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Testing methodologies for REDD+: Deforestation drivers, costs and reference levels etc

Technical Report

Testing methodologies for REDD+: Deforestation drivers, costs and reference levels

Technical Report

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Table of contents

1 Executive Summary **1**

1.1 Introduction 1

1.2 A step-wise approach for RL development 1

1.3 Forests, deforestation and degradation drivers 2

1.4 Opportunity costs and deforestation drivers 3

1.5 Lessons learned from specific country case studies 4

1.6 Results-based incentives 5

2 Introduction **6**

2.1 Background 6

2.2 A stepwise approach for RL and FIB development 6

2.3 Opportunity costs and deforestation drivers 6

2.4 Lessons learned from specific country case studies 7

3 National Circumstances **8**

3.1 Brazil 8

3.1.1 Forests in Brazil 8

3.1.2 Key drivers and processes affecting forest cover and carbon change in Brazil 9

3.2 Cameroon 12

3.2.1 Forests in Cameroon 12

3.2.2 Key drivers and processes affecting forest carbon change in Cameroon 13

3.3 Indonesia 15

3.3.1 Forests in Indonesia 15

3.3.2 Deforestation rates in Indonesia 18

3.3.3 Key drivers and processes affecting forest cover and carbon change in Indonesia 18

3.4 Vietnam 20

3.4.1 Forests in Vietnam 20

3.4.2 Key drivers and processes affecting forest carbon change in Vietnam 21

4 Data for Business As Usual (BAU) development **26**

4.1 Overview of country data for BAU development 26

4.2 Data on forest area change estimates for three IPCC approaches 26

4.3 Carbon stocks and emission factors 28

4.4 Data on deforestation and degradation drivers 29

4.5 A step-wise framework for developing reference levels 31

5 Reference Level (BAU) estimation **33**

5.1 Regression models of BAU baselines 33

5.2 Modelling approaches 33

5.3 BAU regression methods 35
5.4 Quantification of deforestation 36
5.5 Global model 39
5.5.1 Data sources and sampling 39
5.6 Regression results 43
5.7 Regression analysis by country 48
5.7.1 Brazil 48
5.7.2 Indonesia 53
5.7.3 Vietnam 56
5.8 Discussion, conclusions and some implications 61

6 Costs of REDD+ 66
6.1 An overview on issues related to REDD+ cost estimation 66
6.2 Approach for REDD+ cost estimation 69
6.3 Costs by country 69
6.3.1 Brazil 69
6.3.2 Cameroon 70
6.3.3 Indonesia 74
6.3.4 Vietnam 80
6.4 Summary 83

7 Financial incentive benchmarks (FIB) for REDD+ 85
7.1 Additionality 85
7.2 Participation constraints, expected gain and leakage 86
7.3 Effectiveness and efficiency 87
7.4 Payment for costs incurred 89
7.5 FIBs to reflect a fair benefit and cost sharing 92
7.6 Dealing with uncertainty 93

8 Concluding remarks 96

References 97

Appendix A 104
A1 Brazil (Voluntary REDD+ Database, 2011) 104
A2 Cameroon 106
A3 Indonesia 107
A4 Vietnam 109
A6 Country sample 111

Appendix B 114

Appendix C 128

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1 Executive Summary

1.1 Introduction

The definition and setting of forest reference levels (RLs) is important in the design of REDD+[1] under a future climate agreement. Two meanings and uses of RL may be distinguished: (i) the RL used to measure the effect or impact of REDD+ policies, where RL refers to the Business-as-Usual (BAU) scenario; and (ii) the financial incentive benchmark (FIB) used for estimating results-based incentives, e.g. direct payment for emissions reductions (Angelsen, 2008). In this study RL is reserved only for meaning (i) and Financial Incentive Benchmark (FIB) for meaning (ii). This work explores how historical deforestation rates, drivers and costs relate to both RLs and FIBs. Based on availability of relevant data and earlier research undertaken, four tropical countries that are part of CIFOR's Global Comparative Study were selected for in-depth case studies because the data for this exercise were readily available, and because they represent countries with a wide range of national circumstances. The authors would welcome similar work on other countries. These countries are Cameroon, Vietnam, Indonesia and Brazil.

1.2 A step-wise approach for RL development

Estimating RLs requires availability of good quality data, in particular on historical rates of deforestation, degradation and emission factors. Because data quality and availability vary between countries, the uncertainty of RL estimates will also vary. In Durban, the UNFCCC Conference of Parties recognised the potential usefulness of a step-wise approach to develop national forest RLs, reflecting an appreciation of the variability in data on forest area and carbon stock changes, and in knowledge and understanding of forest change drivers (Decision 12/CP.17, UNFCCC, 2011). A step-wise approach may facilitate broad country participation, address national data availability, manage uncertainty by reducing the risk of payment for non-additional efforts, and provide incentives for countries to progress as data availability improves.

This idea of a step-wise approach (summarised in Figure 1) is analogous to the tiered approach introduced by the IPCC Good Practice Guidance for Land-use Change and Forestry (GPG LULUCF) (IPCC, 2003) and provides a way to address uncertain and incomplete national level data to estimate and report on forest carbon stocks and changes. The IPCC guidelines use a hierarchical Tier structure (Tier 1, Tier 2 and Tier 3) where higher tiers reflect increased methodological accuracy.

[1] REDD+ refers to the UNFCCC agenda item *Reduced emissions from deforestation and forest degradation and the role of conservation, sustainable management of forests and enhancement of forest carbon stocks in developing countries*.

	Step 1	Step 2	Step 3
Activity data/area change	Possibly IPCC Approach 1 (national net change) but also 2 (national gross changes) or 3 (national gross changes spatially explicit)	IPCC Approaches 2 or 3 (to estimate gross changes)	IPCC Approach 3 (spatially explicit data required)
Emission factors/ carbon stocks	IPCC Tier 1 (defaults) but also 2 and 3 (national data) if available	Tier 2 or 3 (national data)	Tier 2 or Tier 3 (national data)
Data on drivers and factors of forest change	No driver data available or used	Drivers at national level known with quantitative data for key drivers	Quantitative spatial assessment of drivers/activities; spatial analysis of factors
Approaches as guidance for developing reference levels	Simple trend analysis/projection using national statistics, based on historical data	Country-appropriate methods for interpolation/ extrapolation using historical data and statistical approaches	Potential to use options such as spatially explicit modelling and other statistical methods for considering both drivers and other factors of forest change
Adjustments/ deviation from historical trend	Simple rules (in technical terms)	Assumptions and evidence for adjustments key drivers/activities	Analysis and modelling by drivers and activities

Figure 1: Some dimensions of a stepwise approach for using different data and to develop forests' reference levels (adapted from Herold et al., 2012)

Decision 1/CP.16 (UNFCCC, 2010) encourages countries to identify land use, land-use change and forestry activities in developing countries, in particular those that are linked to the drivers of deforestation and forest degradation, and to assess their potential contribution to the mitigation of climate change. The relationship between available data, possible ways in which to develop adjustments for national circumstances which we assume here, means that reasons for expecting that deforestation in the future will deviate from trends apparent in the recent past, and related uncertainties, are considered in successively greater detail from step to step.

1.3 Forests, deforestation and degradation drivers

This study explores the idea of using a stepwise approach to set RLs that integrate better data as they become available, in order to make emissions projections that better represent country circumstances. The analysis of the countries that have been selected for this study assumes that we have a reasonable understanding of historical activity data (in the IPCC sense of the term), that we have information on carbon stocks and emission factors in key land use systems for the country, and that we have quantitative socioeconomic data on drivers.

Country analysis is presented for:

- Brazil, with an area of 8.5 million km^2, of which about half lies in the Amazon Basin. A large percentage of forests are located within protected areas which are divided into different categories, according to their management objectives and land uses. Deforestation occurs in all ecoregions with different drivers. Deforestation in the Amazon has been principally linked to globalized markets for beef, soybeans and timber.
- Cameroon, where dense moist forest predominates and represents 36% of the country's land cover. The Ministry of the Environment estimates that agriculture causes approximately 80% of forest cover loss. Drivers of this process are mainly slash-and-burn agriculture and expansion of cash crops.
- Indonesia, where the Ministry of Forestry divides the forest area into four categories based on function: production forest, convertible forest, protection forest and conservation forest. Around 40% of the national forest area is currently at some stage of degradation. Deforestation is driven largely by expansion of plantation crops such as palm oil, rubber and pulpwood. The expansion of smallholder agriculture also contributes a significant proportion of the deforestation.
- Vietnam, with forest cover nearly 40% and plantations making up about 22% of the forest. The dynamics and causes of deforestation and forest degradation include the conversion of forests to industrial perennial crops, unsustainable logging, infrastructure development and forest fires.

1.4 Opportunity costs and deforestation drivers

Opportunity costs are one of several categories of costs that a country would incur while reducing rates of forest loss under REDD+. Linking opportunity costs with deforestation drivers will help analysts and policy makers understand the potential of REDD+ programmes to reduce deforestation and degradation, and therefore to design more effective REDD+ policies. This linkage will also help understanding of how the FIB could be set, and help with the development of an integrated landscape approach that links measures for the agricultural sector to REDD+ strategies and policies.

We take a bottom-up approach to assessing the opportunity cost of REDD+ program implementation. Based on a literature review of local studies, opportunity cost ranges are established for country-specific deforestation drivers. The table below shows, as an example of the data collected, an overview of agricultural deforestation drivers and costs for all four of the countries investigated in this report. Implementation and transaction costs that may arise during the three phases of REDD+ implementation are also considered for each of our case study countries as part of this assessment. Chapter 6 provides more detail on the costs, by country, related to other drivers.

