methods to generate national deforestation estimates. Different forest definitions, reference periods, and methods used by countries leads to deforestation results that are not directly comparable across countries or over time.

This lack of comparability may limit the credibility of REDD+ transactions in future carbon markets, which are likely to demand rigorous and internationally comparable results. It also impedes global efforts under the UNFCCC to take stock of progress made collectively by countries in implementing their nationally determined contributions (NDCs) in the forest sector.

The Global Forest Change (GFC) data of Hansen et al. (2013) yield national tree cover loss statistics using a globally consistent forest definition and method. Some in the forest monitoring community have questioned the appropriateness of "off-the-shelf" applications of these global tree cover loss data for national REDD+ reporting. Confusion and controversy surrounding differing estimates is not helping to engender needed trust in REDD+ and, more broadly, in the use of forests for climate change mitigation.

About This Working Paper

This working paper aims to bring greater clarity to nontechnical audiences such as climate policy makers by offering a systematic comparison among methods used and forest monitoring results generated by REDD+ countries and global forest monitoring initiatives. First, we review deforestation estimates in 33 national and subnational forest reference emission level (FREL) submissions to the UNFCCC, which are intended to serve as country baseline data for future conservation efforts. We then explain how much and why these results may differ from the globally consistent tree cover loss estimates derived from Hansen et al. (2013).[3] We discuss the potential use of global approaches in terms of accuracy and cost savings, as well as the potential limitations, and offer recommendations.

Conclusions

The GFC tree cover loss data represent a transparent, complete, consistent, and reasonably accurate way to monitor tropical deforestation in an operational environment that is capable of supporting broad policy initiatives. Even without adjustments made to fully accommodate national forest definitions, GFC tree cover loss data represent an unbiased proxy for tropical deforestation reported across all REDD+ countries. Differences exist at the scale of individual REDD+ countries for a variety of reasons.

With appropriate filtering to accommodate different national forest definitions, the alignment of GFC and national estimates would likely improve in many cases. In other cases, questions remain about the exact reasons for differences between national and global data.

Beyond its utility as a global forest monitoring product, the GFC data are useful in a national context in different ways. To date, 9 of 33 countries have used GFC data either directly or indirectly in their FRELs. This includes those that customized the global algorithm to meet national needs (e.g., Peru, Colombia), adapted the GFC data for use as a stratification tool in sample-based approaches (e.g., Ethiopia, Myanmar, Nigeria, Republic of Congo, Sri Lanka), or used the GFC data to improve and/or fill gaps in a country's own monitoring system (e.g., Honduras, Madagascar, Lao People's Democratic Republic).

Both global and national forest monitoring systems have benefits and applications beyond their role in REDD+, and the GFC tree cover loss data are produced for a fraction of the cost of what has been invested in national forest monitoring systems. This indicates an opportunity to increase the use of global datasets in national accounting and reporting. For many countries, using freely available and fully operational global data products as an input to or direct source of national deforestation monitoring data could help reduce costs and improve long-term sustainability, while maintaining desired levels of accuracy and ownership.

Recommendations

We make several recommendations on how to increase utility and adoption of global datasets for national accounting and reporting under REDD+. They fall under the categories of aligning global vs. national data, adapting off-the-shelf global data to meet national needs, and customizing the GFC algorithm to produce tailored, wall-to-wall national maps of deforestation.

Align global and national deforestation monitoring products for consistency and country needs. Inconsistent results among countries, combined with the high costs of creating and maintaining unique national forest monitoring systems, suggest that REDD+ countries could consider tailoring freely available global tree cover loss data to meet national reporting needs. Conversely, the international remote sensing community could deliver products that align more closely to what countries need for national forest monitoring, such as maps of land use change rather than land cover change.

To help align these data, REDD+ countries should make their spatial forest monitoring data available for public review in a centralized location as part of the FREL technical assessment process. This would enable analysts to critique and compare national and global monitoring efforts more easily, leading to continuous improvement and comparability of forest monitoring at all scales. REDD+ countries stand to benefit collectively from more aligned, cheaper, and more credible forest monitoring systems that achieve greater consistency in results at national and international levels.

Adapt and assess global products to meet national needs for REDD+. The GFC tree cover data can be filtered to accommodate any country's forest definition. Then, the resulting map can be used as an input to stratified sampling to quickly generate a national average historical deforestation rate with a known uncertainty range at relatively low cost. The accuracy of the global, "off the shelf" map can also be assessed for a national context. If the global tree cover loss map that has been adapted for the national context is assessed to be accurate at the national level, if the map errors are unbiased, and if the map-based tree cover loss estimates fall within the uncertainty bounds of sample-based estimates, then the off-the-shelf GFC tree cover loss map and resulting statistics should be deemed as fit for purpose by the climate policy community as an accurate, precise, and cost-effective deforestation monitoring product for the country of interest.

Customize the GFC algorithm to produce more refined national deforestation maps. While sample-based methods allow for estimation of a single national deforestation rate with a known uncertainty range at relatively low cost, countries should consider the additional benefits of a customized, wall-to-wall national deforestation map, which allows for total deforestation to be disaggregated across time and space. This type of map is useful for understanding where deforestation is occurring and for designing location-specific deforestation reduction policies. All available cloud-free Landsat satellite imagery is processed for locations around the world to produce the annual Global Forest Change product. The same data inputs and algorithms can be easily tailored for national or subnational application (by incorporating additional, country-specific training sites to train the tree cover loss classification model) thus producing more accurate national deforestation maps than those currently available as subsets of the GFC product.

INTRODUCTION

Along with reductions in emissions from fossil fuels through shifts to clean energy and transportation systems, forests are a critical component of any global strategy to mitigate climate change. This section introduces the role of forests in the 2015 Paris Climate Agreement, the role of forest monitoring in deforestation reduction schemes, and requirements for robust forest monitoring systems.

The Role of Forests in the Paris Climate Agreement

Deforestation is responsible for approximately 12 percent of global greenhouse gas (GHG) emissions (IPCC 2014), and standing forests act as carbon sinks by removing and sequestering carbon from the atmosphere. The latest models suggest that both halting tropical deforestation and increasing forest carbon sinks will be necessary to achieve the Paris Agreement goals of net zero emissions in the second half of the century and limiting global warming to 2°C.

Article 5 of the Paris Agreement under the United Nations Framework Convention on Climate Change (UNFCCC) encourages all Parties to make full use of forests for climate change mitigation, and explicitly calls for them to move forward with REDD+ implementation. REDD+ is the internationally agreed framework for incorporating forests into the emission reduction strategies of developing countries, specifically through activities that reduce deforestation and forest degradation, promote forest conservation and sustainable management, and/or enhance forest carbon stocks. Critically, REDD+ includes financial incentives in the form of "readiness" and "implementation" funding (similar to traditional development aid) as well as "results-based" payments for verified emission reductions.

The international framework and guidance for implementing REDD+ reflects more than a decade of intense negotiations to ensure the scheme would be effective, efficient, and equitable. (For an excellent summary of how REDD+ evolved in international forest and climate politics, see Seymour and Busch 2016.) Beyond REDD+, countries are also outlining their forest-related strategies and actions to mitigate climate change in their nationally determined contributions (NDCs) under the Paris Agreement.

The Role of Forest Monitoring in REDD+

To receive REDD+ results-based payments, countries must monitor changes in forest cover and quantify the carbon emissions and removals associated with these changes. REDD+ transactions hinge on results-based payments, so measurements should be replicable over time, accurate, timely, and perceived as credible by the international community. Participating developing countries must measure reduced emissions and/or increased removals from forests against a pre-established baseline, known as a forest reference emission level/forest reference level (FREL/FRL; Lee and Sanz 2017).

A key obstacle to realizing REDD+, discussed in UNFCCC negotiations since 2007,[4] was a concern that regularly updated and available data on forest cover change in developing countries were insufficient to support timely and accurate monitoring. Although forest inventories—the traditional means for quantifying forest cover and forest change—have been established in developed countries for decades, developing countries historically lacked the capacity to conduct regular national forest inventories. Furthermore, since inventories are time and resource intensive, they are typically carried out at most only every five years, even in developed countries.

Over the past decade, satellite imagery has emerged as an increasingly efficient, effective, and affordable means to regularly and consistently monitor changes in tropical forest cover across countries and over time. Progress in this field has advanced rapidly due to the increasing availability of free, medium-resolution satellite data,[5] improvement of methods to classify imagery automatically using computer algorithms, and enhancements in cloud computing to enable large-scale data processing.

Brazil was the first developing country to establish an operational deforestation monitoring system using satellite imagery, called the Program for the Calculation of Amazon Deforestation, or Programa de Cálculo do Desflorestamento da Amazônia (PRODES), which has produced annual deforestation maps of the Brazilian Amazon since 1988. In 2013, Hansen et al. published global, medium-resolution maps of 21st century forest cover change for the years 2000 through 2012. Awareness and use of these data grew with the launch of Global Forest Watch in 2014, which facilitates easy online access to these data through an interactive mapping and analysis platform and publishes annual updates to the original dataset.

Through REDD+ finance –nearly $10 billion in public and private sector funds have been pledged to date[6] (Norman and Nakooda 2014) – more developing countries have begun to build their own national forest monitoring systems taking advantage of freely available satellite imagery. As a result, developing countries' overall capacity to monitor forest cover change has improved (Romijn et al. 2015).

Requirements for REDD+ Forest Monitoring Systems

Technical progress in satellite-based forest monitoring helped give UNFCCC negotiators the confidence to advance the political agenda on REDD+. In 2014, they achieved consensus on the "modalities" needed for measuring, reporting, and verifying (MRV) greenhouse gas emissions and removals and for designing national forest monitoring systems (Box 1). MRV, and the national forest monitoring (NFM) systems that underpin it, are the essential tools for linking REDD+ activities to results-based finance.

A crucial part of the MRV process is the formal "technical assessment" of proposed FRELs/FRLs, the benchmark against which performance is measured. The 2013 Warsaw Framework modalities (so called because the framework was agreed at the 2013 UNFCCC Conference of Parties (COP) 19 in Warsaw, Poland) therefore aim to ensure that national forest monitoring systems are adequately robust, transparent, and continuously improved, while allowing for flexibility to account for diverse national circumstances. But the Warsaw Framework also provides ample room for interpretation, which can create challenges for assessing and comparing national approaches.

Box 1 | Modalities for Measuring, Reporting, and Verifying (MRV) Greenhouse Gas Emissions and Removals under REDD+

Under the Warsaw Framework, estimates of the forest reference emission levels/forest reference levels (FREL/FRLs) should:

- Adhere to Intergovernmental Panel on Climate Change (IPCC) principles of transparency, completeness, consistency, and accuracy
- Maintain consistency with anthropogenic forest-related greenhouse gas emissions by sources and removals by sinks as contained in each country's greenhouse gas inventory
- Be guided by the most recent IPCC guidelines and guidance as adopted by the Conference of Parties
- Be consistent with a step-wise approach
- Be adjusted for national circumstances, as appropriate
- Be subnational as an interim measure, although the transition to a national FREL/FRL remains the final goal
- Be updated periodically as appropriate, taking into account new knowledge, new trends, and any modification of scope and methodologies

National forest monitoring (NFM) systems should:

- Use a combination of remote sensing and ground-based inventory approaches for estimating emissions and removals, forest carbon stocks, and forest area changes
- Provide estimates that are transparent, consistent, as far as possible, accurate, and that reduce uncertainties
- Produce monitoring results that are transparent and suitable for review
- Build on existing systems, as appropriate
- Enable assessment of different types of forest in the country, including natural forest, as defined by the Party, to ensure that safeguards are addressed and respected
- Be consistent over time and with the established forest reference emission levels and/or forest reference levels
- Be flexible and allow for improvement over time

ABOUT THIS WORKING PAPER

Data on tropical deforestation are no longer lacking. Instead, a situation has arisen in which different data are being produced by different groups for different purposes, using different methods and time periods, and leading to divergent results.

REDD+ countries are using a diverse range of methods to generate national deforestation estimates, and many REDD+ stakeholders—particularly those working to design more effective forest policies—lack the technical knowledge to assess the quality of methods or validity of results. In addition, the Global Forest Change (GFC) data of Hansen et al. (2013), which provide tree cover loss statistics using a globally consistent forest definition and method, have caused confusion in the forest monitoring community about which deforestation figures are "correct" for a given country or region, and why estimates sometimes differ so much from one another. It has also raised questions from some in the community about the appropriateness of "off-the-shelf" applications of GFC tree cover loss estimates for national REDD+ reporting.

This working paper aims to reduce confusion by systematically comparing methods used and results generated by REDD+ countries and global forest monitoring initiatives. First, we review national and subnational FREL submissions to the UNFCCC. We then attempt to explain how much and why results differ between national deforestation estimates and the globally consistent tree cover loss estimates derived from Hansen et al. (2013).[7] We evaluate the strengths and weaknesses of national versus global approaches. Finally, we discuss the potential benefits of global approaches in terms of accuracy and cost savings, as well as the potential limitations, and make recommendations to increase the utility of global datasets for national application.

The scope of this paper is limited to one REDD+ activity—deforestation— because satellite imagery forms the primary data input for forest cover change used by REDD+ countries for their deforestation estimates and for global forest monitoring initiatives. Because most countries do not yet include FRELs/FRLs for other REDD+ components such as forest degradation or carbon stock enhancement, we do not include these in our assessment. We also limit this paper to the monitoring component related to deforestation area; a similar comparison of deforestation emission factors (estimates of the change in carbon stocks resulting per unit area) derived from national monitoring systems and global remote sensing studies may be covered in a future paper. Finally, our initial analysis is limited to the deforestation rates reported in FRELs submitted by countries to the UNFCCC, and excludes those submitted to the World Bank's Forest Carbon Partnership Facility (FCPF). These may be incorporated into a future working paper.

Table 1 | **Paraguay as an Example of How Different Forest Definitions Were Developed for Different Reporting Purposes**

REPORTING PURPOSE	FOREST DEFINITION		
	MINIMUM AREA (HECTARES)	MINIMUM CROWN COVER (PERCENT)	MINIMUM TREE HEIGHT (METERS)`
FAO Forest Resources Assessment	0.5	10	5
UNFCCC Kyoto Protocol's Clean Development Mechanism	0.5	25	5
UNFCCC REDD+ reporting[a]	1	(western region) 10 (eastern region) 30	(western region) 3 (eastern region) 5

Note: a. In its FREL, Paraguay notes a technical limitation that forest cover below the 30 percent threshold cannot be detected with the use of medium-resolution imagery, so the effectiveness of detection and monitoring of any conversion is limited to areas with greater than 30 percent canopy cover.
Source: WRI authors.

HOW ARE COUNTRIES DEVELOPING THEIR FRELS AND NFM SYSTEMS?

As of mid-2018, 38 FRELs from 34 countries had been submitted to the UNFCCC for technical assessment.[8] We looked at how these countries addressed key methodological elements related to estimating deforestation. The historical average area of deforestation, when combined with emission factor data, represents a benchmark for assessing each country's performance in reducing deforestation-related emissions under REDD+.