Table 1-1 Country-specific importance of agricultural drivers of deforestation and driver-related opportunity costs
***Contribution of the driver to national deforestation (≤ 25% = low, ≤ 50% = medium, ≤ 75% = high, > 75% = very high)**

Deforestation driver		**Brazil**	**Cameroon**	**Indonesia**	**Vietnam**
Agriculture (commercial)	Importance of driver*	Very high	Low	Medium	High
	Opportunity cost range (USD ha^{-1})	194 - 3275	450 - 1500	3 – 3000	N.A.
Agriculture (small scale, including sub-sistence and commercial activities)	Importance of driver	Low	Very high	Low	Medium
	Opportunity cost range (USD ha^{-1})	2 - 374	4 - 10	0.48 - 297	N.A.

1.5 Lessons learned from specific country case studies

Regression analysis can be used to estimate future deforestation by seeking links between current deforestation rates and various explanatory factors, including historical deforestation, forest cover, income level, national circumstances and other drivers. An extensive set of analyses was undertaken, with different methods and model assumptions for sub-national and time series data from Brazil, Indonesia and Vietnam, as well as global FAO-FRA data. The necessary sub-national time series data are currently not available for Cameroon so only a national case study was conducted using FAO-FRA data. Some major conclusions are:

Historical deforestation is the key variable to predict future deforestation and explains most of the current variation across countries and sub-national units. Countries experiencing high rates of deforestation in the recent past are more likely to have high levels of current and future deforestation rates. However, the coefficients in almost all cases are below one, suggesting that a simple extrapolation can be misleading, and that other factors might also be considered. Furthermore, simple extrapolation will not predict significant inflection points in national deforestation rates due to changes in national circumstances.

Evidence of a **forest transition (FT)** is observed. FT theory suggests that high forest cover-low de-
foresting countries

tend to experience accelerating rates of deforestation, while countries with high deforestation rates and low forest cover experience decreasing rates of deforestation. The robustness of FT theory depends, however, on the relative measure of forest stock. FT theory is supported by the data when forest stock is measured relative to the total land area, but the evidence is weak when forest stock is measured in absolute terms. This underscores the description of FT as a wide set of interdependent and context-specific economic, political and institutional processes in agriculture and forestry, where a regular global pattern is difficult to detect.

A number of deforestation drivers were tested, with some contradictory findings across the four different data sets and for different models. For example, the impact of income (GDP per capita) varies across countries. Countries with a high dependence on agriculture, as measured by the sector's share of GDP, are generally observed to have high deforestation rates, but eventually deforestation declines as agricultural income increases. Population density is found to have divergent relationships with high deforestation rates, and the same is true for a set of governance variables tested.

The apparently contradictory relationships of national circumstances may in part be explained by the quality of data used, and because the interrelations of economic, political, cultural and institutional differ across countries, which points to the benefit of using national level rather than global analysis to predict deforestation rates. Overall, and given current constraints in data availability and quality, the analyses suggest that past deforestation rates and possibly the proportion of land covered by forest are the best predictors of future deforestation that can be applied widely.

1.6 Results-based incentives

By definition we consider that in an international system of results-based incentives, financial incentives should be based on FIBs, which might or might not be the same as the RLs which measure action relative to BAU. The relationship between RLs and FIBs is partly political and beyond the scope of this study, but the following considerations may be relevant:

- **Participation and leakage:** FIBs should be set in such a way that broad participation by countries is encouraged and hence international leakage minimized.
- **Fair benefit and burden sharing:** The question of differentiation of capabilities and responsibilities among countries is certainly a matter for the negotiations, but arguments are made for middle income countries assuming higher responsibilities (and costs) than the poorest countries. This may affect differentially the relationship between the FIB and the RL.
- **Additionality:** The relationship to the RL, so that the FIB encourages additional action.
- **Effectiveness and efficiency:** In a fund-based system, effectiveness and efficiency is achieved when the total transfer just equals the REDD+ costs.
- **Uncertainty:** RLs, costs, participation and effectiveness of REDD+ policies are uncertain factors, and countries need to factor this into the equation for setting the FIB. One option is the corridor approach, with a gradual increase in the rate of payment as emissions are reduced.

2 Introduction

2.1 Background

The definition and setting of forest reference levels (RLs) is a critical issue in the design of an effective REDD+ mechanism under the United Nations Framework Convention on Climate Change (UNFCCC). Two different meanings and uses of RL may be distinguished: (i) the RL used to measure the effect or impact of REDD+ policies, in which case the RL refers to the Business-as-Usual (BAU) scenario; and (ii) the benchmark used for estimating results-based incentives, e.g. direct payment for emissions reductions (Angelsen, 2008). In this study RL is reserved only for meaning (i) and Financial Incentive Benchmark (FIB) for meaning (ii). The FIB may differ from the RL, and the study discusses different considerations in setting the FIB once the RL had been established.

This work explores causal links between drivers of deforestation and deforestation rates in order to understand how to incorporate national circumstances and costs into estimation of RLs and FIBs. Four tropical countries were selected for in-depth case studies, based on geographical spread and data availability: Cameroon, Vietnam, Indonesia and Brazil.

2.2 A stepwise approach for RL and FIB development

Estimating RLs and FIBs requires sufficient data, in particular on historical rates of deforestation, degradation and emission factors. Because data quality and availability vary between countries, the uncertainty of RL and FIB estimates will vary also. To address this we propose developing a stepwise approach, analogous with the IPCC system for greenhouse gas inventories. A stepwise approach could also facilitate broad country participation, address national data availability and uncertainty management, and allow countries to progress from one step to another as data availability improves. The application of the stepwise approach is explained in Chapter 4 of this report.

2.3 Opportunity costs and deforestation drivers

Opportunity costs, i.e. the forgone benefits from the best alternative land and resource uses, are one of the several categories of costs that a country would incur while reducing rates of forest loss under REDD+. Linking opportunity costs with deforestation drivers will help analysts and policy makers understand the potential of REDD+ programmes for reducing deforestation and forest degradation and to design more effective REDD+ policies. This link to costs could also inform how an FIB could be set in the context of the RL, and help in the development of an integrated landscape approach that links measures for the agricultural sector to REDD+ strategies and policies. In **Chapter 6** of this study, we take a bottom-up approach to assessing the opportunity costs of REDD+ program implementation in Cameroon, Vietnam, Indonesia and Brazil. Opportunity costs are linked to country-specific deforestation drivers which are described in **Chapter 4** of this report. Implementation and transaction costs, which are not necessarily driver-specific, are also considered in Chapter 6.

2.4 Lessons learned from specific country case studies

Potentially a way to project future deforestation is through regression analysis, which seeks to establish the link between current deforestation rates and various explanatory factors, including historical deforestation, forest cover, income level and specific drivers. Historical deforestation is found to be the key variable to predict future deforestation and explains most of the current variation across countries and sub-national units. The coefficients in almost all cases are below one, suggesting that a simple extrapolation can be misleading, and that other factors might also be considered. The impact of other factors varies. The quality of regulations and governance factors is significant in reducing or driving deforestation. In some cases we find evidence to support the forest transition (FT) hypotheses, i.e. high forest areas tend to have accelerating deforestation. The time period used in the analysis may, however, be too short to detect clear transition pattern. For the short to medium term, a continuation of (high) deforestation rates is also possible as self-reinforcing and economics of scale effects may counteract the brake on deforestation suggested by the FT hypothesis. In chapter 5, the regression approach is applied on a global dataset and on datasets from Brazil, Vietnam and Indonesia. Chapter 7 discusses considerations related to FIBs, i.e. how the RL could be modified to set the FIB due to cost, effectiveness and efficiency, cost and benefit sharing, and uncertainty considerations.

3 National Circumstances

This section summarizes contextual information concerning the example countries that will be used as case studies in the subsequent chapters.

3.1 Brazil

3.1.1 Forests in Brazil

Brazil has an area of 8.5 million km^2, of which about half lies in the Amazon Basin. This is the most commonly known Brazilian forest but there are other forest ecoregions in the country e.g. the Atlantic Forest. Below we present a brief overview of the forested areas of the country

The Amazon basin
The Brazilian Amazon covers 4.1 million km^2 and accounts for one third of the world's remaining tropical forests. When referring to the Brazilian Amazon, it is useful to distinguish between this portion of the basin located within the country's boundaries (48% of the country's surface area) and the 'Legal Amazon' (Amazônia Legal) – a geopolitical region created for administrative purposes that encompasses more than 5.2 million km^2, or 61% of the country's total area, including the states of Amazonas, Acre, Amapá, Pará, Rondônia, Mato Grosso, Tocantins and part of Maranhão.

Various types of tropical forests originally covered an estimated 73% of the Legal Amazon region. Non-forest forms of natural vegetation, such as savannahs, natural grasslands and campirana, also occur in the region. The portions of the Legal Amazon located outside the proper Amazon basin are covered mainly by savannah vegetation and transitional forests, principally within the vegetation type known as cerrado.

The Cerrado
The Cerrado is a vast tropical savanna ecoregion of Brazil with vegetation ranging from tropical broadleaf woodlands to scrublands. This ecosystem is a rich tropical region with enormous ranges of endemic plant and animal biodiversity. It is the second largest ecoregion in Brazil, covering 2 million km^2 in the central area of Brazil; only 20% of which remains intact. It is characterized by vast plains, with soils that are highly weathered, have low fertility and have high aluminium and iron contents. These characteristics hinder the development of natural vegetation. The possibility of mechanizing agriculture in this landscape has been the main driver for land use change. The seasons are divided into a dry winter and a rainy summer.

The Atlantic forest
The Atlantic forest in Brazil is comprised of remnants that, because of difficult access, survived colonization and development. This ecosystem once covered the areas close to the coast from the state of Rio Grande do Norte

in the North, while in the South it occupied areas into Argentina and Uruguay. Today it is one of the most threatened tropical forests in the world, with less than 10% of the original area remaining.

The Caatinga

Caatinga is the name given to the dry savannah of the Brazilian Northeast. It occurs in a semiarid region characterized by sporadic rainfall and high temperatures. As with the Cerrado, the Caatinga is composed of a mosaic of vegetation types with different biomass densities varying from grasslands to forests. This ecosystem has received the least attention among conservationists and policy makers. It is one of the poorer regions in Brazil and most of the population in these areas lives in the cities in the coastal area, despite historic occupation of the interior.

3.1.2 Key drivers and processes affecting forest cover and carbon change in Brazil

Deforestation occurs in all Brazilian ecoregions, with different drivers. Despite well-known monitoring deforestation in the Legal Amazon using satellite images going back to 1988 other biomes have not received the same attention. Below we provide a summary by region and estimated land area, where available.

The Legal Amazon

Deforestation of the Amazon rainforest has historically received the greatest national and international attention. To address this issue the Brazilian Institute for Space Research (INPE) started monitoring deforestation of the Amazon rainforest in 1988 using Landsat imagery. This effort measures changes in forest cover from one year to the next and does not consider regrowth, meaning that an area that is considered deforested in one year is considered deforested forever according to the measurement system adopted.

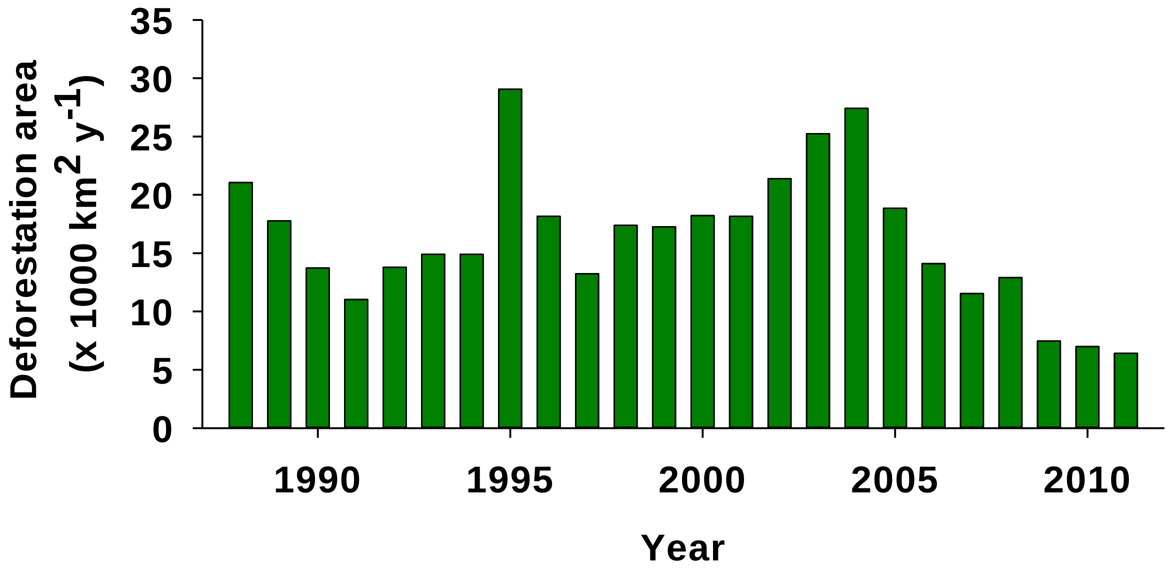

Figure 2: Deforestation of the Amazon forest in the Legal Amazon in Brazil. Source: PRODES website http://www.obt.inpe.br/prodes/.

According to analyses of remote sensing data by INPE (Figure 2), annual deforestation rates in the Brazilian Amazon (1) peaked at approximately 29 000 km^2 in 1995 (about 0.8% of the remaining forestland of approximately 3.7 million km^2), followed by a reduction in the second half of the 1990s. Subsequent rates of annual clearing increased substantially between 2000 and 2004, peaking again at 27 772 km^2 in 2004 (0.78%). Deforestation rates subsequently dropped in the mid 2000s (<0.4%) followed by a slower decline (0.2%) in the past three years.
Approximately 15% (0.75 million km^2) of the total area of Brazil's Legal Amazon has been transformed for agricultural and ranching activities. The predominant land use within the deforested areas is cattle pasture, estimated to cover 82.3% of the deforested land or 0.62 million km^2 in 2007. The remaining cleared areas are devoted to annual crops (mostly rice, bean, maize, soybean and cotton) and perennials (such as coffee, cacao and black pepper). The area devoted to cattle pastures in the Legal Amazon has expanded by 44.2% between 1985 and 2006 (Smeraldi and May 2009).[11]

Around half of all Brazilian CO_2 emissions arise from cattle ranching, predominantly due to deforestation and burning (Bustamante et al. 2010, Imazon cited in Valor Econômico). In addition to deforested areas, a much larger area of the Brazilian Amazon has been subjected to different forms of human intervention. A recent study by the Instituto do Homem e Meio Ambiente da Amazônia (Barreto et al. 2005) estimates that by 2002, 47% of the Brazilian Amazon was under some type of human pressure, including forest clearing, selective logging, fire and mining activities. Thus, forest degradation is probably also an important source of CO_2 emissions, but at the time of writing had not been quantified in Brazil's national greenhouse gas inventory, although relevant research was underway.
Increasingly, deforestation trends in the Brazilian Amazon have been linked to globalised markets for

beef, hides, timber, soybeans, and other commodities. Recent decreases in deforestation rates may be linked to decreases in prices for beef and soybean, as well as other factors, including efforts undertaken by the Brazilian government, especially related to the creation of protected areas in regions such as along the BR-163 corridor, the soybean moratorium and improved enforcement activities, have also yielded positive results (Barreto et al. 2009).

The Cerrado

Deforestation in the Cerrado ecoregion is a new concern and has been receiving increasing attention by policy makers and media. Deforestation was measured in this region for the first time in 2010 and it appears that the area is twice as large as the area deforested in the Amazon forest. About 21,000 square kilometers of Cerrado was deforested annually between 2002-2008, twice the rate of the Amazon biome.

The main driver of deforestation in the Cerrado is the expansion of industrial scale agriculture, particularly the cultivation of soybean. Another important driver (about 30%) is land clearing to produce charcoal for pig iron production. Very large smelting firms buy charcoal from household producers without any form of environmental license or authorisation.

The main underlying cause of this deforestation is a recent shift of soy supply from the northern to the southern hemisphere. Between 1980 and 2007, the area planted to soy in the United States remained constant at around 0.26–0.27 million km^2, whilst the area of plantation in Brazil increased from under 0.1 million km^2 to just over 0.36 million km^2. This trend reflects the fact that Brazil has land available for the expansion of agriculture. National incentives through tax credits and land ownership recognition have encouraged expansion of soybean cultivation in previously forested areas. Meanwhile, in the United States, federal subsidies for biofuel production made corn (maize) a more attractive commercial proposition than planting soy. As a result, major soy traders sought out new high-volume sources and accelerated the expansion of the industry in Latin America. Although soy production is not currently as technically viable in most parts of the Amazon basin as in the drier Cerrado, its expansion—along with that of sugarcane in response to greater demand for ethanol—has also had the indirect effect of pushing pastures further into the forest frontier (Searchinger et al. 2008). Moreover, BSE outbreaks in Europe in the mid-1990s discouraged animal sourced protein in livestock feed, leading to a switch in demand across the region for soy protein sources. Furthermore, in 2007, demand from several developing nations led to growth rates in the high teens. China, for example, now accounts for 45% of all soybean imports from Brazil (Campbell et al. 2010).

The Caatinga

Deforestation in the Caatinga has not been measured and therefore no estimates exist for the amount of land cleared. The main driver of land clearing in this ecoregion is fuel wood production for household consumption.

The Atlantic forest

Deforestation in this ecoregion has been under control for some time, due to the difficult access to remnants as well as strict legislation. The biome has increased its area slightly in the past years.

3.2 Cameroon

3.2.1 Forests in Cameroon

The distribution of natural forest types in Cameroon is controlled primarily by the gradient of annual rainfall that ranges from 500 mm in the north to 1,700 mm in the south. Several land cover classifications have been proposed for Cameroon. Below a classification from the Food and Agriculture Organization of the United Nations (FAO), is presented which is based on a national forest inventory carried out in 2004 [MINFOF/FAO, 2005]. (Table 3-1)

Table 3-1 Forested land and other land uses in Cameroon, based on FAO data

	Area (ha)	% of forest area	% of total land area
Dense Moist Evergreen Forest	11,389,468	53.6	24.0
Semi-deciduous dense moist forest	5 935 155	28.0	12.5
Deciduous forest	361 236	1,7	0.8
Gallery forest	1,706,372	8.0	3.6
Swamp forest	1,779,649	8.4	3.7
Other natural forests	57,963	0.3	0.1
Total dense forest	21,229,843	100.0	
Tree savanna	9,232,433		19.4
Shrub formations	3,482,524		7.3
Grassy vegetation	1,944,742		4.1
Fallow land	2,088,803		4.4
Annual crops	5,105,665		10.7
Perennial crops	1,238,249		2.6
Grazing land	1,308,204		2.8
Plantations	6,631		0.0
Swamps	1,158,866		2.4
Developed land	382,402		0.8
Inland waters	272,839		0.6

Source: MINFOF/FAO, 2005 and FAO, 2010b.