Definitions

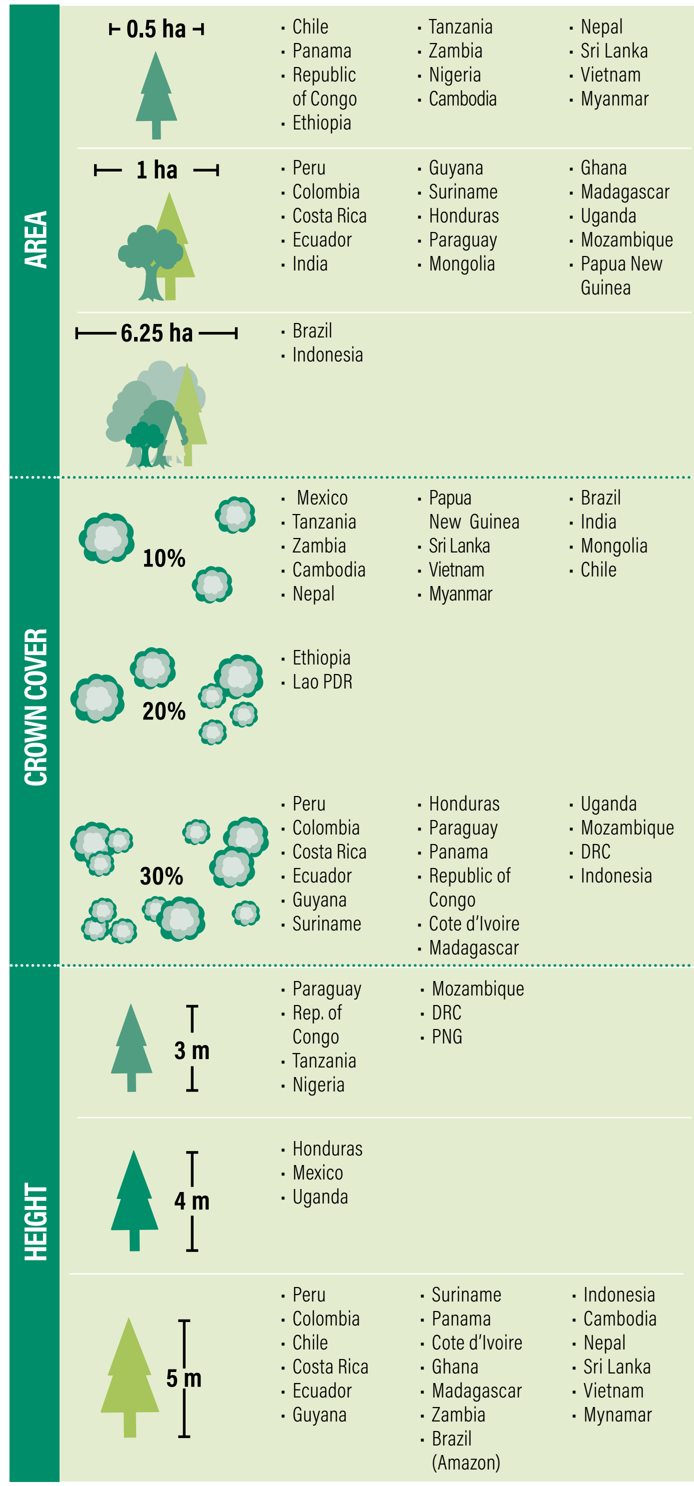
Some differences in deforestation estimates from country to country can be traced to the use of different definitions of key terms such as forest, natural forest, deforestation, and reference period. This section explains how these definitions can vary.

Forest. How a country defines its forest area impacts deforestation monitoring results by prescribing which areas are included and excluded from analysis. Forest definitions can vary across countries and within a country, depending on the reporting purpose and/or region within the country (Table 1). Most forest definitions include thresholds for minimum area, crown cover, and tree height.

The primary objectives of countries in establishing forest definitions are to suit specific policy purposes and to address unique national or subnational forest contexts. In addition, international processes have played a significant and evolving role in shaping national forest definitions.

Biophysical definitions. All countries reporting to the Food and Agriculture Organization of the United Nations' (FAO) Forest Resources Assessment (FRA) are advised to define forest as at least 0.5 hectare, 10 percent crown cover, and 5 meters in height.[9] Under the UNFCCC, countries define forests as they wish when reporting their national GHG inventories but for the UNFCCC's Kyoto Protocol, Parties agreed to define forests using distinct but flexible ranges: minimum area between 0.1 and 1 hectare, crown cover of 10–30 percent, and tree height of 2–5 meters. Most developing countries had little reason to apply the Kyoto Protocol definition, so the creation of REDD+ in 2007 catalyzed many national processes to establish forest definitions, involving lively exchanges among national and international organizations.[10] Figure 1 summarizes how countries have defined their forests for the purposes of REDD+ and demonstrates the variability that reflects each country's unique national circumstance.

Figure 1 | **Forest Definitions Used by Countries for REDD+ Accounting**



Source: Data from REDD+ country FREL submissions to the UNFCCC, compiled and analyzed by WRI authors.
Note: Countries excluded from lists either do not apply a threshold or apply thresholds different from those included in the figure. These include: Area: Cote d'Ivoire (0.1 ha) Congo, Dem. Rep. (0.1 ha); Mexico (50 ha). Crown cover: Ghana (15%), Nigeria (15%), Chile (10% for arid/semi-arid conditions, 25% for "more favorable conditions"). Height: Ethiopia (2 m), Mongolia (2 m), Brazil Cerrado (2 m), India (no height threshold), Lao PDR (no height threshold).

Land use definitions. In addition to the biophysical thresholds of area, crown cover, and tree height often used to define forests, many countries also incorporate information about the prevailing land use into their definition, as characterized by the "total of arrangements, activities, and inputs that people undertake in a certain land cover type" (Di Gregorio and Jansen 1998). This is largely a carryover from FAO reporting; however, GHG reporting for the LULUCF (land use, land use change, and forestry) sector under the UNFCCC also requires a land use definition (IPCC 2006). Therefore, even if land is temporarily devoid of tree cover, a country may still classify it as forest if it is officially designated as a forest land use. Conversely, lands that technically meet biophysical thresholds used to define forest may be classified as other land uses (e.g., urban areas and settlements with trees or agricultural land with trees, depending on its intended use).

For the purposes of defining forests for REDD+, 19 countries have defined forest based purely on biophysical criteria, while 14 also include a land use component in their definition (Table 2).

Table 2 | **Countries Using Biophysical vs Biophysical plus Land Use in their REDD+ Definition of Forest**

COUNTRIES THAT USE BIOPHYSICAL CRITERIA ONLY IN DEFINITION OF FOREST FOR REDD+
Brazil, Colombia,[a] Costa Rica, Congo, Dem. Rep.,[a] Ecuador, Ethiopia, Ghana, Guyana, India, Indonesia,[a] Madagascar, Mongolia,[a] Nepal,[a] Nigeria, Paraguay[a], Peru, Tanzania, Sri Lanka,[a] Zambia[a]

COUNTRIES THAT USE BIOPHYSICAL CRITERIA + LAND USE IN DEFINITION OF FOREST FOR REDD+
Cambodia, Chile, Cote d'Ivoire, Honduras, Mexico, Mozambique, Myanmar, Lao PDR, Panama, Papua New Guinea, Republic of Congo, Suriname, Uganda, Vietnam

a. The official forest definition as stated in the FREL is based on forest cover + land use, but the operational forest definition for REDD+ deforestation monitoring is based on forest cover (biophysical criteria) only.

Natural forest. In 2010, UNFCCC Parties agreed on important requirements and prerequisites to ensure that REDD+ would yield positive results for forests, forest-dependent people, and the climate. The seven agreed "Cancun safeguards"[11] cover a range of issues. One issue involves the distinction between natural and plantation forests to ensure that REDD+ actions would not lead to clearcutting natural forests and replacing them with industrial tree plantations, which could provide some services but would otherwise result in negative impacts.

Most countries include both natural forests and forest plantations in their REDD+ forest definition, but some have not specified if or how changes between natural forests and forest plantations will be tracked (Table 3). While many REDD+ countries include forest plantations (e.g., forests used for timber and pulp production) in their forest definitions, most exclude tree crops grown for an agricultural use (e.g., cocoa, citrus, oil palm, or rubber). Exceptions include Vietnam, which includes rubber plantations as forest; Honduras, which includes agroforestry systems (coffee and cocoa) as forest; and the Democratic Republic of Congo, which includes rubber and cocoa plantations, but not oil palm or coffee, as forest.

Deforestation. Under the UNFCCC, deforestation is defined as the "direct human-induced conversion of forested land to non-forested land."[12] Under FAO's Forest Resources Assessment, deforestation is defined as the conversion of forest to another land use (e.g., removal of forests for agriculture) and, more recently, "the conversion of forest to other land use independently whether human-induced or not" (FAO 2018). This definition includes permanent reduction of tree canopy cover below the minimum 10 percent threshold but excludes areas where trees are expected to regenerate. Thus, in both UNFCCC and FAO definitions, a temporarily unstocked forest is not considered to be deforestation.

Perhaps the greatest source of diversity and ambiguity in deforestation definitions under REDD+ is the case of shifting cultivation, a type of small-scale farming prevalent across the tropics particularly in Sub-Saharan Africa and Southeast Asia. A generalized cycle of shifting cultivation starts when forest is cleared to make a garden or agricultural field. Larger trees are either left standing, felled and used as timber, or left on the ground to decay. The resulting wood residue is burned to clear remaining vegetation and release nutrients which fertilize the soil. After burning, crops are planted and harvested, the land is abandoned to go fallow, and it eventually reverts back to forest if left undisturbed.

Table 3 | **How REDD+ Countries Count Forest Plantations in their REDD+ Forest Definition**

FOREST PLANTATIONS EXCLUDED FROM REDD+ FOREST DEFINITION	FOREST PLANTATIONS INCLUDED IN REDD+ FOREST DEFINITION BUT TRACKED AS A SEPARATE CLASS	FOREST PLANTATIONS INCLUDED IN REDD+ FOREST DEFINITION AND NOT TRACKED AS A SEPARATE CLASS	FOREST PLANTATIONS NOT ADDRESSED IN FREL
Brazil, Chile, Colombia, Indonesia, Madagascar	Cambodia, Ecuador, India, Lao PDR, Mexico, Mozambique, Panama, Papua New Guinea, Paraguay, Uganda, Vietnam	Cote d'Ivoire, Costa Rica, Dem. Rep. of Congo, Ethiopia, Ghana, Myanmar, Nepal, Nigeria, Peru, Tanzania, Sri Lanka, Zambia	Guyana, Honduras, Mongolia, Republic of Congo, Suriname

a. Ghana commissioned a separate study to allow removal of agricultural tree areas (e.g., cocoa) from deforestation totals, but does not track forest plantations as a separate forest class.

The first cycle, the initial clearing of forest, would be considered deforestation under a land-use definition of forest because forest was cleared to create a new agricultural field. But in sparsely populated areas, subsequent fallows are typically long enough (about 8 years in Lao People's Democratic Republic[13] to about 18 years in the Democratic Republic of Congo [Molinario et al. 2017]) for natural forest to recover, although recovery is to a secondary rather than primary forest. When fallow periods are long enough to allow regeneration of an ecosystem that exhibits the structural traits of a forest such as tree cover and height thresholds, shifting cultivation is viewed by some as a sustainable type of land use without long-term negative impacts (Filho et al. 2013). But growing populations and pressure on land will likely result in the expansion of shifting agriculture systems into nearby forests in the future (Molinario et al. 2017), leading to first-time clearing in new forest areas and resulting emissions.

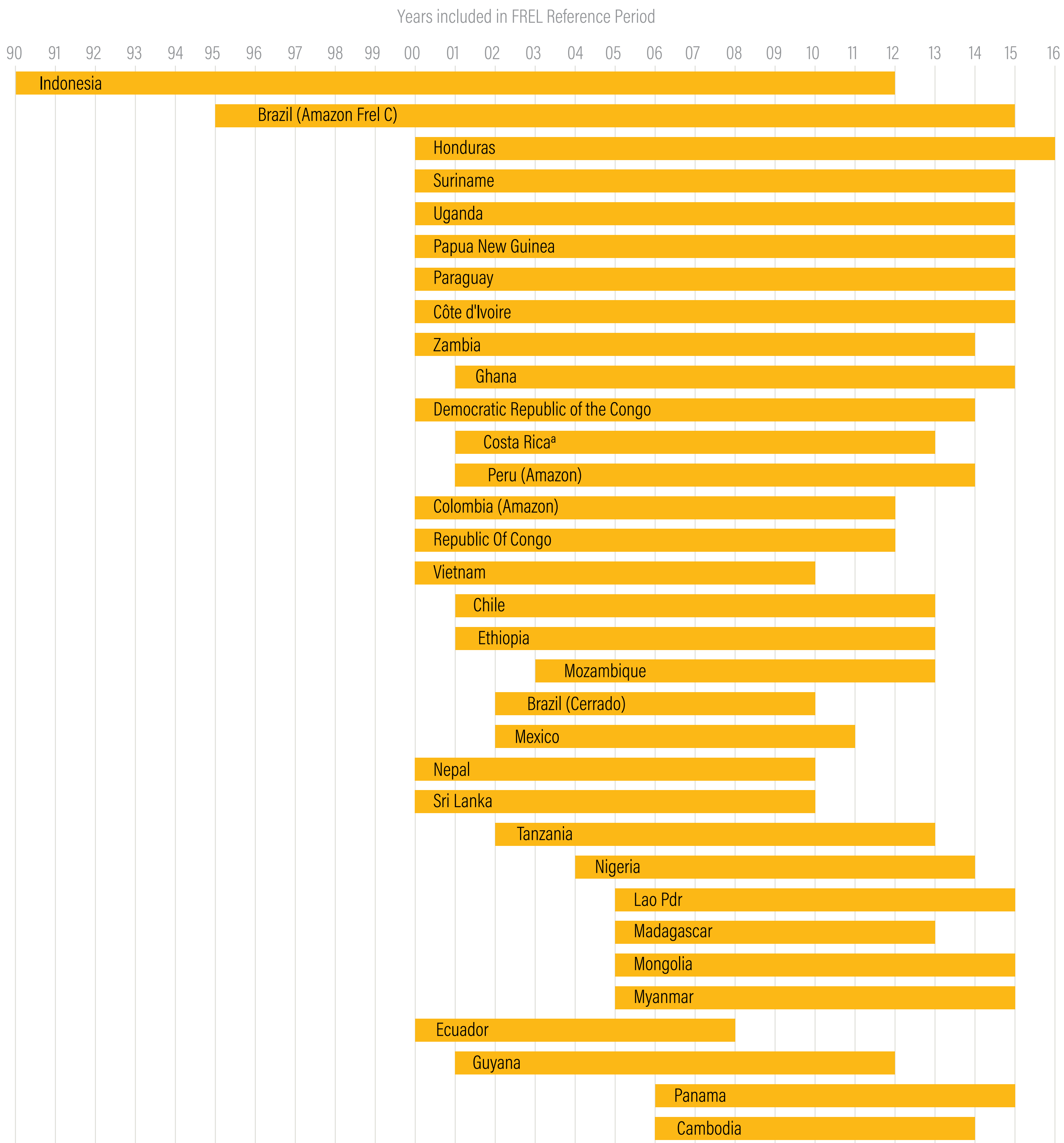
The impermanence of tree cover in areas under existing shifting cultivation cycles has implications for deforestation monitoring, and REDD+ countries are inconsistent in how they account for land areas under shifting cultivation cycles. In Suriname, all areas of shifting cultivation are considered forest, and any conversion of land considered primary forest into shifting cultivation is considered forest degradation rather than deforestation. In neighboring Guyana, existing areas of shifting cultivation are considered cropland (i.e., nonforest land) and excluded from both deforestation and degradation estimates. Papua New Guinea identifies shifting cultivation as a major driver of deforestation, accounting for 63 percent of all deforestation between 2000 and 2015. In Lao PDR, shifting cultivation cycles are split into their component parts and tracked separately, with fallows classified as forest land and crops classified as crop land. In Mozambique's land cover/land use map, a shifting cultivation subclass is included in both the cropland class ("shifting cultivation with open to closed forest areas") and the forest class ("forest with shifting cultivation"). Other African countries where shifting cultivation is prevalent, including Cote d'Ivoire, the Republic of Congo, and the Democratic Republic of the Congo, track gross loss of forest cover, meaning that the clearing of secondary forests on shifting cultivation fallows is counted as a deforestation event as well as primary forest clearing. Unless regrowth is carefully tracked, deforestation will be overestimated in these countries compared to others where gain/loss dynamics of shifting cultivation land uses are excluded or tracked separately.

Reference Period

To participate in REDD+, a country must determine what the deforestation rate would have been in the absence of REDD+ incentives. Unless this rate is adjusted upward or downward to consider specific national circumstances,[14] the historical average deforestation rate is used as an input into the FREL/FRL.

The reference period is typically set by countries to cover approximately the past 10 years, although the exact dates differ from country to country (Figure 2) based on data availability. The choice of years in the reference period can impact the FREL/FRL, and countries might strategically opt for reference periods that maximize the average historical deforestation rate and thus the potential for future REDD+ payments if it declines. Indonesia and Brazil, two countries with historically high deforestation rates, chose longer reference periods stretching back to the 1990s, resulting in higher average historical deforestation rates than would be the case if only more recent years were included in the reference period.

Figure 2 | Reference Periods Used by Countries in Estimating Rates of Historical Deforestation



Note: a. Costa Rica's first reference period stretches back to 1986, but second reference period begins in 2009.
Source: WRI authors.

Method Used for Estimating Deforestation Rates

All REDD+ countries use satellite imagery to estimate historical deforestation, but the type of imagery and the method used to interpret it vary (Figure 3). Wall-to-wall map-based approaches (analyses that cover the full spatial extent of forested areas) and sample-based approaches (analyses that derive estimates based on statistically representative sample areas) are both suitable methods for analyzing forest cover change. Whichever method is selected, best practice guidance requires that results are repeatable by different analysts (GOFC-GOLD 2016).

Wall-to-wall map-based approaches

Creating maps of land cover and land cover change involves a mix of computer algorithms and human expertise to interpret satellite imagery. Many methods can be used to classify images, and the selection depends on the available human, data, and financial resources, the availability of image processing software, and the type of forest to be monitored. Several methods to estimate rates of deforestation using wall-to-wall map-based approaches are described below.

Post-classification change detection. This method involves mapping land cover or land use at specific time steps, lining up the maps, and summing the forest areas that transition to nonforest over time. If the map images are not annual, an average annual deforestation rate is calculated by dividing the total area of deforestation by the number of years elapsed between mapped years. This approach is referred to as "post-classification" change detection because change is calculated after land cover classes have been assigned to each time step. This method can be used to track changes among Intergovernmental Panel on Climate Change (IPCC) land use/land cover categories (e.g., forest land, crop land, settlements) and/or among forest types (e.g., natural forest vs. plantation forest).

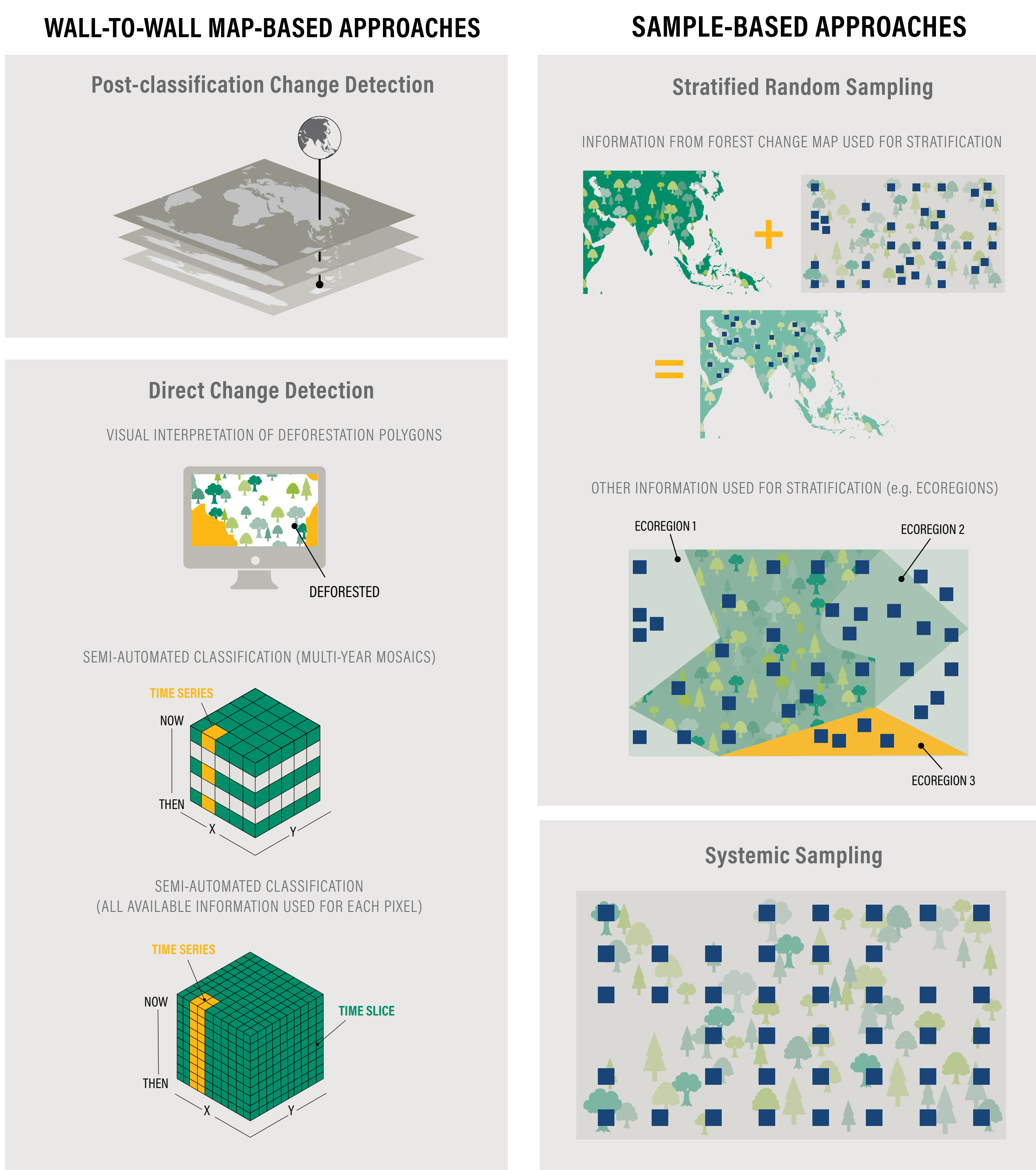
However, this method is prone to error in the resulting change statistics because it progressively propagates classification errors that may be present at each time step, particularly if maps for different years were created by different groups or using different classification methods. The accuracy of this method also depends on how many land cover/land use categories are included in the resulting change matrix; high accuracy of many different change classes is difficult to achieve. Map classes can be aggregated to increase measures of accuracy, because what matters for estimating a deforestation rate for REDD+ is the accuracy of the change class from forest to nonforest. **Countries that use post-classification change detection include: Ecuador, Ghana, India, Indonesia, and Uganda.**

Direct change detection. This method produces the same end product as the post-classification method – a map of forest cover change for a given year or series of years – but uses a different approach to detect change. In this method, satellite images for two or more points in time are examined for spectral similarities and dissimilarities to identify areas containing a likely change in land cover, thus eliminating the step of assigning land cover classes to the two points in time as required for post-classification change detection. Direct change detection can be done visually or using digital image processing algorithms, in which "training sites" are classified visually by an interpreter and then used to train an automated computer algorithm to classify other areas in the map that are similar to the training sites. The total area of deforestation may be calculated directly from the change maps, or the maps may be used as an input for stratified sampling (see below).

Many national analyses applying the direct change detection method use single image footprints, or scenes, as the basic unit of analysis. This compromises consistency between scenes and requires analysts to apply complex data processing techniques before metrics between different dates can be compared. Such data processing steps include corrections for different atmospheric conditions, sun positions, and satellite calibrations. Until recently, many of these techniques were not automated and in many developing countries, capacity to quickly process thousands of images from a raw state to a finished land cover change product was limited.

Hansen et al. (2013) developed a standardized and automated processing scheme for deriving cloud-free time-series metrics from Landsat data, enabling preprocessed satellite data to be compiled and assembled quickly into time-series metrics and composites. All available data are used to characterize change, such that two neighboring pixels could use data from different dates depending on the availability of cloud-free imagery. Once all pixels have been classified and those containing change have been identified, they can be assigned to the year in which change occurred. Time-series analysis can be thought of as stock market analysis, with an algorithm tuned to search for a signal that shows a sudden and persistent drop in value, in this case a decrease in

Figure 3 | **Two Approaches to Estimate Historical Deforestation Rates**



Source: WRI authors.

vegetation cover that indicates deforestation. This method uses all available data and can therefore potentially detect change more accurately, and the change map can be derived and iterated quickly for the entire area. The use of standard preprocessed data inputs also promotes consistency across countries that use this method.

However, this type of direct change detection is much more computationally intensive than other methods. For many years, the high cost of obtaining and processing satellite data prevented the application of this time-series method for deforestation monitoring at scale. Advances in cloud computing and the availability of free Landsat imagery enabled the creation of annual maps of global forest change using direct change detection. After the publication of this method (Hansen et al. 2013), the same researchers at the Global Land Analysis and Discovery (GLAD) team at the University of Maryland, began collaborating with many countries to reproduce their system at a national scale using the same pixel-based time-series approach, but customized for national conditions using locally specific training data. **Countries that use direct change detection include: Mexico, Vietnam, Cambodia, Chile (visual interpretation); Brazil, Costa Rica, Guyana, Lao PDR, Honduras, Madagascar (classification model based on direct change detection between two dates); and Colombia, Peru (classification model based on Hansen et al. time-series analysis).**

Sample-based approaches

While the remote sensing community has historically recommended wall-to-wall map-based approaches (Olander et al. 2008, GOFC-GOLD 2016) to estimate land cover change at a national scale, some statisticians (e.g., Oloffson et al. 2014) have voiced strong concerns that calculating deforestation areas by summing change areas identified through computerized classification algorithms may result in systematically biased deforestation estimates due to map classification errors. Citing IPCC good practice guidance that emissions/removals should be "neither over- nor underestimated" and that uncertainties should be reduced "as far as is practicable" (Penman et al. 2003), they have encouraged countries developing FRELs to derive deforestation estimates through statistical analysis of reference samples that are visually interpreted by analysts using more precise data and/or better interpretation techniques. Because deforestation is interpreted only for the sample areas, sampling has long been considered a cost-efficient alternative to wall-to-wall mapping. Furthermore, a well-designed sampling approach can provide a measure of precision to quantify uncertainty and construct confidence bounds around a sample-based deforestation estimate. There are two types of sampling, described below.

Stratified random sampling. A stratified random sampling approach uses information about the study area

Table 4 | **Advantages and Disadvantages of Two Methods of Estimating Deforestation Rates Used by Countries in Their FREL Submissions**

METHOD	ADVANTAGES	DISADVANTAGES
Wall-to-wall map-based approaches (with visual checks)	■ Can be more easily reproduced than sample-based approaches ■ Map can be used to identify specific locations and years where deforestation is occurring ■ Rapid and automatic updates possible, including annual estimates ■ Allows for versioning/updating to reflect improvements over time through the incorporation of new input data	■ More difficult to develop and implement ■ Classification algorithms used may lead to bias in the resulting deforestation estimate ■ Uncertainty of area estimate is unknown in the absence of reference sample data
Sample-based approaches	■ Most similar to classic forest inventory approaches ■ Easy to implement ■ Can attribute additional contextual information to each sample, e.g., land use ■ Deforestation estimate is constrained by a quantified measure of uncertainty	■ Time consuming ■ Deforestation estimates apply only at the scale for which sampling was designed ■ Statistics derived from samples no longer match deforestation areas in the map, leading to inconsistencies especially if the map is used to derive other area statistics beyond REDD+ ■ Accuracy of results is highly dependent upon the skill of individual interpreters and is difficult to quantitatively measure; uncertain reproducibility of results

to constrain the selection of sample points; the stratification design may or may not be informed by land cover change maps. For REDD+ deforestation monitoring purposes, reference samples are distributed within "strata" typically defined from relevant map classes of a forest change map (e.g., forest, nonforest, forest loss, forest gain), but strata could also be administrative regions, ecoregions, or any other nonoverlapping division of land area (Oloffson et al. 2014). Each sample point within a stratum is interpreted visually over the defined reference period (e.g., 2006 to 2015) using high-quality reference data such as high-resolution satellite imagery. After all samples are visually interpreted, the area of deforestation is calculated based on information about the total area contained within each stratum and the proportion of samples within each stratum that registered as deforestation. A stratified design requires far fewer samples to obtain a similar level of accuracy and precision as a systematic sampling design (Broich et al. 2009).

The result is an estimate of the annual average deforestation rate over the reference period bounded by a given confidence interval, the size of which is determined by the uncertainty associated with sampling. Sample-based deforestation estimates can be considerably higher or lower than those calculated from wall-to-wall map-based approaches, even when the same maps were used for stratification. No change map is produced through sample-based approaches, but reference samples can also be used to assess the accuracy of an existing forest change map. **Countries that use stratified random sampling include: Cote d'Ivoire, Democratic Republic of the Congo, Ethiopia, Myanmar, Nepal, Nigeria, Republic of Congo, Sri Lanka, Suriname, Tanzania, Zambia, and Paraguay.**

Systematic sampling. Systematic sampling is similar to stratified random sampling, except samples are distributed across the country in a regularly spaced grid, often in the same locations as national forest inventory plots, instead of using a map to design a stratified random sample. High resolution imagery is visually interpreted at each point over the defined reference period to classify samples into specific land cover/land use categories. With systematic sampling, it can be difficult to capture rare classes of change that occur over small areas, particularly deforestation. Like stratified sampling, systematic sampling produces an estimate of deforestation for the reference period bound by a confidence interval representing the uncertainty of a sample-based estimate. **Countries that use systematic sampling include: Panama, Papua New Guinea, Mozambique, and Mongolia.**

Which method is best?

There is currently no consensus approach to forest monitoring over large areas. Expert opinion in the discourse about the merits of wall-to-wall, map-based approaches vs. sample-based approaches continues to evolve, as do the data and technology available to estimate deforestation rates. Prior to the 2008 delivery of the full Landsat archive by the U.S. Geological Survey (USGS) at no cost to scientists, the remote sensing community was accustomed to purchasing single Landsat scenes[15] to incorporate as reference samples into stratified sampling designs for large-area deforestation mapping using lower-resolution satellite data from systems other than Landsat (Achard et al. 2002; Hansen et al. 2008; Brioch et al. 2009; Zhu et al. 2014). Deforestation as estimated by remote sensing specialists, who visually interpreted each individual Landsat scene, was the "truth" against which all other deforestation models were compared. With the opening of the Landsat archive and other free sources of medium-resolution satellite imagery, estimating areas and rates of deforestation using wall-to-wall map-based approaches proliferated, with IPCC's spatially explicit "Approach 3"[16] recommended (GOFC-GOLD 2007). Map-based approaches more easily enable disaggregation of national deforestation spatially (by region), temporally (by year), or by disturbance type (driver).

More recently, free satellite imagery with higher-resolution than Landsat became available in Google Earth. This, combined with the limited experience and capacity of many developing countries to implement complex data preprocessing steps and land cover change classification models, led the expert community engaged in REDD+ capacity building to encourage use of sample-based approaches to estimate deforestation area (GFOI 2016) in lieu of (or as a complement to) wall-to-wall map-based approaches. Sample-based approaches are easier to implement, but differences in visual image interpretation by different analysts can lead to inconsistent results.

All methods summarized above for estimating deforestation rates are valid if implemented correctly. Regardless of which method is chosen (Table 4), image analysis by a skilled interpreter is an indispensable requirement for estimating land cover/land use change with high accuracy. The decision on which method to use should consider various factors including cost, required effort, data processing and analysis speed, need for spatial information about forests for other purposes beyond REDD+, and the need for consistency of results at national and international levels (Potapov et al. 2014).

Accuracy vs. Uncertainty

All methods described above result in errors due to data limitations, imperfect classification algorithms, and analyst errors and bias. Uncertainty was not as large of a focus in early FREL submissions (e.g., Brazil, Guyana) as in later submissions, which have been encouraged through the technical assessment process to explicitly address this issue. The uncertainty of results obtained through sample-based approaches are expressed through the calculation of confidence intervals around an average deforestation rate. Wall-to-wall deforestation maps on their own cannot provide information about how good or bad the estimates derived from the maps are. Therefore, reference samples serve as the "truth" to estimate the accuracy of maps.

Table 5 shows the accuracy of deforestation maps developed by countries in their FREL process, where reported. Three accuracy measures are given: user's accuracy, producer's accuracy, and overall accuracy. User's accuracy indicates how much deforestation detected in the map reflects actual deforestation on the ground. Producer's accuracy measures how much deforestation occurs on the ground that is missed by the map. Overall accuracy incorporates the accuracy of both change and nonchange classes. In most cases, nonchange pixels (e.g., forest remaining as forest) significantly outnumber change pixels, so looking only at overall map accuracy can be deceptive. Many correctly classified nonchange pixels can cause overall accuracy to be high even if the accuracy of change pixels (in this case, deforestation) is low.