Since 1995, a zoning plan has stipulated that the southern Cameroon forest (14 Mha) should be divided up into permanent forest estate (DFP) and non-permanent forest estate (DFNP). The DFP includes the production and protection forests that belong to the state and to local communes. In the DFNP non-forestry activities like agriculture, livestock rearing, etc. are combined with forestry activities, like timber sales. Within the DFNP, community forests (~650,000 ha or 15% of the DFNP) are subject to the implementation of a management plan and an environmental impact assessment.

3.2.2 Key drivers and processes affecting forest carbon change in Cameroon

The net annual deforestation rate in the dense forest zone was estimated to be 0.14% between 1990 and 2000 and the net annual degradation rate was estimated to be 0.01% (Duveiller et al., 2008). However, for the entire country, between 2000 and 2005, the annual deforestation rate was calculated at 1% (MINFOF/FAO, 2005), and according to FAO, this rate increased 0.6% from 1980 to 1995, and then 0.9% from 1990 to 2000. A remote sensing survey by the EU's Joint Research Centre provided somewhat different results (Table 3-2)

Table 3-2

1990-2000						2000-2005		
Country	*n*	Gross Deforestation	Gross Reforestation	Net Deforestation	*n*	Gross Deforestation	Gross Reforestation	Net Deforestation
Cameroon	*51*	0.10±0.05%	0.02±0.01%	0.08%	*20*	0.17±0.14%	0.14±0.19%	0.03%

According to the Ministry of the Environment and Forests (MINEF), GHG emissions from deforestation accounted for half of all the emissions in Cameroon in 1994 (MINEF, 2005). This is consistent with the estimate in the National Communication from Cameroon on the UNFCCC website.

Agriculture is the main cause of deforestation in Cameroon and is responsible for 80% of the loss of forest cover (CARPE, 2005). The recent trends have intensified as shown in Table 3-3, due to greater food demands. Agricuture includes includes fallow land (23%), annual crops (22%), perennial crops (20%), community forests (15%) and inhabited areas (5%) (MINFOF/FAO, 2005). Cash crops are also common in the north of the country, where cotton is encroaching into the savanna and open woodlands situated to the south of the traditional cotton-growing area. Elsewhere, population pressure in densely inhabited zones such as the Bamiléké Highlands in the Lékié Department result in the migration of rural populations to sparsely populated regions.

Agriculture represents 21% of the gross domestic product (GDP), with only a small percentage (4%) going to exports (INS, 2010). This is a rich, diversified sector, with considerable subsistence production or production for informal local and regional markets, aimed at neighbouring towns and countries (Equatorial Guinea, Gabon). The pressure from cash crops (coffee, cacao, cotton, oil palm, sugar, rubber trees, banana, tea, etc.) varies from one region to another. Agriculture is likely to continue to expand in the country and this expansion will increasingly be driven by external investors e.g. China.

Table 3-3 Trends in agricultural land ares in Cameroon (x 1000 ha)

	Subsistence agriculture (source: AgriStat spécial N°12 & N°15)	Total agriculture (source: FAOSTAT : FAO Statistics Division 2010)
1999		3,403
2000		3,583
2001	2,446	3,751
2002	2,604	3,955
2003	2,804	4,239
2004	2,992	4,458
2005	3,179	4,688
2006	2,661	4,589
2007		4,575
2008		4,491

There are other less important drivers of deforestation, most notably mining and infrastructure development. Mining of iron, cobalt, diamonds, gold, nickel, manganese, bauxite, etc. is becoming an important economic activity, particularly in the south of Cameroon. However, quantitative estimates of their importance as drivers of deforestation are not available.

Infrastructure development e.g. roads and railways for different industries (mining, forestry, dams, etc.) is responsible for a small portion of deforestation. Transport corridors open up the forests to migrants who farm the land, raise livestock and carry out other activities that are direct drivers of deforestation and forest degradation.

Degradation

Forest degradation is also an important source of GHG emissions. We define forest degradation as any activity that results in a decline in carbon stocks, but that does not result in the disappearance of forest cover. Domestic consumption of wood is estimated to be in the order of 10 million m^3 of roundwood equivalents (RWE) per year. This leads to an increasing scarcity of wood resources in the Sahelian zone[2] and around large towns. The gathering of firewood is thus an important driver of degradation and deforestation.

[2] A total ban on the exploitation of growing stock and the production of charcoal in Chad has led to large amounts being taken from the bordering Cameroonian Departments.

Economic adjustments and the devaluation of the CFA Franc in the 1990s increased the pressure on the forest resources in Cameroon. The devaluation led to a rise in the price of petroleum products, increased unemployment and a worsening of economic conditions, generally. This resulted in a growing use of wood energy by the population and notably by the urban population (half of the population of Cameroon).

The timber industry is an important part of Cameroon's economy, accounting for around 5% of GDP. Wood is the country's second most important export (13%), behind oil products. After a significant growth in exports due in part to the devaluation of the CFA Franc the country exported at its peak ~3.4 Mm^3 RWE annually. This pressure on forests has declined in recent years; in 2005 exports were 2.3 Mm^3 RWE and in 2008 they were only 1.0 Mm^3 RWE[3].

Illegal logging by the informal sector for Cameroon's domestic market and markets in neighbouring countries is a significant driver of forest degradation. The best estimate suggests that 540,000 m^3 is lost annually through illegal harvesting, mainly from the dense forest (Cerrutti & Tacconi, 2006). Semi-deciduous forests, the moist savannah zone, are also subject to high levels of pressure, including overexploitation of wood for energy and lumber, overgrazing and the clearance for agriculture. There is exploitation of designated forest reserves and reforestation. Finally, open woodland and savannas in the north of the country are receding due to pressure from humans and animals, bush fires, lack of water and unsuitable agricultural methods. This pressure does not necessarily lead to deforestation, but can cause significant forest degradation.

Poorly managed bush fires especially late in the dry season (Sahel and montane zones), are major drivers of forest degradation. Fires started to prepare land for cultivation often escape into surrounding bush areas because of the very dry conditions at the time.

Small scale agriculture also plays a role in forest degradation. Certain crops, such as cacao, need a canopy cover in order to thrive, and are thus planted in forests after a reduction in the density of the overstory trees. Crop combinations like this also offer opportunities for expanding wooded areas through agroforestry.

3.3 Indonesia

3.3.1 Forests in Indonesia

There are many types of forest in Indonesia including coastal forests; tidal forests such as mangroves and nipah palms; heath forests (kerangas) occur on sandy soils; wetland forests including peat swamps; evergreen forests, bamboo, and montane forests. Dipterocarp forests are found throughout Indonesia in both lowland and hill areas. These evergreen forests are rich in biodiversity and harbour

[3] COMCAM (2008).

charismatic species including orang-utans, tigers, rhinoceros, elephants, leopards and proboscis monkeys (WWF, 2010).

The Planning Agency of the Ministry of Forestry (Bapplan, 2008) has interpreted satellite images from 2007, classifying approximately 71% of the country as *kawasan hutan*[4] or legal Forest Estate and 29% as non-forest land area. Large areas of forest in the national forest estate have been deforested and degraded due to various activities. Only one-third of the forest estate is covered by primary forests, one-third by logged-over areas and one-third by vegetation other than forest. Some of non-forest estate land is covered by forest.

The Ministry of Forestry in Indonesia divides the forest area into four categories based on function: Production Forest, Convertible Forest, Protection Forest and Conservation Forest (Table 3-4). Production forest is for timber and non-timber production and includes natural forests and industrial timber plantations. Convertible forest is destined for conversion to other land uses, for example agriculture or human settlements. Protection forests are designated to sustain important ecosystem functions like protection of the headwaters of river systems, water storage to prevent flooding, erosion control, protection against seawater intrusion, and maintenance of soil fertility. Conservation Forest includes various types of conservation areas for conservation of biodiversity and unique ecosysems.

[4] The Forest Estate is land managed by the Ministry of Forestry (MoF). Not all land in the Forest Estate has forest vegetation cover but all lands within the Estate fall under MoF jurisdiction. There is also land outside the Forest Estate that is covered by forest vegetation that is not managed by MoF.