For many countries, only the overall accuracy of land cover maps for specific years is provided in the FREL documentation (Table 5). Where reported, the accuracy of the loss/deforestation class over the reference period varies widely among countries, ranging from 12 to 98 percent. These accuracy statistics reflect both the accuracy of the map, but also potentially the uneven quality and inconsistency in the interpretation of reference samples by different image analysts (Box 2). Validation of static land cover maps is difficult, and change products are even more challenging to appropriately validate. Table 5 shows that accuracies of the GFC maps as used in a national context appear comparable to the reported accuracies of national deforestation maps, but more information is needed about the accuracy of the loss class specifically in national maps before this conclusion can be drawn.

Process and Costs of National Monitoring Systems

The international community has invested considerable resources to support national forest monitoring efforts, particularly related to capacity building in developing countries for MRV. Each country's forest monitoring system for REDD+ has been influenced by the approaches, methods and definitions of the organizations and academic institutions that led the capacity building.

Costs of developing national monitoring systems are substantial, but it remains difficult to quantify the investments made by countries and donors in their monitoring capabilities. Brazil's monitoring system alone costs approximately $1.5 million per year[17] to run, although this estimate reflects the long-term operational cost and does not include the initial up-front costs of development, testing, infrastructure investments, or capacity building that led to the system's now routine operation.

Estimating the costs of developing FRELs and building national forest monitoring systems from scratch for other countries is more complex. Drawing on data compiled for the REDDX (REDD eXpenditures) Initiative from 2009 to 2014, a global analysis by Silva-Chavez et al. (2015) showed that nearly $6 billion had been pledged for REDD+ across 13 key countries, but most of the REDD+ projects tracked had multiple REDD+ activities (e.g., stakeholder engagement, rights, and tenure) and so it was impossible to disaggregate the relative breakdown of financial support going specifically to develop FRELs or MRV systems. However, 377 of 877 donor initiatives, or nearly 40 percent, focused on MRV and reference levels (Figure 4). Furthermore, many donors are supporting the creation of national forest monitoring systems for more than the sole objective of reporting REDD+ results.

More recently, Lujan and Silva-Chavez (2018) broke down available REDD+ finance into the three phases: readiness, implementation, and results-based finance. The development of FRELs and NFM systems falls in the readiness phase. Available and forthcoming finance for REDD+ readiness totals at least $6 billion in public funds from the World Bank, UN-REDD, U.S. Agency for International Development (USAID), and the Governments of Germany, Norway, and the United Kingdom (Table 6). Private foundations and domestic investments provide additional finance.

Table 5 | **Accuracy of Maps Used to Inform Deforestation Estimates in Country FREL Submissions (percent accurate)**

REGION	GFC MAP ACCURACY (NATIONAL CONTEXT): COUNTRY	GFC: LOSS CLASS USER'S	GFC: LOSS CLASS PRODUCER'S	GFC: OVERALL ACCURACY	NATIONAL MAP ACCURACY: COUNTRY	NATIONAL: LOSS CLASS USER'S	NATIONAL: LOSS CLASS PRODUCER'S	NATIONAL: OVERALL ACCURACY	CHANGE MAPS NOT USED TO INFORM DEFORESTATION ESTIMATE
LATIN AMERICA	Peru	86%	67%	97%	Brazil (Amazon)	X	X	99%	Panama
	Colombia	X	X	X	Brazil (Cerrado)	X	X	97%	
					Chile	X	X	X	
					Costa Rica	X	X	X	
					Ecuador	X	X	94-96%	
					Guyana	X	X	>97%	
					Honduras[a]	97-98%	89-98%	96%	
					Paraguay	X	X	88-89%	
					Mexico	X	X	X	
					Suriname	X	X	99%	
AFRICA	Rep. of Congo	73%	64%	90%	Cote d'Ivoire	66%	68%	81%	Mozambique
	Ethiopia	24%	51%	75%	Dem. Rep. Congo	X	X	X	
	Nigeria (Cross River)	12%	9%	75%	Ghana	X	X	X	
					Madagascar[a]	48-58%	58-75%	76-89%	
					Tanzania	76%	79%	75%	
					Uganda	12-74%	2-27%	59-80%	
					Zambia	X	X	85%	
SOUTH & SOUTHEAST ASIA	Sri Lanka	79%	89%	75%	Cambodia	X	X	74-85%	Mongolia Papua New Guinea
	Myanmar	21%	42%	57%	India	X	X	X	
					Indonesia	X	X	98%	
					Lao PDR*	X	X	X	
					Nepal	82%	99%	83%	
					Vietnam	X	X	95%	

X = No data reported in the forest reference emission level (FREL).
a. Countries that used the GFC dataset either directly or indirectly in their FREL submission

Box 2 | The Importance of Consistent and Accurate Interpretation in Sample-Based Assessments

Visual interpretation of satellite images is often not as easy or straightforward as it might seem. Even with very high-resolution images (greater than 1 meter) in which individual trees and shrubs can be seen in the imagery, consistent classification of land area into a single, discrete land cover category is not always clear. Different interpretation of the same images can lead to very different outcomes.

In Ethiopia, World Resources Institute is working with nonspecialist imagery interpreters in "mapathons," where people from a certain region of a country are brought together in a classroom setting to receive one-day trainings in the visual interpretation of 50 x 50 meter sample points on very high-resolution satellite imagery. Rules are established to count trees and assign land cover classes based on what is seen in the imagery. Each interpreter classifies approximately 100 points per day, and several interpreters work side by side to interpret approximately 10,000 points in a week.

When developing land cover maps from these sample points, it became clear that different interpreters had very different interpretations of the same image. Where one interpreter saw agricultural fields (during the dry season), another interpreted the same land as shrub land, or as bare land. As can be seen in the confusion matrix below, interpreters also mixed shrubland with forest, and cropland with all other classes of land cover.

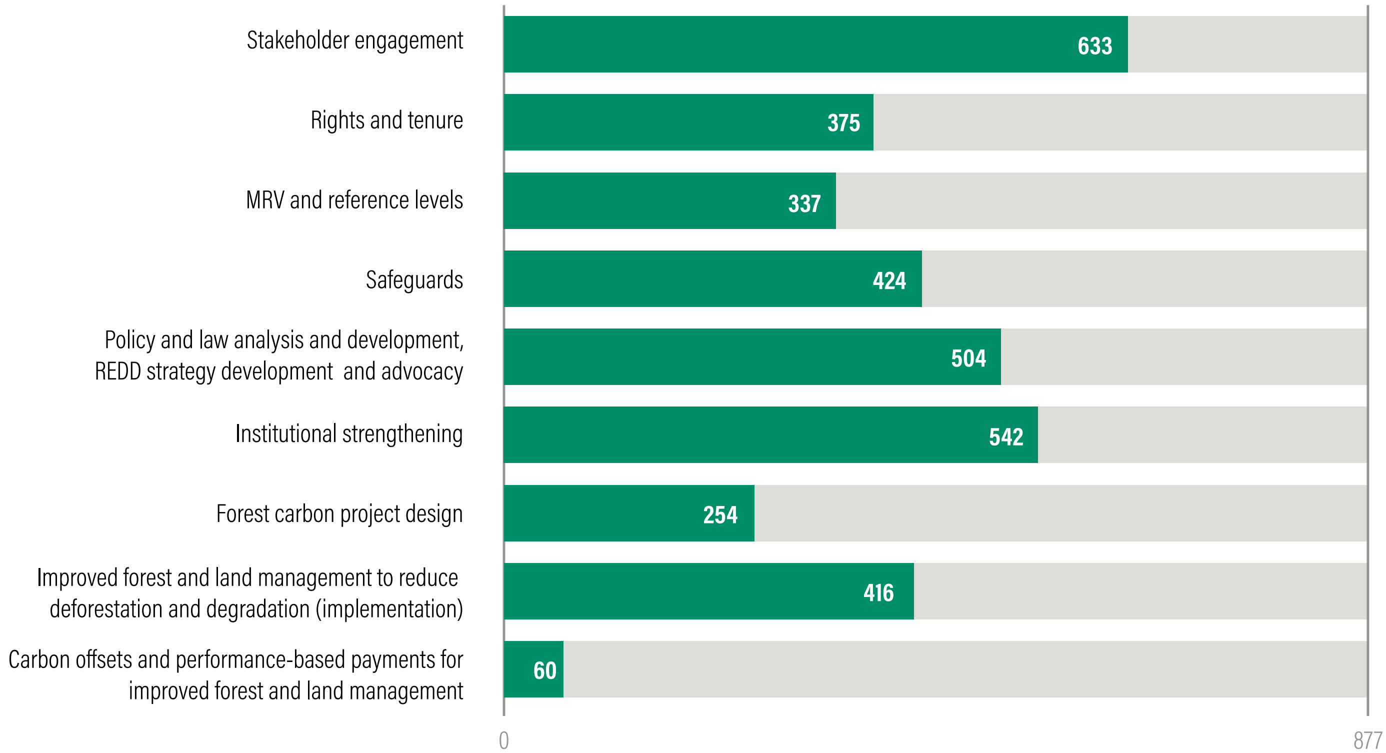
In sample-based approaches, visual interpretation of sample points is considered the "truth" data upon which deforestation estimates are derived. Thus despite the fact that a resulting deforestation estimate has a quantified uncertainty, the accuracy of the interpretation of sampled points (i.e., measurement error) goes unquantified. As such, rigorous classification protocols implemented by highly skilled interpreters are essential for accurate and consistent sample interpretation, particularly in complex and/or highly fragmented landscapes.

TABLE B2-1 | CONFUSION MATRIX FOR SODO DISTRICT, ETHIOPIA

	FOREST	CROPLAND	GRASSLAND	SHRUBLAND	SCRUBLAND	TOTAL	ACCURACY (PERCENT)
FOREST	642	113	5	136	6	**902**	71%
CROPLAND	42	6,042	13	63	42	**6,202**	97%
GRASSLAND	15	207	57	20	6	**305**	19%
SHRUBLAND	137	214	7	472	12	**842**	56%
SCRUBLAND	24	514	11	38	85	**672**	13%
TOTAL	**860**	**7,090**	**93**	**729**	**151**	**8,923**	
ACCURACY (PERCENT)	**75%**	**85%**	**61%**	**65%**	**56%**	**Overall Accuracy**	**82%**

Note: The table shows how often points independently selected and visually interpreted (8,923 points, shown in the rows of the table) are in agreement with the land use map, which was trained on 95,000 visually interpreted points. The rows show the newly interpreted points; the columns show the category these points fall under when overlaid onto the map. Thus a high number in the cells that intersect the same categories means that the interpretation of newly interpreted points were mainly in agreement with the interpretation of points used to train the land use classification model.
Source: WRI authors.

Figure 4 | **Proportion of Total (877) Donor Initiatives Supporting Various REDD+ Activities**



Source: Silva-Chavez et al. 2015.

Conclusions from Multicountry Comparative Analysis of FREL Submissions

After reviewing 33 FREL submissions in which deforestation was included as a REDD+ activity, we conclude the following:

- Countries are applying common guidance for developing FRELs as outlined in the Warsaw Framework, but direct comparison of deforestation rates across countries is not straightforward due to the different definitions used, years analyzed, and methods applied. Results represent a "fruit basket" of national and subnational estimates, which impedes the "apples to apples" comparison of deforestation rates across countries that many stakeholders in the REDD+ community and beyond may desire (and may assume is possible).

- In addition to impeding cross-country comparison, different methodological choices have major implications for resulting deforestation estimates in FRELs and future monitoring estimates, and subsequently for a country's potential to obtain future results-based payments. For example, a key area of methodological inconsistency and ambiguity is how countries are addressing the impermanence of tree cover within shifting cultivation cycles and the resulting impacts on their deforestation and degradation estimates.

- While much of this variability can be attributed to the different forest contexts of REDD+ countries, the development of national forest monitoring systems has also been influenced by advice provided by different capacity-building

Table 6 | **Major Sources of Finance for REDD+ Readiness Phase**

FUND	YEARS	AMOUNT (MILLION US$)
World Bank Forest Carbon Partnership Facility (FCPF) Readiness Fund	2008–17	370
UN-REDD	2008–16	280
	2018–20	27
USAID	2015–16	200
	2017	86
Governments of Germany, Norway, and the United Kingdom	2015–20	5,000
Total	**2008–20**	**5,963**

Source: Lujan and Silva-Chavez, 2018.

organizations with respect to methods. Greater consistency and comparability could potentially be achieved if there were greater international consensus on implementing best practice monitoring methods for REDD+.[18]

- The accuracy and precision of country-reported deforestation rates is highly variable and sometimes goes unreported. Results from both sample-based and wall-to-wall map-based approaches can produce accurate and precise results if properly implemented and inaccurate and imprecise results if not. While debates tend to center on the choice of methods, it is perhaps more useful to focus on quality of implementation and how it can be improved.

- Available and forthcoming finance for the REDD+ readiness phase totals at least $6 billion, but no comprehensive information exists to quantify investments channeled specifically to develop the national forest monitoring systems assessed in this paper. This information is needed for a cost-effectiveness analysis that could further inform decisions about the most appropriate and sustainable methods for monitoring deforestation under REDD+. While countries may aspire to create the most accurate systems possible, a key question should be the marginal cost of incremental gains in accuracy and precision.

GLOBAL FOREST MONITORING

Prior to the publication of Global Forest Change (GFC) data by Hansen et al. (2013), global estimates of forest cover or forest cover change were produced by aggregating national inventory data. Some earlier sample-based satellite monitoring products had global coverage (e.g., FAO's FRA2010 Remote Sensing Survey [FAO, JRC, SDSU, and UCL 2009]) and the TREES project (Achard et al. 2002), but the GFC data represent the first globally consistent, wall-to-wall maps of tree cover loss and gain that could also be disaggregated into easily downloadable national and subnational change statistics.

Definitions in the GFC Product

Forest. The GFC dataset does not define forest per se, but rather defines tree cover in the year 2000 as any vegetation greater than 5 meters in height across a range of canopy densities (1–100 percent) present within a single Landsat pixel with an area of approximately 0.1 hectare. This definition is a biophysical one and does not incorporate information about land use. The tree cover map can be filtered to include areas above a certain tree canopy density threshold (e.g., greater than 30 percent).

Natural forest. The GFC dataset does not define or distinguish natural forest from other forms of tree cover, including forest plantations and tree crops. Some have criticized the GFC dataset because it fails to distinguish conversion of natural forest from cyclical forestry dynamics and plantation rotations (Tropek et al. 2014). However, the same Global Land Analysis and Discovery (GLAD) team at the University of Maryland that produced the GFC maps has also produced maps and data that can be used in combination with the GFC data to approximate these distinctions, including various components or proxies of natural forests such as "intact forest landscapes" (Potapov et al. 2008, 2017), "tropical hinterland forests" (Tyukavina et al. 2016), and Indonesian "primary" forests (Margono et al. 2014). In addition, forest and tree plantations were mapped in six tropical countries using visual interpretation of high resolution satellite imagery (Petersen et al. 2016).

Deforestation. The GFC dataset neither defines nor purports to measure deforestation. Rather, it maps "tree cover loss," defined as the complete loss of tree cover within a 30-meter pixel. Deforestation, while variably defined, is a subset of all tree cover loss. For these reasons, the Global Forest Watch website, which is the best known point of access for the GFC data, uses the term "tree cover loss" to describe the GFC data rather than "deforestation." Other forms of tree cover loss that may not be considered deforestation according to UNFCCC and FAO definitions include loss associated with natural disturbances such as hurricanes and windstorms, or with land management practices such as rotational forestry, smallholder agroforestry systems, or shifting agriculture. Because the GFC dataset does not specifically measure deforestation without using additional data and analysis to classify various forms of tree cover loss), its applicability for REDD+ has been debated by the forest monitoring community.

Reference Period

The GFC data were published in 2013 and included global tree cover extent in 2000 and gross changes (annual loss and total period gain) between 2001 and 2012. The annual loss data are updated annually, most recently through the year 2017.[19]

Method Used for Estimating Deforestation Rates

The GFC dataset maps tree cover loss across all land except Antarctica and Arctic islands using the "direct change detection" approach described above, in which Landsat multispectral satellite imagery[20] is analyzed at a spatial resolution of approximately 30 meters. Cloud-free observations were assembled and a classification algorithm was applied with training data to identify pixels of tree cover loss. More than 1.5 million satellite images have been processed and analyzed, including more than 600,000 Landsat 7 images for the initial period 2000–12 and an additional 900,000 Landsat 5, 7, and 8 images for annual updates through 2017. The GFC maps have been used either directly or indirectly in 9 of the 33 deforestation FREL submissions (Table 7). Some countries have used sample-based approaches with the GFC map used as a stratification tool, while others have nationalized the GFC algorithm and developed additional analytical processes to differentiate deforestation from other forms of tree cover loss. No REDD+ country has estimated deforestation as the sum of tree cover loss pixels in the GFC map.

Table 7 | **REDD+ Countries Working with the Global Land Analysis and Discovery (GLAD) Team at the University of Maryland (UMD) on National Forest Change Mapping, and/or Using the GFC Data in their FREL Submissions**

REGION	COUNTRY	WORKED WITH GLAD TEAM AT UNIVERSITY OF MARYLAND	PARTNERS/ DONORS	HOW GFC DATA WERE USED IN FREL
LATIN AMERICA	Peru[a]	Forest monitoring in support of REDD+ and IPCC GHG reporting, 2000-current. Operational forest monitoring	MINAM, SilvaCarbon	Nationalized GFC algorithm
	Colombia[a]	Comprehensive land-cover monitoring for IPCC GHG reporting. 2000-ongoing	IDEAM, SilvaCarbon	Nationalized GFC algorithm
	Ecuador	Forest cover change quantification 2000-2011	SilvaCarbon	Project outputs not (yet) used for FREL
	Guatemala	Tree canopy cover monitoring 2000-current in support of REDD+ and NFI		Project outputs not (yet) used for FREL
	Honduras[a]			GFC map used to make comparisons and improve the national data generated
	Mexico	Forest extent, structure, and change assessment, 1985-2014	CONABIO	Project outputs not (yet) used for FREL
AFRICA	Ethiopia[a]			Stratifier
	Dem. Rep. Congo	Forest monitoring 2000-current, forest type mapping, habitat modelling	USAID, OSFAC, JGI	Project outputs not (yet) used for FREL
	Madagascar[a]			GFC map used to fill pixels with shadows and clouds in national map
	Nigeria			Stratifier
	Rep. of the Congo[a]	Forest monitoring 2000-current, forest type mapping, habitat modelling	USAID, CNIAF	Stratifier
	Cameroon	Forest monitoring 2000-current, forest type mapping, habitat modelling	USAID, SilvaCarbon	Project outputs not (yet) used for FREL
SOUTH AND SOUTEAST ASIA	Vietnam	National forest monitoring in support of NFI	FIPI, SilvaCarbon	Project outputs not (yet) used for FREL
	Bangladesh	Tree canopy cover monitoring 2000-current in support of REDD+ and NFI	RIMS, SilvaCarbon	Project outputs not (yet) used for FREL
	Cambodia	Tree canopy cover monitoring 2000-current in support of REDD+ and NFI		Project outputs not (yet) used for FREL
	Indonesia	Forest cover change quantification 1980-2000, forest monitoring system, wetlands mapping	CLUA, USFS, MoF, LAPAN	Project outputs not (yet) used for FREL
	Lao PDR[a]			GFC data used to assess length of shifting cultivation cycle
	Myanmar[a]			Stratifier
	Nepal			Project outputs not (yet) used for FREL
	Sri Lanka[a]			Stratifier

Note: a. Countries that both worked with the UMD/GLAD team and used the GFC dataset either directly or indirectly in their FREL submissions.
Source: WRI authors.

Accuracy of GFC Data

The GFC data's authors have published two accuracy assessments, the first in the original publication by Hansen et al. (2013) and the second in a subsequent publication by Tyukavina et al. (2015). In the first study, the authors evaluated the "true" change of 1,500 sample blocks (120 meters on each side) using Landsat, Moderate Resolution Imaging Spectroradiometer (MODIS), and Google Earth imagery. These reference data were then compared to the GFC maps. At the global scale, the loss map had user's accuracy of 87 percent and producer's accuracy of 88 percent (Table 8). The authors also evaluated the temporal accuracy of the loss data and found that the year assigned to the observed tree cover loss was correct 75 percent of the time, and was correct within one year before or after 97 percent of the time.

The second study, by Tyukavina et al. (2015), assessed the accuracy of the GFC loss map specifically for tropical forests within each of seven forest cover strata associated with varying thresholds of forest height, canopy cover, and intactness (Figure 5). On each continent, user's and producer's accuracies for the forest loss class were above 80 percent except for Sub-Saharan Africa, where low producer's accuracies (i.e., extensive areas of "missed" loss) were likely related to the prevalence of small-scale disturbance, which is harder to detect at 30-meter resolution (Table 9). They also found that most of the missed loss occurred within one pixel of mapped loss, suggesting that most of the missed loss occurs on the edges of other loss patches. Based on these results, the authors conclude that Landsat resolution assessments of forest change may lead to significant underestimation of forest cover loss in forests with low canopy cover and in areas of small-scale disturbance such as shifting cultivation areas.

One disadvantage of sample-based accuracy assessments is that they are applicable only at the scale for which they were designed; the accuracy of the GFC tree loss data has been assessed only for the global and strata-specific scales of interest. This means that the accuracy of the GFC data within each REDD+ country cannot be assessed until a national accuracy assessment is carried out with its own sampling design.

Process and Costs

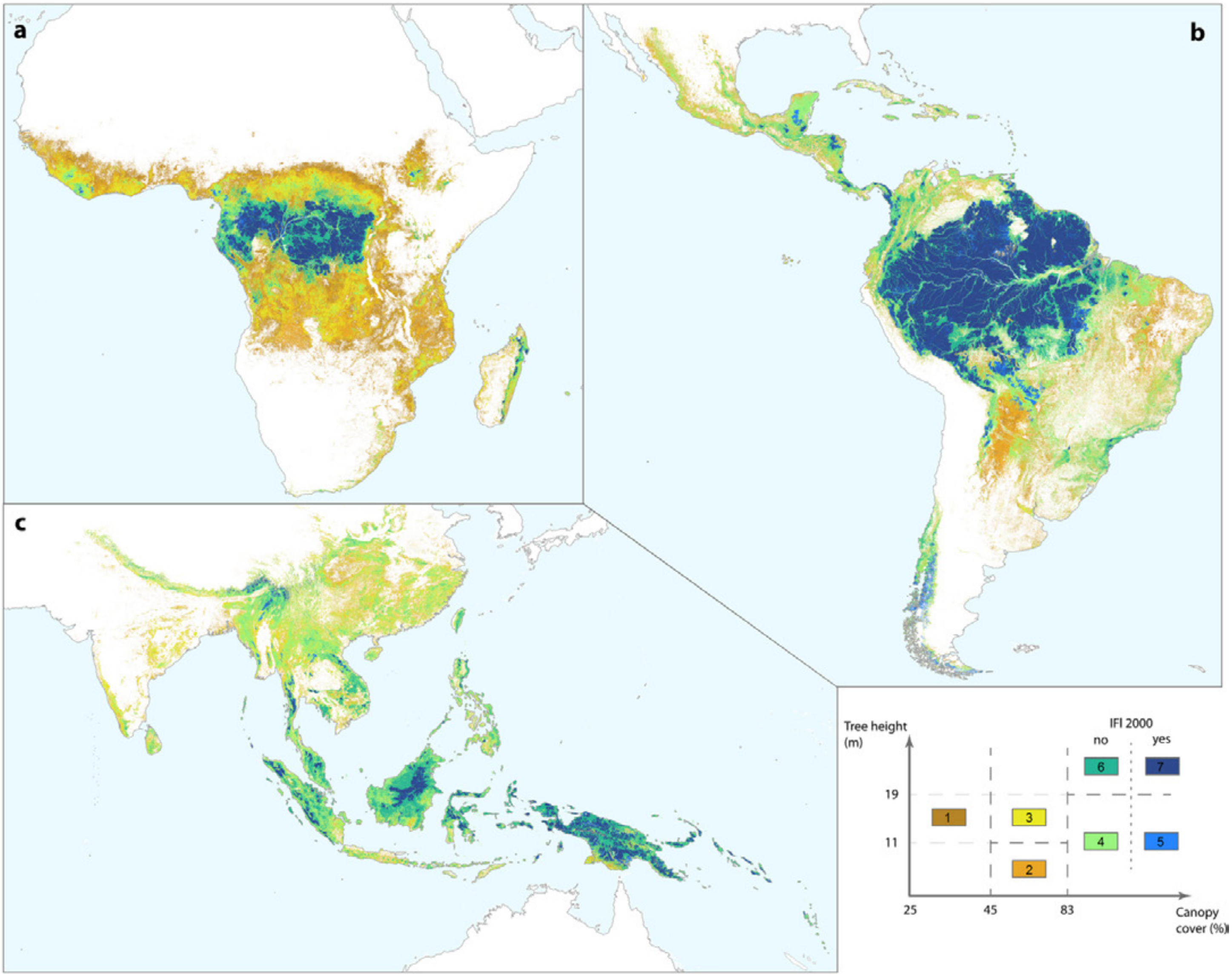
Hansen et al. (2013) apply the direct change detection approach described above that involves an automated workflow followed by visual checks. They created the original tree cover loss maps from 2001 to 2012 using Google Earth Engine (GEE), a cloud computing platform for Earth observation data. GEE automatically handled data management tasks such as data format conversion, reprojection and resampling, and associating image metadata with pixel data.

Table 8 | **Accuracy Assessment of Forest Loss at Climate Domain and Global Scales, 2000–12**

CLIMATE DOMAIN	USER'S ACCURACY (PERCENT)	PRODUCER'S ACCURACY (PERCENT)	OVERALL ACCURACY (PERCENT)	SAMPLE SIZE
Tropical	87.0	83.1	99.5	628
Subtropical	79.3	79.4	99.7	295
Temperate	88.2	93.9	99.8	298
Boreal	88.0	93.9	99.3	258
Global	**87.0**	**87.8**	**99.6**	**1500**

Source: Hansen et al. 2013.

Figure 5 | **Stratification Design Used to Develop Accuracy Measures for the Global Forest Change Tree Cover Loss Product for Three Tropical Forest Regions**



Source: Tyukavina et al. 2015.

Note: Factors used in the stratification were tree height (meters), tree canopy cover (percent), and intactness (IFL2000, see Potapov et al. 2008). Numbers in key refer to forest strata: 1- low cover; 2 - medium cover short; 3 – medium cover tall; 4 – dense cover short; 5 – dense cover short intact; 6 – dense cover tall; 7 – dense cover tall intact.

Source: Tyukavina et al. (2015).

Table 9 | **Accuracies of the Forest Loss Class in the GFC Data for Three Tropical Forest Regions**

	STRATUM	ACCURACY OF TREE COVER LOSS MAP (PERCENT)	
		USER'S	PRODUCER'S
LATIN AMERICA	1	89	34
	2	92	75
	3	100	89
	4	98	89
	5	93	87
	6	93	97
	7	100	96
	Total	**96**	**83**
AFRICA	1	93	32
	2	100	37
	3	91	54
	4	100	84
	5	100	100
	6	100	80
	7	93	93
	Total	**96**	**52**
SOUTH AND SOUTHEAST ASIA	1	100	33
	2	100	64
	3	89	82
	4	88	82
	5	74	82
	6	97	100
	7	100	100
	Total	92	86

Note: Strata 1-7 for each continent represent progressively taller, more intact forests with more closed canopies; see Figure 5 for stratification design.
Source: Tyukavina et al., 2015.

The original GFC dataset has been updated five times since its creation and now includes forest loss up to 2017 (Version 1.5). The analysis method has been modified in many ways, resulting in improved accuracy in recent updates but also inconsistency of methods across the full time series. Key modifications affecting the 2011–17 data include the incorporation of new data (e.g., incorporation of Landsat 8 in the model) for the target year, reprocessed data for previous years,[21] and improved modelling and calibration. These modifications have resulted in better detection of boreal loss due to fire, shifting agriculture in tropical forests, selective logging, and plantations with short rotation cycles. Eventually, a "Version 2.0" is expected to apply the updated methods to the 2000–10 data. The 2013 update was notable because it incorporated all Landsat sensors (including Landsat 5 and 8), as opposed to the original model which relied solely on Landsat 7. The historical images from Landsat 5 helped fill in gaps caused by cloud cover, smoke, and limited satellite coverage, while new clear images from Landsat 8 helped recalibrate the mapping algorithms and make them more sensitive to change. As a result, the new analysis detected 6 percent more tree cover loss globally for 2011 than the original dataset, and 22 percent more loss for 2012. The 2014 data release also reprocessed loss data for the years 2012 and 2013 and the new satellite imagery inputs and improved calibration resulted in additional loss detection for those years.[22]

The operational cost to update the GFC data product annually is approximately US$500,000 per year; this excludes costs associated with making these data accessible to a broad audience through the Global Forest Watch platform. The costs of initial development and continued enhancement of the GFC system, including purchase of major technological infrastructure, are likely substantially higher but are difficult to estimate. The GFC product builds on prototyping activities that began under a World Resources Institute project on forests and landscapes in Indonesia (known as Project POTICO)[23] and the CARPE program[24] in Central Africa funded by USAID. In-kind cloud computing contributions from Google supported global scaling of the method. Additional investments have been made to nationalize the GFC dataset in the countries listed in Table 7, and we do not have information regarding the costs of these efforts.

Conclusions Regarding Overall Benefits and Limitations of the GFC Data for REDD+

- The GFC tree cover loss algorithm is semi-automated, updated annually, and provided free of charge to the global forest monitoring community at relatively low operational cost.
- The GFC dataset neither defines nor measures deforestation as a subset of tree cover loss, although this is also true for many of the national forest monitoring systems described earlier. Several countries have taken steps to apply and/or nationalize the GFC data to arrive at deforestation estimates for REDD+.
- The GFC tree cover loss data are derived using wall-to-wall direct change detection methods, and reported accuracy at both global and tropical scales is on the higher end of the range of map accuracies reported in country FRELs. The lack of national scale accuracy assessments for the GFC dataset in all countries precludes direct comparison, but the GFC loss data have been shown to be most accurate in monitoring the loss of tall, closed canopy intact forests and least accurate in areas with open forest cover and where small-scale clearing dominates.
- The GFC dataset can be adjusted for local forest definitions by changing the minimum tree cover canopy density (e.g., from 30 percent to 10 percent), filtering out plantations, and/or filtering out tree cover below a country's defined minimum forest area (e.g., from 0.1 hectare to 1 hectare). The GFC data currently cannot be adjusted to local definitions of forest height; it is fixed at 5 meters.
- Incremental changes to the GFC methodology to improve accuracy have created inconsistency in the time series, specifically for data before and after 2011, although the University of Maryland/GLAD team plans to reprocess the entire time series using a consistent method in the future. Further, the GFC data extend back only to 2001, whereas some national reference periods extend to an earlier date.

COMPARING NATIONAL TO GLOBAL DATA: HOW MUCH DO THEY DIFFER AND WHY?

Since the launch of Global Forest Watch, there has been substantial curiosity – and confusion – from the global community about how much and why GFC loss data differ from country-generated deforestation estimates. Below we compare the annual GFC loss data against deforestation estimates provided for 33 country-defined geographic boundaries, reference periods, and tree canopy density thresholds to ensure the best "apples to apples" comparison possible with readily available data.