	Forest	Non-forest	Total[a]	Deforestation rate 2003–2006	Relative annual deforestation rate	Forest remaining in 2020
Kawasan Hutan (Forest Estate)	(10^6 ha)			(x1000 ha y^{-1})	(%)	(10^6 ha)
Reserve and protection forests	38.2	9.7	49.6	185.9	0.49	35.6
Production forests	40.9	18.6	60.5	466.6	1.14	34.4
Conversion forests	11.0	11.0	22.4	108.7	0.99	9.5
Total Forest Estate	**90.1**	**39.3**	**132.5**	**761.2**	**0.84**	**79.4**
Non-Forest Estate	8.3	46.5	55.4	412.9	4.97	2.5
Grand total	**98.5**	**85.8**	**187.9**	**1174.1**	**1.19**	**82.0**

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Table 3-4 Land cover classification by Indonesia's Ministry of Forestry and expected changes with deforestation continuing at current rates

3.3.2 Deforestation rates in Indonesia

Although deforestation rates in the forest estate are below 1%, rates in reserve and protected areas that should have no deforestation remain significant. These lands account for 35% of the annual deforestation in Indonesia. Deforestation is also widespread outside on the non-forest estate, at 4.97% per annum, more than five times higher on a relative basis than inside the forest estate, at 0.84% per annum. Policies affecting these forests fall under the jurisdiction of several agencies with different mandates and priorities. The classification of the way these lands are used, the method for assessing the value of the land, including its carbon value, and the assessment of pressure for land cover change depend on which agency has jurisdiction. Obtaining consistent data on high carbon stock forests and policies to maximise their potential for emissions reductions would require strong interagency coordination and alignment of objectives and activities within these areas.

The summary of the most recent National Communication to the UNFCCC by Boer et al. (2009) quotes two very different national GHG emission levels from forests and peatlands. The first is based on a report by Indonesian organisation PEACE that estimates an emissions level of 3014 million tonnes of CO_2 annually through 2005 (Sari et al. 2007). The second estimate, presented by the GoI, is of 1991 million tonnes for of CO_2 in 2005. These differences are significant as are their implications for the resources needed and the options available to achieve a 26% (or a 41%) reduction target for total national emissions.

3.3.3 Key drivers and processes affecting forest cover and carbon change in Indonesia

The drivers of deforestation in Indonesia originate from both within the forestry sector and from outside the sector in the pursuit of national development goals. According to recent GoI figures, deforestation is driven largely by the expansion of plantation crops and pulpwood production. Expansion of agriculture for food production contributes a smaller, yet significant proportion. Deforestation can be categorized as planned and unplanned deforestation. Forest area which is classified by the Ministry of Forestry (MoF) as ‘convertible forest’ and forests on land that is not part of the national forest estate are allowed to be converted to other land uses, so deforestation in this area is considered to be in the category of ‘planned deforestation’. Unplanned forest losses can result from fires and illegal encroachment. A similar definition for planned and unplanned activities can also be applied to forest degradation. Planned degradation is caused primarily by the unsustainable levels of logging from legally permitted forest concessions, while unplanned forest degradation is mainly due to illegal logging activities in forested land area.

Forest Fire

Forest fire in Indonesia has become a common phenomenon and in particular during El Niño events. Uncontrolled fires have destroyed and devastated large areas of tropical rainforest. When forests have been previously degraded, repetitive forest fires can cause deforestation as the forests are completely burnt. Once areas are destroyed by fire, they are more likely to be considered for conversion to other land uses.

Forestry activities

Logging: Unsustainable practices of forest management in forest concessions, which are owned privately or managed under state owned enterprises, have caused severe degradation of Indonesian forest. With current wood industry capacity, timber production from natural forests is insufficient to meet mill capacities and this has led to the increase in illegal logging activities. It is estimated that an additional supply of timber from illegal logging may be equal to that from the legal logging. The highest logging activities occurred in production forests (60%), followed by protected forests (30%) and forest conservation areas (10%). The level of illegal logging is estimated to be very high in the non-concession forest area of production forests (Tim Pokja Kementrian Kehutanan, 2010).

Timber plantation: Plantation of timber using *Eucalyptus* and A*cacia* predominate the development of industrial forest plantations. Indonesia possesses 4 Mha of industrial plantations, primarily to supply pulpwood consumptions that make up more than 75% of the concessions licensed by the MoF (MoF 2009). Plantation occurs on mineral soils, peat lands and degraded imperata grasslands. While timber plantation occurs mostly outside of peatlands, the fraction within peatlands contributes disproportionately to emissions and these emissions are sustained as long as these soils are drained.

Timber plantation by communities: In addition to increasing the supply of raw materials for roundwood and pulpwood industries, community plantation schemes aim to revitalize the traditional wood-processing sector such as plywood and sawn-timber. There is a 2016 target in place for the plantations to rehabilitate and improve productivity of degraded 5.4 million hectares of forest lands.

Non-forestry activities

Agriculture: Agricultural expansion through shifting cultivation, colonization (transmigration, resettlement) and expansion of oil palm plantation (perkebunan) is the largest cause of deforestation. Much of this is legally sanctioned by local governments that apply to the Ministry of Forestry to reclassify forest land area to non-forest land area.

Agricultural encroachment on forest land areas by communities for subsistence is another important driver of deforestation. In many cases the population in these areas gradually grows and new villages are formed. Based on data from MoF and the Indonesian Statistical Centre (BPS) (2009), in 2008 there were about 9,800 villages in the forest land area and 38% of these were in the protected forest areas, 17% in the forest-conservation areas, 33% in production forest areas and 13% in convertible production forest. Due to the increase of population in the coming decades, without effective policies to address this issue, the deforestation due to agricultural encroachment may continue.

Political administration extension: Expansion of administrative regions or the formation of new autonomous regions is considered an important factor causing deforestation in Indonesia. The emergence of new district governments is followed by construction and establishment of public infrastructure that include transportation, market, services as well as private infrastructure which cause deforestation. In many cases, the extent of natural resources, such as forest resources serves as the driver to establish an independent district government. The resource is used to generate revenue for the district by issuing permits to log the forest that will result in reduction of carbon stock.

Mining: Forests in Indonesia contain rich mineral deposits, exploitation of which are part of the development plans for the country. Rights to use the resources are granted by the government through a land leasing scheme for a fixed period of time. Mining of the deposit starts by clearing, not only woody biomass of the forest but also below ground biomasses and dead organic matter. The activities produce high emissions and the forest vegetation will be difficult to restore as the fertility of the soil will be depleted. In many cases, forest areas are left heavily degraded when the permit expires.

High prices have led to rapid growth in the value and extent of the mining industry in Indonesia. The industry's export revenues increased from $ 9.4 billion in 2005 to about $ 21 billion in 2006. Coal is a fast growing commodity in the mining sector, driven in large part by growing demand from China. Recent growth rates for this commodity have been on the order of 13 – 15% per annum. Indonesia's target for growth in 2011 is 19%. Thus, this sector may continue to be a significant driver of deforestation in future.

3.4 Vietnam

3.4.1 Forests in Vietnam

Vietnam has an land area of 32,894,398 ha, and a coastline of 3,260 km running from the North (Mong Cai, Quang Ninh province) to the South (Ca Mau cape, Ca Mau province).

Between 1943 and 1995, Vietnam lost about 6 Mha of natural forests and the forest cover decreased from 43% to 28% of the national territory (Table 3-5). This represents an average loss of about 100,000 ha/year. However, between 1995 and 2008, the forest area continuously increased. Data from the 1999 National Forest Inventory showed that Vietnam began to recover forest area around 1995, when plantation forests attained 16% of the forest area. Currently the forest cover is almost 40% and plantations make up about 22% of the forest (MARD 2009).

Table 3-5 Change of forest area and coverage in Vietnam for the period 1943 – 2009

Year	Total forest area		Area by forest types (1,000 ha)	
	Area (1,000 ha)	Coverage (%)	Natural forest	Plantation forest
1943	14,300	43.0	14,300	0
1976	11,169	33.0	11,077	92
1980	10,908	32.1	10,486	422
1985	9,892	30.0	9,308	584

1990	9,175	27.0	8,430	745
1995	9,302	28.0	8,252	1,050
1999	10,915	33.2	9,444	1,471
2002	11,784	35.0	9,865	1,919
2003	12,095	36.1	10,005	2,090
2004	12,306	36.7	10,088	2,218
2005	12,616	37.0	10,283	2,333
2006	12,723	38.0	10,304	2,419
2007	12,836	38.2	10,283	2,553
2008	13,118	38.7	10,348	2,770
2009	13,258	39.1	10,339	2,919

Source: GSO, http://www.gso.gov.vn/default.aspx?tabid=390&idmid=3&ItemID=9996

The increase in forest area has been partly the result of plantation development (Bleaney *et al.* 2009), and is also explained by the re-categorisation and inclusion of previously omitted limestone forests in the category of forest. Natural regeneration of the forest is also a factor in bamboo forest areas (Vu *et al.* 2011). National forest tenure reform, the availability of new technologies, market opportunities for cash crops and the liberalisation of agricultural markets contributed to the increase in forest area (Sikor 2001).

Despite the significant increase in forest area since 1995, forest quality is still low. Inventory data from 2004 showed that primary forest accounted for only 7% of the forest area and most of the remaining natural forests were secondary forests. Primary forests are only found in the central highlands. Lowland forests have been almost entirely lost, whilst Vietnam's mangrove forests have been significantly degraded (Vu *et al.* 2011). Most plantations are monocultures; and the 70% of the forest area that is secondary forests are in poor condition or regenerating; fragmentation and degradation continue (Forest Protection Department 2004, Meyfroidt and Lambin 2008, Vu *et al.* 2011).