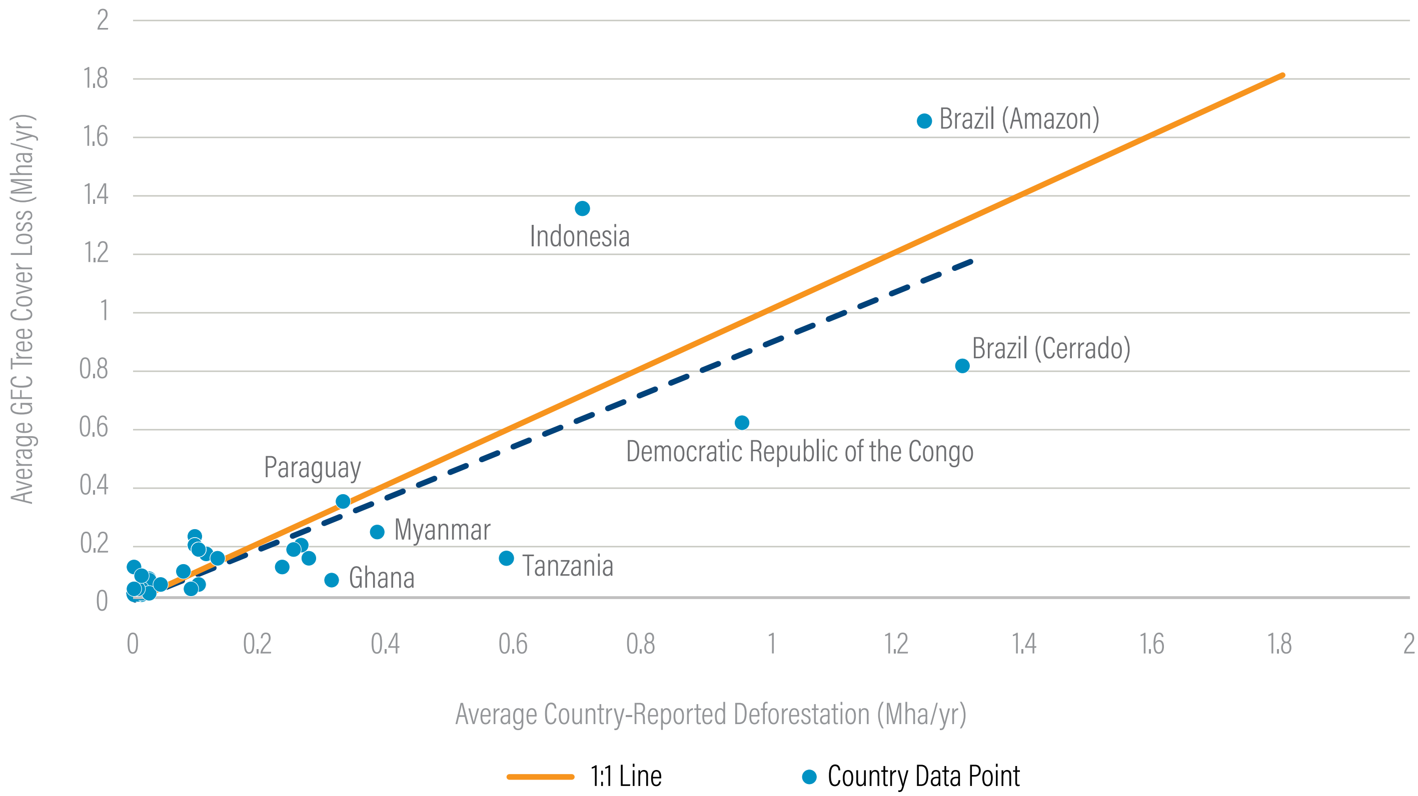
How Much Do Estimates Differ?

Across all 33 REDD+ countries evaluated,[25] the sum of nationally determined average deforestation rates was 7.9 million hectares per year (Mha/yr) vs. an annual average rate of GFC tree cover loss of 6.9 Mha/yr. Deforestation rates of REDD+ countries in Latin America were almost identical to GFC tree cover loss (3.38 vs. 3.40 Mha/yr) and differed by approximately 17 percent for REDD+ countries in South and Southeast Asia (1.7 vs. 2.0 Mha/yr). Brazil's deforestation estimate was lower than GFC in the Amazon biome but higher than GFC in the Cerrado biome, so the overall deforestation rate for the two biomes combined reported by Brazil are similar to GFC tree cover loss estimates (2.5 vs. 2.4 Mha/yr for Brazil vs. GFC, respectively). In contrast, nationally reported deforestation rates for REDD+ countries in Africa were approximately twice as high as the GFC rate (2.8 vs. 1.4 Mha/yr).

Figure 6 indicates that across all REDD+ countries in aggregate, GFC tree cover loss represents a relatively unbiased proxy for deforestation, but large differences between nationally reported and GFC data remain for certain countries, particularly in Africa (Figure 7).

It is beyond the scope of this paper to explain discrepancies for all countries; in the following section we highlight five representative case studies about why national deforestation estimates may differ from the GFC tree cover loss data.

Figure 6 | **Comparison of Average Annual Deforestation Rates Between REDD+ Country-Reported Estimates and GFC Tree Cover Loss Data**



Source: WRI authors.
Note: The blue dotted line represents a linear trendline through all country data points. Points above the 1:1 line reflect GFC estimates that are higher than the country estimates, and points below the 1:1 line reflect GFC estimates that are lower than the country estimates.

Why Do Country-Reported Deforestation Estimates Differ from GFC Estimates? Five Case Studies

As demonstrated in Figure 7, tree cover loss estimates generated from the GFC product can be substantially different from national deforestation data reported in FRELs. In some cases, national estimates may be better than the global data, but in others questions remain about the quality of the country data and the execution of the methods used. In still other cases, estimates may differ substantially when compared directly, but align more closely once global tree cover loss data are filtered (e.g., to match national forest definitions). Below, we describe possible reasons for discrepancies as exemplified through five case studies.

1. Different forest definitions: Indonesia

For the period of overlap (2000–12), the GFC estimate of tree cover loss for Indonesia is nearly double the deforestation estimate reported in Indonesia's FREL. Through the analysis described below, we demonstrate that this discrepancy likely arises from differing definitions of forest.

First, we compared the total forest extent in Indonesia for the year 2000 as depicted by a map produced using the GFC tree cover data and a map published by the Indonesian Ministry of Environment and Forestry (MoEF). We found large discrepancies between the GFC and MoEF maps with respect to the location (Figure 8A) and amount (Figure 8B) of forest cover. Both maps applied Indonesia's definitional criteria of minimum tree height (5 meters) and crown cover (30 percent)

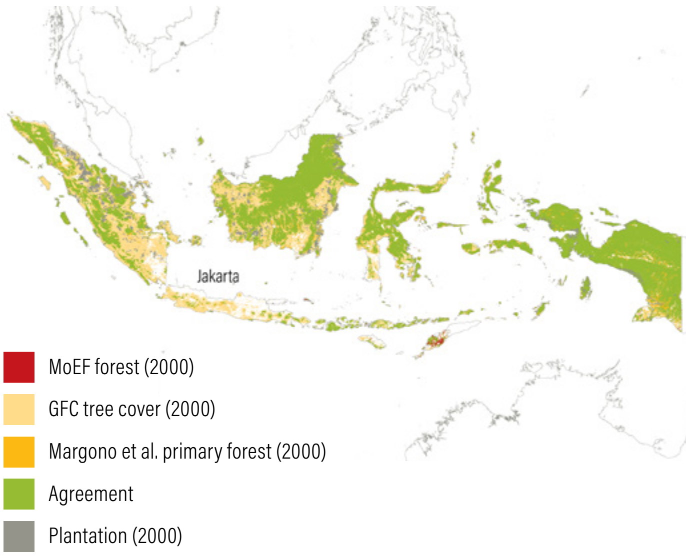
Figure 7 | **Comparison of Average Annual Deforestation Rates from REDD+ Countries vs. Average Annual Rate of Tree Cover Loss from the University of Maryland's GFC Data**

Figure 7 | **Comparison of Average Annual Deforestation Rates from REDD+ Countries vs. Average Annual Rate of Tree Cover Loss from the University of Maryland's GFC Data (Continued)**

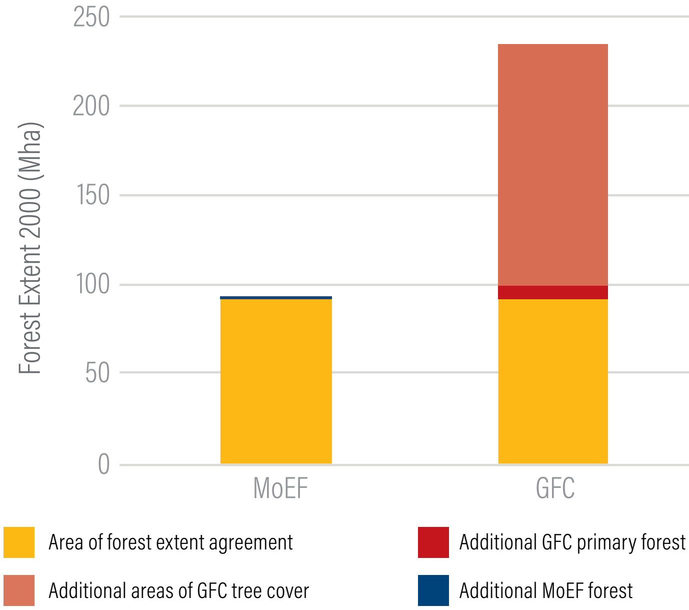
Source: WRI authors.
Note: GFC tree cover loss was counted only for areas in 2000 that exceeded the canopy density threshold used by the country to define its forest. Units on the vertical axis are shown in Mha/yr; individual data values are shown in ha/yr. Note difference in scale on the vertical axis for countries in different rows of the figure.

Figure 8 | Deforestation Estimates in Indonesia Varied Because of Different Definitions of Forest

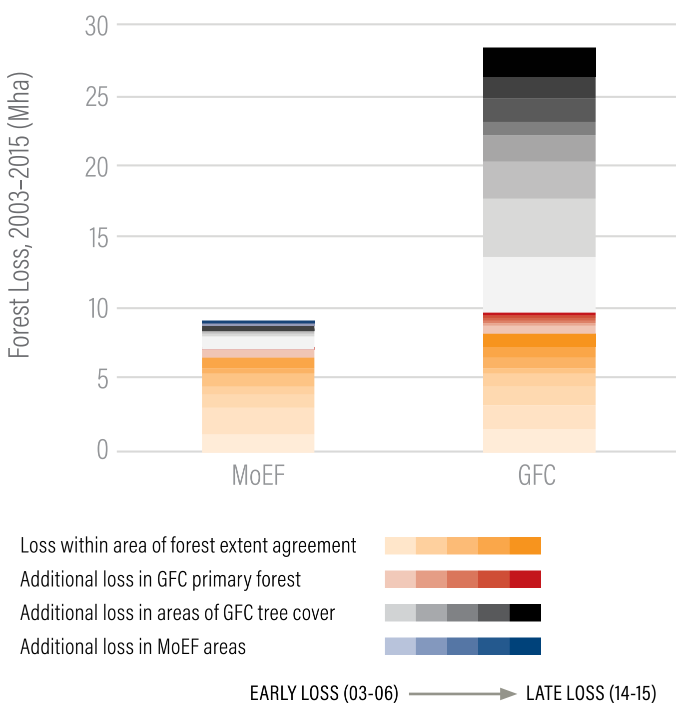
A. Comparison of Mapped Forest Extent, 2000



B. Comparison of Forest Extent, 2000



C. Comparison is forest/tree cover loss, 2003-15



D. Areas Where Difference in Forest Loss Estimates between MoEF and GFC Are Greatest

Source: WRI authors.

Note: Comparison of forest monitoring data from University of Maryland's (UMD's) Global Forest Change (GFC) data and national data produced by Indonesia's Ministry of Environment and Forestry (MoEF). (A) Spatial comparison of forest/tree cover extent in the year 2000 (applying a canopy density threshold of 30 percent for the UMD data; plantation boundaries for the year 2000 also shown); (B) Numerical comparison of forest/tree cover extent in the year 2000; (C) Numerical comparison of forest cover loss between 2003 and 2015 between MoEF and GFC; (D) spatial comparison of districts where differences in forest loss are highest between MoEF and GFC.

since the GFC data can be easily adjusted for these parameters. However, the maps use different minimum mapping units: the MoEF map considers only forest patches exceeding 6.25 hectares while the GFC map identifies areas with tree cover as small as 0.1 hectare, meaning that the GFC map better matches Indonesia's official minimum area for defining forest (0.25 hectare) than the MoEF map. However, the GFC map includes tree cover classes that do not meet the criteria of Indonesia's forest definition for REDD+. As a result, the GFC map overestimates forest area by including both forest and agricultural tree plantations. However, Figure 8A also suggests that the MoEF map excludes large areas of tree cover that technically met Indonesia's biophysical forest definition (e.g., 30 percent tree cover threshold), but that were not counted by Indonesia as forests because they were mapped as a different (nonforest) land cover class. Only 7 percent of areas with over 30 percent tree cover in the GFC map that were not mapped by MoEF as natural forests were mapped by MoEF as forest plantations; the majority were classified by MoEF instead as scrubland, swamp scrubland or "dry rice land with scrub." The MoEF map more closely matches primary forests mapped by Margono et al. (2014; Figure 8B).

Differences between forest base maps in Indonesia in 2000 help to explain differences in estimates of forest loss mapped since that year. Because the GFC data identify a much larger forest area to start, it also identifies more change over time. When we compared rates of forest loss only in areas where the GFC and MoEF maps agree about forest extent, we found a much closer alignment—the GFC estimate of loss is approximately 10 percent higher than MoEF deforestation for the period 2003 to 2015 (Figure 8C). GFC and MoEF rates of forest loss differ most in Riau and West Papua provinces (Figure 8D).

2. Different methods: Ethiopia, Myanmar, Nigeria, Republic of Congo, Sri Lanka

In countries where GFC maps were used to inform a stratified sampling design, deforestation estimates from both map- and sample-based assessments were provided in the FREL. In all cases, sample-based approaches yielded higher deforestation estimates than those derived from the GFC map alone (Table 10). Assuming the sample-based assessments were designed and implemented correctly and contained enough sample points to be representative of the stratum (see Box 2), this difference suggests that the GFC maps of tree cover loss significantly underestimate deforestation in these countries. This is likely true, as these countries typify the locations where the GFC algorithm has been shown to underestimate tree cover loss, namely in smallholder landscapes and in open, dry forest areas.