3.4.2 Key drivers and processes affecting forest carbon change in Vietnam

The factors driving deforestation in Vietnam have changed over the course of the country's history. The period of greatest forest loss occurred between 1943 and 1995 where it has been estimated that forest cover declined from at least 43% to 28%. Much of this was a result of war and agricultural expansion by the predominately lowland Kinh people who migrated into forested areas. By the middle of the 1990s with the forest estate severely depleted and degraded, there was a change in policy to stabilise and increase the forest areas through the introduction of national forest initiatives, most notably the 661 Program. The program was successful in reversing the national trends of deforestation and forest degradation, but deforestation still occurs in several regions. Although there are other drivers of deforestation (such as invasive species, mining and biofuels), currently main direct causes of deforestation and forest degradation are generally agreed to be conversion to agriculture (particularly to industrial perennial crops), unsustainable logging (notably illegal logging), impacts of infrastructure development, and forest fires followed by land use conversion.

Details of deforestation by regions and provinces are shown in Table 3-6

Table 3-6 Gross deforestation area (ha) by Vietnamese regions from 1995 – 2009

Region/Province	Red River Delta	Northern	Midlands and mountain areas North Central	Area and Central coastal area Central	Highlands South East	Mekong River	Delta Total
1995	115	2,199	2,487	10,134	1,387	2,592	18,914
1996	66	479	1,440	2,758	779	7	5,527
1997	517	545	993	3,357	1,257	455	7,123
1998	518	2,116	713	3,093	751	313	7,503
1999	9	265	1,040	3,154	714	15	5,196
2000	212	333	656	1,548	589	206	3,543
2001	505	218	200	1,305	482	110	2,820
2002	940	239	383	1,983	949	572	5,066
2003	536	180	221	567	453	85	2,041
2004	394	208	269	457	887	40	2,254
2005	66	239	179	1,009	1,828	27	3,347
2006	7	241	226	996	1,605	49	3,125
2007	3	229	125	481	484	26	1,348
2008	3	360	332	1,041	1,420	17	3,172
2009	9	309	84	715	428	18	1,563

Source: GSO, http://www.gso.gov.vn/default.aspx?tabid=390&idmid=3&ItemID=9996

Deforestation through conversion of lands for agriculture

Vietnam is one of the world leaders in the export of agricultural commodities, including coffee, cashew, pepper, shrimps, rice and increasingly rubber. Most of the recent expansion in perennial industrial crops has concentrated in two agro-ecological zones: the Central Highlands and the Southeast.

Over the past 10 years these regions have experienced some of the highest levels of deforestation. Work carried out by ICRAF in Dak Nong Province (Central Highlands) found that the main direct driver of deforestation and degradation is conversion of natural forest to industrial perennial crops and its interaction with shifting cultivation in acquiring land. Local groups, such as ethnic minority groups, were found to be acquiring this land in order to sell it on for producing industrial perennial crops. There has also been a large increase in the area used for aquaculture, primarily shrimp production. The government continues to set high targets for the increase in the value of aquaculture, so the trend in mangrove loss is likely to continue. Mangroves typically store 7 – 10 times as much carbon as upland forests, so their loss has a disproportionate impact on GHG emissions. The country lost 60%of its mangroves between 1945 and 1995 (Vaiela et al 2001).

National statistics show that the area of industrial crops, particularly rubber has increased very quickly (see Table 3-7). The rubber development is growing fast in the south, especially central highland region where conditions are favourable. The causes for such a development are demand, and the government policies to convert forestland to rubber (Vu Tan Phuong 2010). Cereal crops have also expanded by 30% since 1990, but have recently stabilized.

Table 3-7 Area of industrial and cereal crops from 1990 – 2009 (Unit: thousand ha)

Year	Tea	Coffee	Rubber	Pepper	Cashew	Coconut	Cereals
1990	60.0	119.3	221.7	9.2		212.3	6476.9
1995	66.7	186.4	278.4	7.0	159.1	172.9	7324.3
2000	87.7	561.9	412.0	27.9	195.6	161.3	8399.1
2005	122.5	497.4	482.7	49.1	348.1	132.0	8383.4
2009	128.1	537.0	674.2	50.5	398.1	139.3	8528.4

Source: http://www.gso.gov.vn/default.aspx?tabid=390&idmid=3&ItemID=9996

There continues to be poverty in Vietnam particularly amongst the ethnic minorities who predominantly live in upland forested areas. Shifting cultivation is applied to produce sufficient food for subsistence in order to alleviate poverty. In the Central Highlands much of the cultivation into new forested areas appears to be motivated by acquiring more land, often sold on for commercial purposes to grow industrial crops. In the North Central region, where there are fewer opportunities for industrial crops, shifting cultivation is practiced more for subsistence purposes. It is unclear how much current expansion is into newly forested areas. Further analysis needs to be carried out to understand the potential trends.

A final underlying factor that drives expansion of both industrial crops and subsistence agriculture is the growing population from both internal migration and population increase. Generally, migration is diminishing due to the scarcity of arable lands, the restriction applied by the host Provinces, and the increasing availability of off-farm employment in the home regions. The remaining areas where internal migration occurs are areas with available fertile land such as the Eastern parts of the Central Highlands. Fertility rates are higher amongst ethnic minority groups (roughly 3.4 children compared to 2.1 for Kinh), which may imply that more population growth pressure comes from such groups.

Degradation through unsustainable logging

Forest degradation is caused by unsustainable logging, which is mainly result from poor management practices and/or illegal activities. Some illegal activities are committed by local households driven by poverty and desperation, while much is driven and controlled by criminal gangs and networks.

There is a large and growing demand for timber for inexpensive furniture made from tropical hardwood. Vietnam has become a major hub for the export of furniture, making wood products Vietnam's fifth largest export earner. The current rate of domestic timber production does not satisfy the growing wood demand for this industry. In addition, policies that restrict harvesting in natural forests are resulting in displaced wood extraction in neighboring countries to meet the demand of forest product industries – primarily furniture manufacturing. A recent study suggests that the amount of wood sourced from abroad is approximately 40% of the volume of wood regrowth that is taking place in Vietnam's forests (Mayfroidth and Lambin, 2009).

The issue of the illegal trade in timber as well as the illegal extraction in Vietnam has serious implications for the future of the industry as well as the potential benefits from REDD+. With stricter requirements to show proof of legal provenance (e.g. from the US Lacey Act and the EU FLEG-T initiative) there is a growing incentive for Vietnam to eliminate the use of timber from illegal sources.

The scale of illegal practices is difficult to estimate According to recent statistics in 2009 there were 25,817 violations of state regulations (with 48,605m^3 of timber confiscated) with respect to illegal logging, timber and forest products trade. However, due to a lack of monitoring, poor case handling and incentives that discourage local authorities from providing accurate and complete reports, it is likely that considerably more violations go undetected and unreported.

Another issue for understanding future emissions from the forestry sector is the on-going change to the current administration of the forest sector. The process of decentralization that is on-going in Vietnam has the potential to bring greater benefits to the local communities, but unless it is carried out in a participatory manner there is a risk of further marginalising the poor while creating and placing greater powers with the local elites. How this issue is resolved will affect future deforestation and degradation trajectories.

Infrastructure development

Road building and dam construction are the most destructive of all the potential infrastructural developments in terms of forest loss and degradation. Vietnam's roads have more than doubled in length since 1990. While the forest cleared to make way for the construction may not be significant, the greater accessibility of such areas to encroachment and unsustainable exploitation can have a multiplier effect.

Vietnam faces increasing demand for electricity which is driving a rapid increase in the use of hydropower. The North West region of Vietnam currently produces most of the hydropower for the country and has the greatest potential for future hydropower development. Construction of dams along the Dong Nai River has destroyed more than 15,000 hectares of natural forest. The estimated impact of 21 planned large scale dams (with a capacity over 4610MW) will lead to a loss of around 21,133ha (including 4,227 ha of natural forests, 1,367 ha of plantations). The total resource value of the forest lost (including environmental service functions) is estimated to be $72.4 million. Indirect impacts on other forested areas will likely be the result from migration and resettlement of the 60,000 people that will be displaced by these schemes. In particular in areas that already have high population density, such resettlement is considered a serious risk to the surrounding forest areas.

Forest Fires and associated land conversion

About 6 Mha of Vietnam's forests are considered to be vulnerable to fire. In particular the whole area of the Northwest, the Central Highlands, the Southeast and the Mekong Delta have witnessed extensive loss of forests as a result of forest fires. Although forest fires originate from a number of sources, slash and burn agriculture practiced by the upland communities is believed to be the main cause. Tillage or clearing of fields after the harvest occurs at the same time as the dry season. A further underlying cause is the warmer and drier weather conditions. For example, in 2010 there was a large increase in fires due to the much drier conditions, which have been attributed to El Niño. Projections of climate change show that the North West and the Mekong Delta are two of the areas which will likely experience warmer conditions and perhaps greater forest loss due to fire.

4 Data for Business As Usual (BAU) development

This section describes a stepwise approach that could be used to develop business as usual (BAU) projections for carbon emissions from deforestation and forest degradation. This chapter considers data availability for the four focus countries, and proposes a stepwise model for providing the data on drivers on the basis of different countries' circumstances. These data sets can then be used to develop RLs for REDD+.

4.1 Overview of country data for BAU development

Five types of data have been considered for each country case:

- Activity data describing the forest area change at the national level
- Emission factors reflecting the amount of carbon loss per unit area for a specific type of forest change due to deforestation, and potentially degradation and other activities)
- Drivers - to describe how much of the deforestation and associated emissions are caused by each activity
- Data on existing national monitoring capacities
- Ancillary data including proxies and spatial factors that feed into the deforestation and driver analysis such as road networks, socio-economic and demographic data etc.