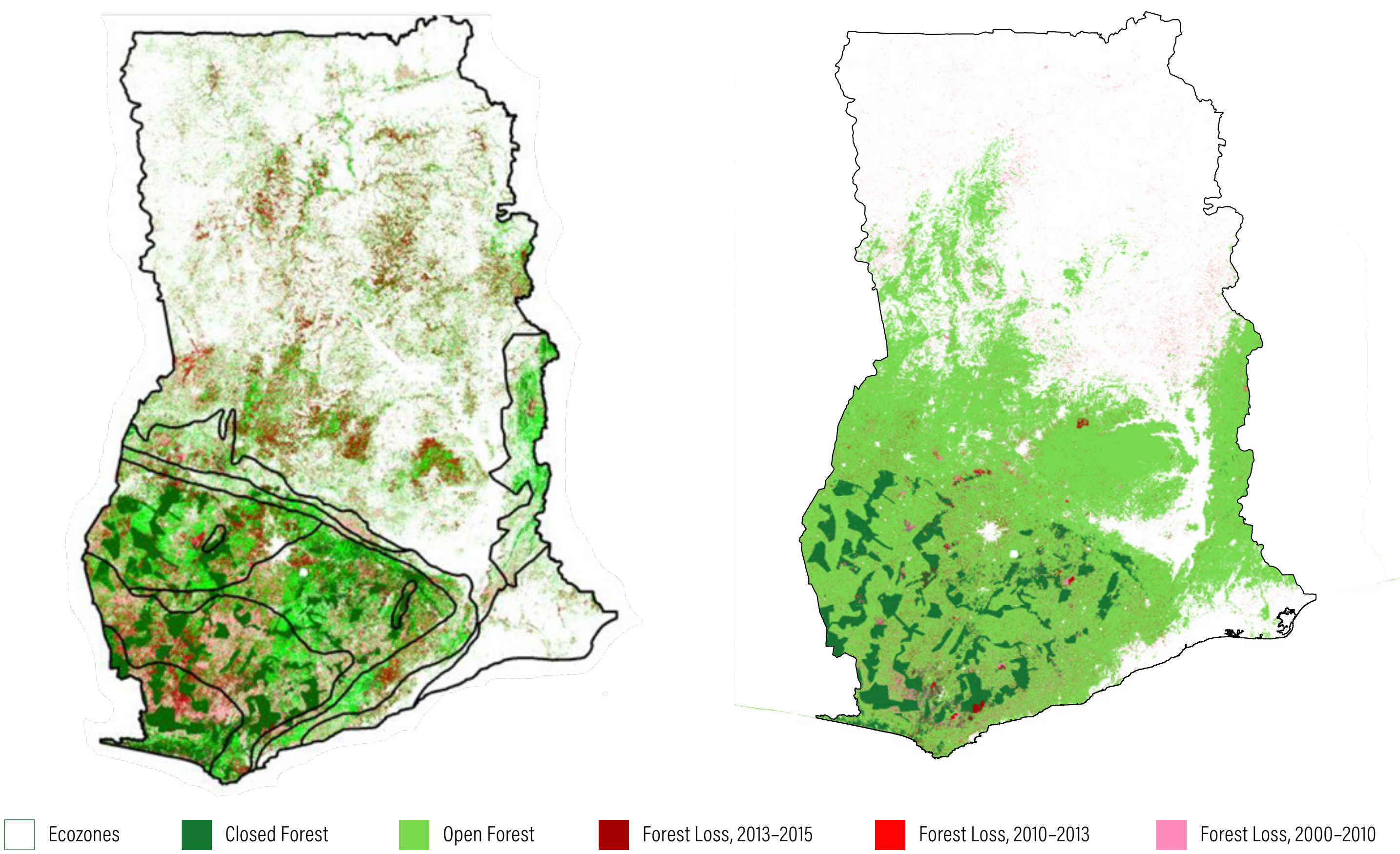
Table 10 | **Difference between Annual Deforestation Rates Derived from Wall-to-Wall Maps vs. Stratified Sampling**

COUNTRY	REFERENCE PERIOD	MAP-BASED ESTIMATE (HA/YR)	SAMPLE-BASED ESTIMATE (HA/YR)	MAGNITUDE OF DIFFERENCE BETWEEN MAP AND SAMPLE ESTIMATES (PERCENT)	NUMBER OF SAMPLES IN LOSS STRATUM	PERCENT OF TOTAL SAMPLES IN LOSS STRATUM
Ethiopia	2000–13	28,630	91,769	3.2x (+221 percent)	84	4
Myanmar	2005–15	2,457	8,495	3.5x (+246)	310	16
Nigeria	2004–14	4,238	15,440	3.6x (+264)	26	6
Republic of Congo	2000–12	10,583	12,083	1.1x (+14)	200	22
Sri Lanka	2000–10	2,339	8,088	3.5x (+246)	102	11

Figure 9 | **Comparison of maps of forest extent and deforestation in Ghana, 2001–15**

A. Map with Data from Ghana's Forestry Commission

B. Map with Data from the GFC Algorithm



Source: Ghana FREL submission to UNFCCC, p 29. (B) WRI authors.
Note: In accordance with Ghana's definition, closed forest was defined in the GFC map as areas with canopy density greater than 60 percent and open forest was defined as areas with canopy density between 15 percent and 60 percent.

3. Uncertainty in quality of methods: Ghana

Although the accuracy of Ghana's deforestation map has not yet been assessed, in its FREL submission Ghana indicates an intention to perform an accuracy assessment. Spatial data for Ghana (Figure 9) were not publicly available to enable a detailed comparison against the GFC data like we performed for the Indonesia example above. However, comparisons were still possible based on the technical details included in Ghana's FREL.

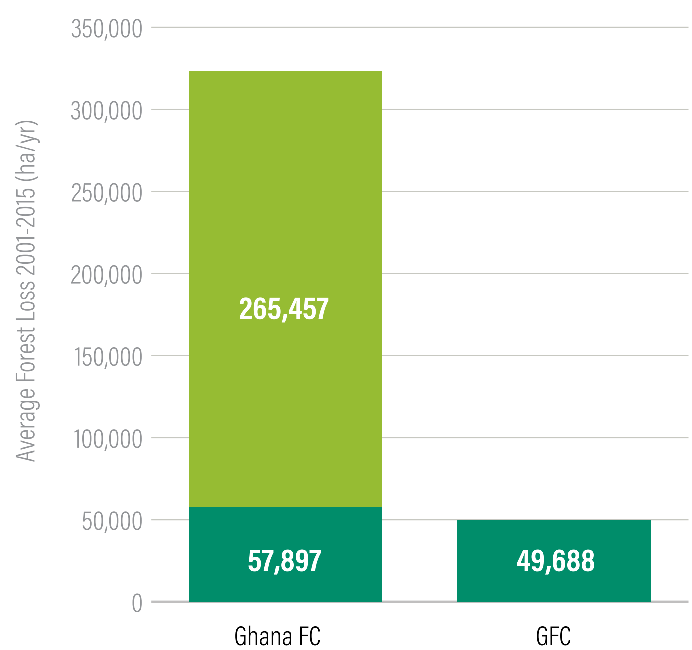
Ghana defines its forest using a minimum area threshold of 1 hectare, a height threshold of 5 meters and a canopy cover threshold of 15 percent. Under Ghana's Forest Preservation Program, closed forests are classified as those with canopy cover exceeding 60 percent and open forests are classified as those with canopy cover of 15–60 percent. To map deforestation between 2000 and 2015, Ghana used a post-classification change detection method, using 2000 and 2010 maps produced for an earlier project and 2013 and 2015 maps produced later by the Ghana Forestry Commission. All maps used Landsat 7 and 8 images; the 2010 map also used ALOS (radar) images. Figure 9 shows a spatial comparison between Ghana's data and GFC data (with a minimum 15 percent canopy density threshold applied to the GFC data to match Ghana's definition), and Figure 10 compares rates of deforestation/tree cover loss for Ghana's reference period of 2001–15. For closed forests, the difference between Ghana's average rate of deforestation differs from GFC's overall rate of tree cover loss by approximately 15 percent. However, Ghana also includes vast areas of deforestation in open forests that are not detected in the GFC map (Figure 9), leading to a reported deforestation rate five times higher than that estimated from GFC data. This level of discrepancy was seen in other countries with large areas of dry, open forests (Ethiopia, Nigeria); these countries addressed the underdetection of tree cover loss in the GFC product using sample-based approaches.

Ghana did not use a sample-based approach but instead used a post-classification change detection methodology, which combines errors from each map in the series and can therefore lead to inaccurate results. The ability of this method to accurately depict change depends on the quality of each map in the time series. Several potential issues with Ghana's land cover change maps were identified in the FREL:

- Maps for different years were produced by different teams using different sources of imagery and potentially different methods for preprocessing and classifying images.
- The 2015 map shows large areas of open forest all over the country that are not present in earlier maps.
- A large shift from grasslands to open forest was apparent between 2013 and 2015.
- In the 2013 map, some areas have grassland pixels in the middle of lakes.
- Large areas in the Upper East region in the 2013 map appear to change drastically from the 2010 map, mostly arising from confusion between cropland, grassland, and open forest. This may be due to seasonal differences in imagery dates.

Therefore, Ghana is an example of a country where large discrepancies may arise between nationally reported and GFC data due to a number of factors that cannot be evaluated in isolation; in this case, uncertainty about the loss of open forests is confounded by potential issues with the accuracy of changes mapped using a post-classification change detection methodology.

Figure 10 | **Comparison of Data from Ghana's Forestry Commission and the GFC for the Average Rates of Forest/Tree Cover Loss, 2001–15.**



Ghana FC = Ghana's Forestry Commission; GFC = Global Forest Change data.

Source: WRI authors.
Note: In Ghana's estimate, dark green represents loss in closed forests (canopy density greater than 60 percent) and light green represents loss in open forests (canopy density between 15 and 60 percent). In GFC's estimate, dark green represents forest loss in all areas with canopy density greater than 15 percent.

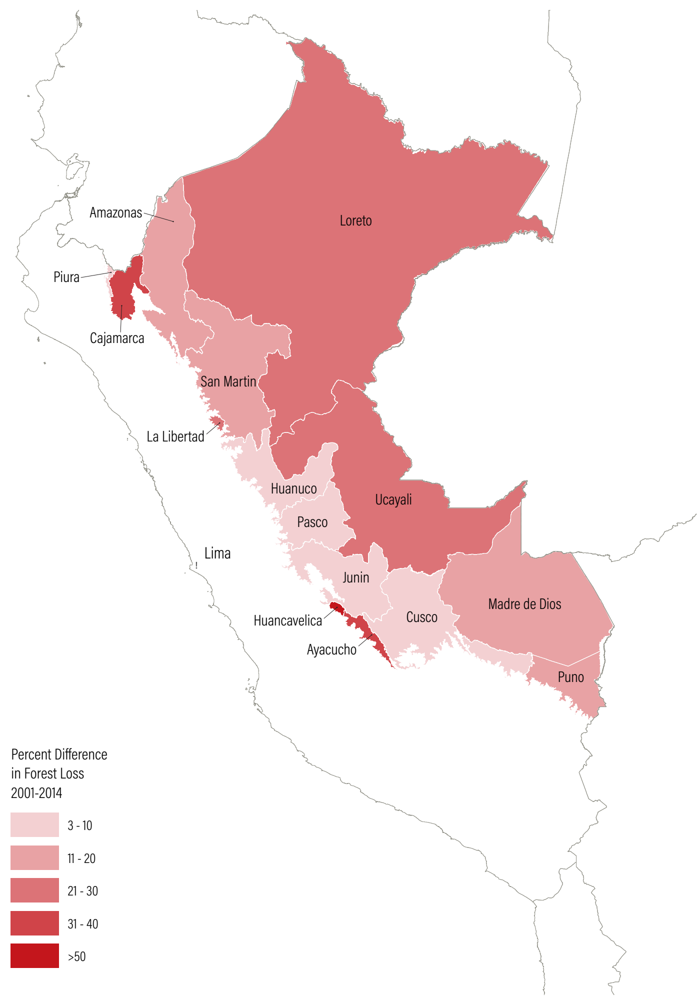
4. Global vs. national algorithm: Peru

Peru is one of two countries that has "nationalized" the GFC algorithm and is running it in an operational environment. By nationalized we mean that the country has adapted the GFC algorithm to the national context by using country-specific training points that are visually interpreted and used to train the loss classification model. This nationalized model is used to generate deforestation data for FRELs. After aligning forest extent maps to analyze loss only within areas defined as forest by both UMD and Peru's Ministerio del Ambiente (MINAM) (Figure 11A), loss estimated over the reference period using the GFC global vs. national algorithm differed by approximately 15 percent (see Table 9). Differences varied regionally, with the largest differences high in the Andes Mountains (Figure 11B) where permanent cloud cover leads to satellite data limitations. Although loss statistics are relatively well aligned between the two datasets at the national and subnational scales, the mapped location of loss varied more significantly. Less than half of all loss mapped between 2001 and 2014 using the global algorithm occurred in the exact same pixel locations as loss mapped using the nationalized algorithm;

Figure 11 | **Deforestation estimates in Peru differed because of different definitions of deforestation and different training points**

A. Differences in mapped forest extent in the Peruvian Amazon in the year 2000

B. Difference in estimates of forest loss by province using global vs nationalized GFC model, 2001-2014



MINAM = Ministerio del Ambiente; GFC = Global Forest Change product

Source: WRI authors.
Note: Differences in B reflect only those resulting from the loss algorithm used and not from differences in forest extent.

the remainder of loss pixels were mapped in one or the other dataset but not both. Although both global and nationalized approaches use the same underlying satellite imagery, differences in results arise from the use of different training data to develop the forest loss classification model that transforms raw satellite data into a map of forest loss.

How closely the loss estimates match between the global and national algorithms also depends on year, with 2012 as a particularly divergent year (Table 11). One potential reason for this relates to the updating of the GFC global algorithm for 2013 and 2014, including improved calibration for Peru specifically. During these updates, 2012 GFC loss estimates for Peru were revised (Table 12). However, we show that this change in data and methods was not a primary reason for the large difference between global and nationalized results; 2012 estimates from the original global algorithm for Peru were already much higher than national estimates, and the updated data and methods caused 2012 global results to increase in Peru by only 13 percent.

Table 11 | **Annual and Total Forest Loss in the Peruvian Amazon 2001–14, Comparing Estimates Derived from Global and Nationally Tuned Forest Change Models**

YEAR	FOREST LOSS 2001-2014 (HECTARES)			PERCENT DIFFERENCE BETWEEN PERU AND GFC LOSS ESTIMATES (FOR SAME EXTENT IN 2000)
	LOSS: GFC GLOBAL	LOSS: GFC GLOBAL	LOSS: NATIONALIZED GFC FOR PERU	
	EXTENT: GFC 2000	EXTENT: PERU 2000	EXTENT: PERU 2000	
2001	85,731	83,334	83,995	0.8
2002	80,189	77,267	79,831	3
2003	73,521	71,486	72,873	2
2004	101,016	98,455	93,146	6
2005	162,595	159,650	147,623	8
2006	88,671	85,290	74,501	14
2007	115,475	112,952	106,186	6
2008	126,322	123,372	105,704	15
2009	177,655	174,902	152,160	14
2010	142,025	139,746	136,205	3
2011	125,013	123,094	123,562	0.4
2012	**274,751**	**270,167**	**149,476**	**58**
2013	209,063	205,380	150,288	31
2014	205,199	202,088	177,570	13
Total	**1,967,226**	**1,927,184**	**1,653,121**	**15**
Annual Average	**140,516**	**137,656**	**118,080**	**15**

Note: Units represent tree cover loss in hectares. The year 2012 is highlighted as a year where GFC data diverge significantly from national data.
Source: WRI authors.

A more likely reason for the divergent results for the year 2012 relates to the fact that Peru does not report tree cover loss caused by natural disturbances as deforestation. Once loss classification model results are generated, all loss due to flooding and river meandering (Figure 12A) is mapped automatically using annual water masks collected from all cloud-free image observations and removed. Then, visual analysis of change areas is performed and used to identify and label losses due to fires, landslides, and windstorms, with the remaining loss attributed to anthropogenic forest clearing. While the total area of natural disturbance in Peru is small, the annual rate of change due to natural disturbance fluctuates significantly (Potapov et al. 2014). In 2012, 18 departments in Peru declared a state of emergency due to flooding (REACH 2012), and large areas of tree cover loss in the GFC product can be seen in river valleys (Figure 12B). Therefore, most of the difference in tree cover loss estimates between the global vs. national algorithm in 2012 is likely related to the filtering out of natural disturbances by Peru to isolate tree cover loss caused by anthropogenic disturbance only.

Table 12 | **Annual Estimates of Tree Cover Loss for Peru across Multiple Updates of the GFC Data**

YEAR	ORIGINAL (2001-2012)	2013 UPDATE	2014 UPDATE	2015 UPDATE	2016 UPDATE	2017 UPDATE
2001	86,783	86,793	86,793	86,793	86,793	86,793
2002	81,057	81,135	81,135	81,135	81,135	81,135
2003	74,495	74,519	74,519	74,519	74,519	74,519
2004	102,072	101,979	101,979	101,979	101,979	101,979
2005	163,943	163,919	163,919	163,919	163,919	163,919
2006	89,595	89,494	89,494	89,494	89,494	89,494
2007	116,312	116,345	116,345	116,345	116,345	116,345
2008	127,126	127,252	127,252	127,252	127,252	127,252
2009	178,869	178,840	178,840	178,840	178,840	178,840
2010	143,055	143,065	143,065	143,065	143,065	143,065
2011	118,385	126,206	126,206	126,206	126,206	126,206
2012	**247,151**	**270,602**	**278,379**	**278,379**	**278,379**	**278,379**
2013		197,374	214,824	214,824	214,824	214,824
2014			188,016	211,643	211,643	211,643
2015				170,777	170,777	170,777
2016					238,078	238,078
2017						315,723

Note: Values reflect all tree cover loss without a canopy density threshold applied.