4.2 Data on forest area change estimates for three IPCC approaches

IPCC Good Practice Guidance (2003) introduces three approaches to estimating land areas associated with different activities. In principle any approach can be used with any of the three Tiers (i.e. progressively more detailed methods) of emissions estimation, though in practice higher Tiers are likely to use Approaches 2 or 3. Table 4-1 summarizes the Approaches:

Table 4-1 Activity data on the national level can be estimated from the different approaches as suggested by the IPCC GPG:

	Approach 1	Approach 2	Approach 3
Data on forest change (or emissions) following IPCC approaches	Data (e.g. from FAO FRA) on net forest change for 3 epochs (i.e. using data from 1990, 2000, 2005, 2010). No land use change matrix is possible unless additional information is available.	National level data on gross forest changes through a change matrix (i.e. deforestation vs. reforestation), ideally disaggregated by administrative regions	Time series of spatially explicit forest change data, often from remote sensing.

The table below gives an overview of the available activity data for the four countries.

Table 4-2 Overview of availability of data for the 4 countries for approach 3 activity data

	Brazil	Cameroon	Indonesia	Vietnam
Approach 3 Spatially explicit data available	PRODES (Amazon region, Landsat based gross deforestation annual since 1988)	Study by JRC/TRESS 3 and UCL – increased sample for Cameroon (0,5x0,5 deg.) using Landsat 1990, 2000, 2005 – only as statistics available	MOFOR national deforestation data 2000-2010 CRISP data (MODIS) 2000-10	Deforestation and reforestation data by province

For Brazil, the present study used the PRODES data. These come from Landsat data analysis and are annual and spatially explicit, but limited to the Amazon region. For Cameroon, besides FAO statistics and the UNFCCC National Communication, the most suitable data come from a sample-based remote sensing analysis that is at this point only available as national numbers and of lower quality than for the other countries. For Vietnam, the study uses national data on the province level that are not spatially explicit but allow for sufficient sub-national analysis. The MOFOR national deforestation data are from remote sensing analysis and used for the case of Indonesia.

4.3 Carbon stocks and emission factors

Data on carbon stocks and emissions factors beyond IPCC Tier 1 are generally more rare and uncertain than for activity data. Emission factors often vary depending on different activities and drivers, and are not yet commonly available at Tier 2 or Tier 3. In case of deforestation at Tier 1, estimates can be limited to biomass and applied consistently for historical periods; in this case changes in emissions are really driven only by activity data, although still reported as emissions using default assumptions. Data on carbon stocks and changes are expected to improve in the medium term in many REDD+ readiness countries, but perhaps more slowly than activity data. The use of activity data can sometimes distort the historical analysis if there are specific land categories that have significantly different emission profiles to others. This is the case for emissions from deforestation on peatlands where the emissions from the soils are the most important source pool. This would need to be taken into account in future analysis, using country-specific data.

For this study the following approach has been used to calculate deforestation emissions using a simple and transparent method. For deforestation it is assumed that all of the biomass is removed and emitted as part of the deforestation. The study will use Tier 1 estimates and the assumption will generally be conservative since including additional pools would tend to increase the estimated emissions reductions. In the case of Indonesia the soil carbon pool will be considered because of the importance of peat. Table 4-3 sets out the approach.

Table 4-3 Data sources for the sample countries

Country	Activity data	Approach to calculate deforestation emissions
Brazil	PRODES annual, spatially explicit deforestation data for the Amazon.	Use 100 tC/ha as conservative estimate as suggested in the Amazon fund
Cameroon	National level statistics from FAO, NC and JRC study	Use 1 value for Cameroon (100t/C) from Tier 1 map or FAO data
Indonesia	Synergy MOFOR and CRISP data for	Use Tier 1 map from Ruesch and Gibbs, 2008 and some proxies to account for soil carbon emissions in deforested peats
Vietnam	Province level deforestation data (5 year sums)	Use Tier 1 map from Ruesch and Gibbs, 2008 for average forest carbon stocks on province level

In general, the approach is country specific and provides a suitable solution for each case, but does not really allow for direct comparisons of overall emissions for the different countries. It also neglects degradation emissions, which would need to be estimated using another default method, e.g. gain-loss, with proper allowance for collateral damage, or by using proxy data on the extent of disturbances.

4.4 Data on deforestation and degradation drivers

The UNFCCC negotiations have encouraged Parties to identify land use, land-use change and forestry activities in developing countries, in particular those that are linked to the drivers of deforestation and forest degradation, and to assess their potential contribution to the mitigation of climate change.

Explorations of expected future developments are directly related to specific activities and their underlying causes. Assumptions about expected future developments that differ from the observed historical trends in forest changes and emissions should be justified and underpinned by understanding of activities and drivers on the national level. The underlying causes of forest change may be related to international (i.e. markets, commodity prices), national (i.e. population growth, domestic markets, national policies) and local circumstances (i.e. subsistence land use etc.). Thus, the development of reference levels also requires, in addition to data on historical forest area change and associated emissions, information on drivers and their specific contribution to the overall national emissions profile. For both forest area change and carbon stock changes different approaches or Tiers are provided by the IPCC good practice guidelines (IPCC, 2003) depending on country available data and capacities.

Estimates of how much of the deforestation emissions in a country is caused by specific activities i.e. agriculture expansion versus infrastructure, can in principle be addressed by regression analysis, and this study reports some progress in doing this, though currently this the necessary data are available for only a few countries, and the role of degradation cannot presently be addressed by this approach. Currently the most reliable indicator of future deforestation that is reasonably widely applicable is the historical rate. An intermediate approach that allows some consideration of specific drivers is to use proxies or international evidence for policy analysis and setting RLs and FIBs. The table below provides a synthesis for the different country cases from multiple data sources.

Table 4-4 The level of information on drivers of deforestation varies

National data situation	Requirements and alternative estimation
1. No or incomplete national data available on drivers and activities to cover all types of deforestation or forest degradation	Assumptions on drivers and activities can be made only from local or international studies and proxy indicators
2. All nationally-relevant drivers can be named, listed (and qualitatively described) or ranked in terms of their importance causing deforestation and degradation	Missing quantitative information may be estimated using proxies and empirical international studies
3. Quantitative and spatial data describing activities and fractional contribution to total national deforestation and (potentially) forest degradation	Requires approach 3 activity data (spatially explicit) and ideally attribution of activity (i.e. from remote sensing analysis (i.e. spatial/temporal pattern analysis) and other spatial datasets (i.e. concessions, forest allocation, planning etc.)

Table 4-5 provides a summary the importance of different drivers for the four countries discussed here. The quantitative estimates are expert judgements based on the references given in the right hand column.

Table 4-5 Current deforestation and forest degradation drivers of four developing countries – table shows, as a dimensionless index summing to unity the relative importance of deforestation and degradation causes of four tropical rainforest countries derived from readiness reports, and other sources

	DEFORESTATION CAUSES					DEGRADATION CAUSES			
Country	**Agriculture (commercial)**	**Agriculture (local/slash and burn)**	**Mining**	**Infrastructure**	**Urban expansion**	**Timber/ Logging**	**Fuel-wood/ Charcoal**	**Uncontrolled fires**	**Data Source**
Brazil	76%	23%	<1%	<1%	<1%	100%	-	<1%	NC Mongabay Matthews et al. CIFOR
Cameroon	4%	88%	4%	4%		14%	69%	16%	CIFOR Mongabay R-Pin Matthews et al.
Indonesia	52%	20%	17%	11%	12%	9%	<1	<1	CIFOR R-PP NC Mongabay.com Matthews et al.
Vietnam	72%	27%		2%		82%	15%	3%	CIFOR R-PP Matthews et al.

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4.5 A step-wise framework for developing reference levels

Given the different levels of available data, a stepwise approach may be useful to provide a framework to provide data on drivers and compare different country circumstances and methods for setting RLs. Based on the assumptions presented above, a stepwise approach based on the IPCC GPG approaches (for activity data) and Tiers (for emissions estimation) is proposed (see also Table 1 in Herold et al., 2012).

Step 1 uses coarse national level data only. It will be challenging to provide quantitative evidence for deviating from the projected historical trend, and only simple rules in technical terms, agreed at the political level could be used for potential adjustments to take account of national circumstances. Examples of a Step 1 methodology are the approaches used for the Brazilian Amazon Fund (a sub-national approach) and Guyana (a national approach). All countries should be able to undertake a Step 1 approach with only modest effort.

Step 2 makes a first attempt to include quantitatively national circumstances, based on a driver-based assessment to adjust historical rates. However, at this stage historical trend data are likely to dominate the estimate of future trends. This is exemplified in the result from the regression analyses presented later, where predictions are made based on sub-national activity data for at least decade or so in Brazil, Indonesia and Vietnam. Currently only a few countries have the data available to undertake a Step 2 approach.

Step 3 develops the Step 2 approach further. This approach may use more spatially explicit deforestation data and driver specific data to support, for example, the use of more complex spatial models. It will also include more precise estimates of the emissions per unit of forest land converted or degraded (requiring better emission factors). The approach may actually avoid using historical deforestation as the key predictor since specific drivers and activities may be analysed, modeled and predicted individually (calibrated with historical trends) using more complex econometric approaches. So far no REDD+ country has developed RLs at Step 3.

5 Reference Level (BAU) estimation

This section gives an introduction to regression models to predict deforestation, and presents results using four different datasets (global, Brazil, Indonesia and Vietnam). The results using the global dataset correspond to Step 1 in the overall approach suggested in this report, while the three country regressions are examples of Step 2 methods.