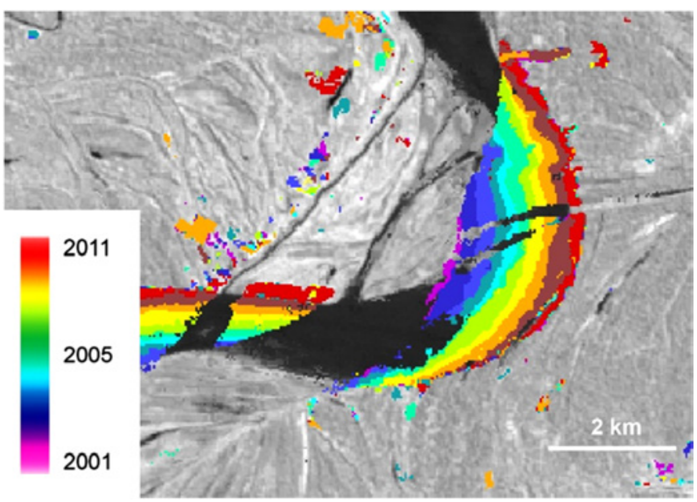
5. Native vs. plantation forest: Chile

In many developing countries, tree cover loss is a good proxy for deforestation because deforestation is the dominant forest change dynamic. There is less agreement between tree cover loss and deforestation in countries like Chile, where forestry is the dominant change dynamic rather than permanent forest conversion for new agricultural land. Chile is a country with a long history of intensive plantation forestry operations, with large areas planted in stands of eucalyptus and pine that are harvested and regrown on short rotation cycles (Figure 13A). In its FREL, Chile defines its forest as native forest and excludes planted forest. The majority of Chile's deforestation from 2001 to 2013 was reported to be caused by large forest fires and the eruption of the Chaitén volcano in 2008. Unlike Peru in the example above, Chile counts these areas as deforestation despite their being caused by natural rather than anthropogenic disturbance.

The GFC estimate of tree cover loss for Chile is nearly four times higher than the deforestation estimate reported in Chile's FREL for the reference period 2001–13, even after excluding GFC loss occurring within Chile's plantations (Figure 13B). The source of Chile's deforestation data is cadastral maps, which are based on a combination of satellite and ground data. Deforestation data are broken into six regions, all reflecting different time periods with years ranging from 2006 to 2013. Methods for how these maps were created are not described clearly in the FREL, and the acccuracy of the change maps is not reported.

Figure 12 | **Deforestation Estimates Differed in Peru Because Peru Does Not Count Tree Cover Loss Caused by Natural Disasters Like Floods**

A. Tree cover loss due to river meandering was removed from Peru's deforestation estimates



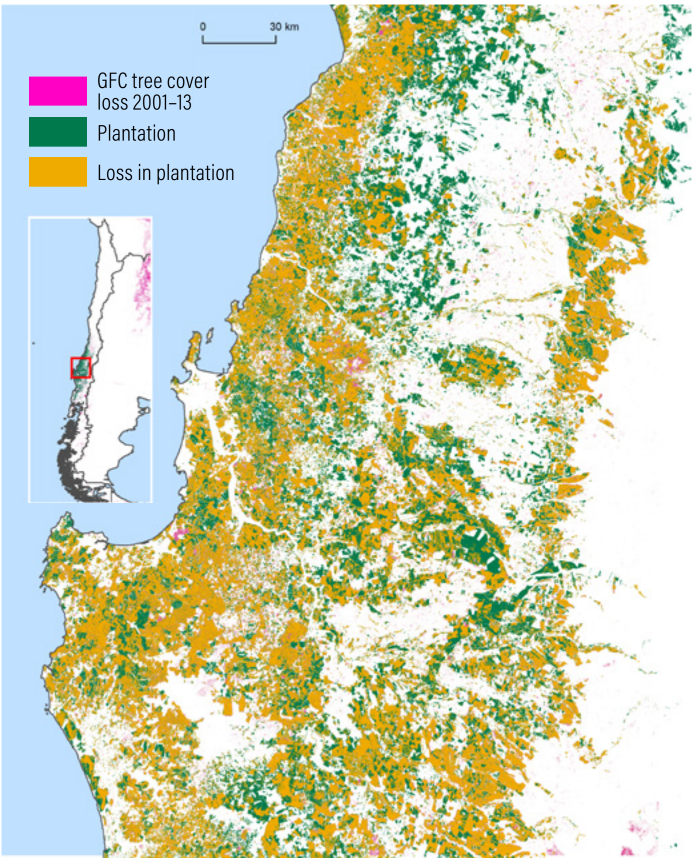
B. 2012 tree cover loss in GFC product due to river meandering as a result of 2012 floods

Note: (A) Pattern of annual natural forest loss due to river meandering that was removed from Peru's national deforestation estimates in their FREL. (B) Example of 2012 tree cover loss from Global Forest Watch in Peru that is likely due to river meandering as a result of 2012 floods. This loss is included in the GFC tree cover loss estimate for Peru, but would be excluded in Peru's 2012 national deforestation estimate.

Source: A. Potapov et al. 2014. B. Global Forest Watch. globalforestwatch.org

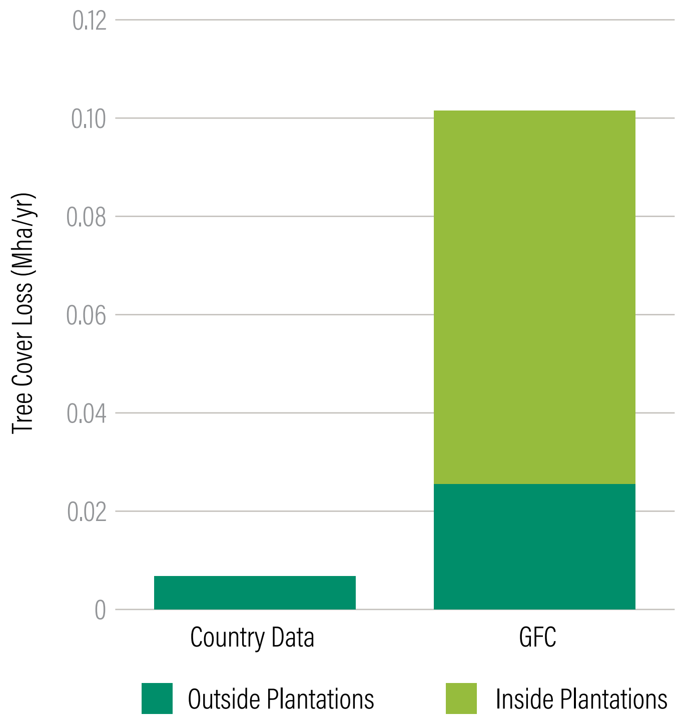
Figure 13 | In Chile, National and GFC Estimates Differed Because of Different Ways of Classifying Forest Plantations

A. Tree Cover Loss Inside and Outside Areas Mapped as Plantations, 2001–13



Source: Plantation boundaries from Instituto Forestal de Chile (INFOR).

B. Annual Deforestation and Tree Cover Loss Data from Chile and GFC



CONCLUSIONS AND RECOMMENDATIONS TO INCREASE UTILITY OF GLOBAL DATASETS FOR NATIONAL ACCOUNTING AND REPORTING

How countries measure and report emission reductions from avoided deforestation is of critical importance to the success of REDD+. Countries' forest monitoring systems and MRV efforts must be widely perceived as credible by domestic and international stakeholders to enable flow of results-based payments. Even outside of REDD+, robust forest monitoring systems are also needed if countries plan to use forest emission reductions to meet their nationally determined contributions (NDCs) under the Paris Agreement. However, most REDD+ stakeholders lack the technical expertise necessary to understand the increasingly diverse and complex landscape of methods used by countries and international research organizations to monitor forests and estimate rates of deforestation. Resulting confusion and controversy surrounding differing estimates is not helping to engender needed trust in REDD+.

In an attempt to bring greater clarity to this issue, this paper provided an overview of methods, results, and associated costs for estimating deforestation as well as a systematic analysis of how and why estimates from different sources vary. In particular, we compared methods and estimates arising from countries via their FREL submissions with those from Hansen et al.'s (2013) Global Forest Change dataset.

Conclusions

The GFC tree cover loss data represent a transparent, complete, consistent, and reasonably accurate way to monitor tropical deforestation in countries where deforestation is the dominant forest disturbance dynamic. Even without adjustments made to accommodate national land use definitions, GFC tree cover loss data align well with REDD+ country deforestation data in aggregate. GFC loss data are most accurate in monitoring the loss of tall, closed canopy intact forests and least accurate in areas with open forest cover and where small-scale clearing dominates. With appropriate filtering to accommodate different national forest definitions, the alignment in many cases would likely improve. In other cases, open questions remain about the exact reasons for differences between national and global data.

The GFC data are useful in a national context in different ways. To date, 9 of 33 countries have used GFC data either directly or indirectly in their FRELs. This includes adapting the global algorithm to meet national needs (e.g., Peru, Colombia), using the GFC data as a stratifier in sample-based approaches (e.g., Ethiopia, Myanmar, Nigeria, Republic of Congo, Sri Lanka), or using the GFC data to improve and/or fill gaps in a country's own monitoring system (e.g., Honduras, Madagascar).

Both global and national forest monitoring systems have benefits and applications beyond their role in REDD+, and the GFC tree cover loss data are produced for a fraction of the cost of what has been invested to date in national forest monitoring systems. This indicates an opportunity to increase the use of global datasets in national accounting and reporting. National systems established for forest monitoring will entail long-term operational costs as well as costs to improve methods and leverage new technologies as they become available. For many countries, using freely available global data products as an input to or direct source of national deforestation monitoring could help reduce costs and improve long-term sustainability, while still maintaining desired levels of accuracy.

Recommendations

We make several recommendations on how to increase utility and adoption of global datasets for national accounting and reporting under REDD+. They fall under the categories of aligning global vs. national data, adapting off-the-shelf global data to meet national needs, and customizing the GFC algorithm to produce tailored, wall-to-wall national maps of deforestation.

Align global and national deforestation monitoring products for consistency and country needs. Inconsistent results among countries, combined with the high costs of creating and maintaining unique national forest monitoring systems, suggest that REDD+ countries could consider tailoring freely available global tree cover loss data to meet national reporting needs. Conversely, the international remote sensing community could deliver products that align more closely to what countries need for national forest monitoring, such as maps of land use change rather than land cover change.

To help align these data, REDD+ countries

should make their spatial forest monitoring data available for public review in a centralized location as part of the FREL technical assessment process. This would enable analysts to critique and compare national and global monitoring efforts more easily, leading to continuous improvement and comparability of forest monitoring at all scales. REDD+ countries stand to benefit collectively from more aligned, cheaper, and more credible forest monitoring systems that achieve greater consistency in results at national and international levels.

Adapt and assess global products to meet national needs for REDD+. The GFC tree cover data can be filtered to accommodate any country's forest definition. Then, the resulting map can be used as an input to stratified sampling to quickly generate a national average historical deforestation rate with a known uncertainty range at relatively low cost. The accuracy of the global, "off the shelf" map can also be assessed for a national context. If the global tree cover loss map that has been adapted for the national context is assessed to be accurate at the national level, if the map errors are unbiased, and if the map-based tree cover loss estimates fall within the uncertainty bounds of sample-based estimates, then the off-the-shelf GFC tree cover loss map and resulting statistics should be deemed as fit for purpose by the climate policy community as an accurate, precise, and cost-effective deforestation monitoring product for the country of interest.

Customize the GFC algorithm to produce more refined national deforestation maps. While sample-based methods allow for estimation of a single national deforestation rate with a known uncertainty range at relatively low cost, countries should consider the additional benefits of a customized, wall-to-wall national deforestation map, which allows for total deforestation to be disaggregated across time and space. This type of map is useful for understanding where deforestation is occurring and for designing location-specific deforestation reduction policies. All available cloud-free Landsat satellite imagery is processed for locations around the world to produce the annual Global Forest Change product. The same data inputs and algorithms can be easily tailored for national or subnational application (by incorporating additional, country-specific training sites to train the tree cover loss classification model) thus producing more accurate national deforestation maps than those currently available as subsets of the GFC product.

ENDNOTES

1. And the annual updates thereafter, visualized on Global Forest Watch at globalforestwatch.org.
2. The five REDD+ activities include Reducing Emissions from Deforestation and Forest Degradation, "plus" the role of forest conservation, sustainable forest management, and enhancement of forest carbon stocks.
3. And the annual updates thereafter, visualized on Global Forest Watch at globalforestwatch.org.
4. With the agreement on the Bali Road Map and Action Plan.
5. For example, the United States Landsat and European Sentinel programs.
6. Includes funds from public and private sectors and represents aggregate pledges and investments for the period between 2006 and 2014. The majority of the finance pledged to date has been focused on capacity building and other "readiness" activities, rather than on paying for verified emission reductions from reduced deforestation.
7. And the annual updates thereafter, visualized on Global Forest Watch at globalforestwatch.org.
8. Of this total, this paper covers the 33 FREL submissions to the UNFCCC that include deforestation as a REDD+ activity; we did not analyze Malaysia because deforestation is not an included activity. For countries where more than one FREL was submitted (e.g., Brazilian Amazon), we reviewed only the latest submission. We reviewed modified submissions (those submitted by countries in response to technical assessment) where available.
9. The FRA forest definition has changed since reporting began. The first assessment in 1948 gave the same global forest area as today because the forest definition became more inclusive.
10. The final Conference of Parties decisions on REDD+ contain somewhat conflicting guidance on the need for consistency in national reporting. One paragraph states that the forest definition used by a country for REDD+ is not required to match that used in its national greenhouse gas inventory or its reporting to other international organizations such as FAO. If it does not match, the country must explain why and how the definition used for the FREL was chosen. However, another paragraph states that there should be consistency between the FREL and the national GHG inventory, and this is evaluated during the technical assessment process.
11. UNFCCC Decision 1/CP16.
12. UNFCCC Decision 16/CMP.1, Annex 1d.
13. Lao PDR FREL submission, p. 8.

14. For example, Colombia adjusted its historical average deforestation rate upward in the FREL over a transitional period of five years to account for the then-possibility of ending the country's long armed conflict and beginning a stable and lasting peace, which was expected to generate new dynamics of occupation and land use where deforestation patterns may be altered and differ from historical averages.
15. In the mid-1980s, companies that marketed Landsat images charged up to $4,400 for a single 185x170 kilometer "scene" for a single date in time (Reichardt 1999).
16. Approach 3 is characterized by spatially explicit observations of land use categories and land use conversions, often tracking patterns at specific point locations and/or using gridded map products derived from remote sensing imagery. The data may be obtained by various sampling, wall-to-wall map-based techniques, or a combination of the two methods (IPCC 2006).
17. Horizonete. "10 Soluções Ambientais Que Dariam para Ser Feitas com o Dinheiro de Geddel." http://www.edhorizonte.com.br/noticias/meio-ambiente-e-geddel/.
18. The Global Forest Observation Initiative (GFOI) has produced a methods and guidance document to achieve this goal, but not all countries have applied it when developing their FRELs.
19. These data can be accessed via the Global Forest Watch at www.globalforestwatch.org or through https://earthenginepartners.appspot.com/science-2013-global-forest.
20. Includes data from Landsat 5 thematic mapper (TM), the Landsat 7 thematic mapper plus (ETM+), and the Landsat 8 Operational Land Imager (OLI) sensors.
21. Reprocessing of years 2011 and 2012 for the Version 1.1 update, 2012 and 2013 for the Version 1.2 update, and 2014 for the Version 1.3 update. The 2015 and 2016 global tree cover loss data did not include reprocessed estimates for previous years.
22. Global Forest Watch. "A Fresh Look at Forests 2011-2013." Blog. https://blog.globalforestwatch.org/data/a-fresh-look-at-forests-2011-2013.html.
23. World Resources Institute. Forests and Landscapes Indonesia. http://www.wri.org/our-work/project/forests-and-landscapes-indonesia.
24. USAID. Central Africa Program for the Environment. http://carpe.umd.edu/.
25. We used the same geographic boundaries and years (after 2000) included in each country's FREL. Because of the different time periods analyzed for each country, it was not possible to assign a specific time period for the total deforestation rate summed across all countries that is reported in this section.

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