5.1 Regression models of BAU baselines

As noted in the introduction, the term baseline, reference level (RL) or reference emission levels (REL) are used in at least two different meanings in the current debate and in the literature: First, 'baseline' can refer to the projected business as usual (BAU) scenario, or the counterfactual scenario used in project analysis: how would emissions from deforestation and forest degradation evolve without the REDD+ activity? Second, 'baseline' can refer to what is sometimes referred to as the crediting or compensation baseline (Meridian 2011), which in this report is termed Financial Incentive Benchmark (FIB): the level of emissions from which a country would receive payments for its efforts to reduce REDD+. The difference between the two meanings is illustrated in Box 1, Chapter 6.

With this terminology a RL is the benchmark for judging the impact of the REDD+ measures implemented relative to BAU and the FIB is the benchmark for international payments. While a distinction between RLs and crediting baselines is often not made explicit in the UNFCCC debate, it is useful both in analytical work and in assessing the arguments from two different angles: (1) What variables constitute good predictors of future deforestation and degradation (BAU)? This could, in principle, be answered based on current knowledge on causes of deforestation and degradation, and is exactly what is attempted in this chapter. (2) What are legitimate arguments for setting the FIB? This is addressed in chapter 5. While the first question is mainly a technical issue, the latter also involves significant negotiation or political judgement.

The modelling approach used here is based on changes in area (deforestation). To translate area predictions into emission predictions, one typically uses an average forest carbon density and implicitly assumes that degradation does not affect behaviour to the extent of undermining the socio-economic relationships being investigated. These seem necessary assumptions given the present state of analysis. Although these assumptions may be relaxed in future it is of interest to see how far present model results correspond with expectations.

5.2 Modelling approaches

Modelling and predicting land use and deforestation have stimulated debate in research as REDD+ has become high on the global climate agenda, but land use modelling is not new: in the late 1990s there were already over 150 studies focusing on understanding and explaining deforestation through economic modelling (Kaimowitz and Angelsen, 1998). The focus has, however, shifted in several ways:

First, while the earlier literature focused on understanding what had happened, the current objective is oriented to predicting what will occur. Models constructed to predict the future differ from those explaining the past, since there is a stronger focus on the general fit of the model, instead of focusing on the significance of individual factors affecting land use change. In particular, predictive models can use historical deforestation to predict the future, which makes them qualitatively different from explanatory models

Second, use of spatial data has increased substantially, driven by the higher availability of such data, although for the present this is restricted to a few countries. As our brief review of predictive deforestation models finds, only a few models are available, and the work is still heavily constrained by the lack of adequate data. Therefore, there are countries that have deforestation models while others have none. As such, there are still countries in which no quantitative assessment of deforestation drivers has been undertaken, and are often without existing deforestation models. This poses an extra challenge to determine REDD+ RLs, as costs of collecting data can be considerable.

Third, spatially explicit models are – or at least can potentially be – increasingly used in land use planning, policy formulation and targeting conservation efforts to treat high deforestation areas, which means that research results can have direct impact on policy actions, with benefits extending beyond REDD+.

Fourth, as a consequence of the focus on emissions, recently some models have carbon as an additional or alternative outcome. REDD+ is concerned with avoiding carbon emissions, which can be seen as a function of two factors: (i) changes in land uses (movements between land uses of different carbon densities, such as deforestation), and (ii) changes in the carbon densities within one land use (such as forest degradation). Since data on carbon density of vegetation remain scarce, most authors assume a direct correlation between carbon emissions and area deforested. A notable attempt to overcome the data issue is the work by Gibbs et al. (2007), who combines a series of methods to create national carbon stock estimates.

Models can be classified according to different criteria (Agarwal et al., 2001), but have overlapping characteristics. Sometimes a distinction is made between models based on historical data and forward-looking models, but this too can be an artificial as historical rates of deforestation are important predictors of future deforestation.

For this report we have used regression models for at least three reasons. First, regression models are less complex than most simulation models, and therefore more likely to be accepted as inputs into climate negotiations. Regression models are, however, dependent on good data, assume that the past is representative of the future, and that historical data show sufficient variation in the variables of interest (because it is hard to predict far outside the range of historical data). Simulation models are stylized representations of a reality, and useful to explore the impacts of policies prior to implementation, and when one moves into unknown policy territories. The credibility of the predicted changes depends on the degree simulation models mirror the forest system, including behaviour of key actors and markets.

Second, different and potentially important predictors of deforestation can easily be tested on different datasets with regression models, and therefore inform the discussion on, for example, relevant national circumstances for setting BAU baselines. Third, once the data are collected, regression models are straightforward to run with a large number of methods available, suitable for the particular data and problem at hand. On the downside, regression models are data-demanding. Regressing BAU baselines requires time series data (forest cover for at least three periods in time), and observations on lower spatial units rather than higher units (e.g. sub-national data for country studies).

To make predictions based on regression models, coefficients which link the predictors to the outcome (deforestation) are estimated based on past data. Then future values or predictor variables are plugged into the estimated equation to get future deforestation estimates. To make this assumption more flexible (and to answer policy questions) authors usually build policy scenarios under which some of the variables in the model are constrained. The reliability of these models depends, however, on how well the model fits the historic trends, and they are normally not suitable to handle breaks with the past ("out of sample predictions"), i.e. the estimated relationships (coefficients) may not hold. Another uncertainty – in any type of predictive models - relates to the future values of the predictors, for example, what agricultural prices will be in 10 years.

5.3 BAU regression methods

Regression models allow predictions concerning future events to be made with information about past or present events. The question of interest is, how a set of country specific factors observed at time t is related to the stock of forests from time t to time t+1? This question can be presented in form of general equation as follows:

$$Forstock_{c(t+1)} = \delta + \alpha Natcicurm_{ct} + e_{ct} \qquad (1)$$

where $Forstock_{c(t+1)}$ denotes forest stock of a country averaged over the period from time *t* to time *t*+1 , δ is the intercept (the value at the initial time), α is a vector of slope coefficients, $Natcicurm_{ct}$ denotes a vector of country specific factors or national circumstances, and e_{ct} is the error term. To estimate (1), most predictive research has relied on using Ordinary Least Squares (OLS) regression approach, although the statistical inference and model predictability depend on the choice of standard errors (Fama and French, 1988; Hodrick, 1992). We use OLS with panel corrected standard errors (OLS-PCSE), which assumes errors are heteroschedastic and contemporaneously correlated across panels (Beck and Katz, 1995). Estimation of OLS-PCSE allows the use of historical information concerning the dependent variable to be used as a predictor variable. This enables us to assess how historical deforestation best predicts current deforestation[5].

The OLS approach has been applied in a large number of empirical studies building on predictive models of Fama and French (1988) and Hodrick (1992). Beck and Katz's (1995) review of a number of studies using OLS-PCSE on times series cross-sectional data to test key hypotheses concerning the political and institutional determinants of economic policies and performances.

Equation (1) can be rewritten as:

$$Drate_{ct} = \alpha_H HistDrate_{HD} + \alpha_F Forstock_{ct} + \alpha_E Econfactors_{ct} + \alpha_O Otherfactors_{ct} + \varepsilon_{ct} \qquad (2)$$

where $Drate_{ct}$ is the annual deforestation rate for country *c* in period *t*. $HistDrate_{HD}$ is the historical deforestation rate given by the loss of forest cover for a specified period of time. $Forstock_{ct}$ is the forest stock in period *t*. $Econfactors_{ct}$ and $Otherfactors_{ct}$ are vectors of economic and other factors respectively. α_H - α_O are respective parameters to be estimated. ε_{ct} is the composite error term consisting of unobserved (time variant and invariant) country and time specific effects. We estimate (2) without the intercept to be able to determine how well a given variable, holding all else fixed, can predict BAU baseline (Santilli *et al.*, 2005).

The regression approach is applied on four datasets: a global dataset largely from FAO with countries as the unit analysis for the period 1990 – 2010, and three sub-national level datasets from Brazil for the 2000 – 2009 period (municipalities), Vietnam for the 1995 – 2009 period (provinces), and Indonesia for the period 2000 – 2009 (districts). The modelling approach is the same across datasets, except for Indonesia where we use OLS with robust standard errors instead OLS-PCSE because of data limitations. We restrict the analysis to gross deforestation for which data are available. Data on degradation and reforestation are hardly available[6].

5.4 Quantification of deforestation

How to express deforestation quantitatively should be guided by two considerations: (i) the simplicity of interpreting the results, and (ii) more importantly, how it may bias the results. Quantification in absolute terms, such as in hectares or square km, makes it easier to interpret the results and predict carbon emissions. The problem with this choice is that countries or sub-national units vary a lot in

[5] An alternative to OLS is to use panel least squares approach such as fixed effects or random effects estimation (Wooldridge, 2007). Panel least squares approaches account for unobserved country and period specific heterogeneity that explains the variation in forest stock across countries and time periods. However, the necessary data to apply this approach are expensive to collect and not readily available.

[6] In the FAO data, described later, we find only 18 countries, at one point in time between 2000 and 2010, had reforestation activities. That is, forest cover increased from one period to the next. We treat such countries to have had no deforestation at that specific time.

size, which can give rise to outliers that may bias the results. Even if this problem can be lessened by transforming deforested area and forest cover using logarithms, studies that have used absolute units have yielded mixed results. For example, studies using FAO country-level data (Ehrhardt-Martinez, 1998; Ehrhardt-Martinez *et al*., 2002; Jorgenson, 2006; Jorgenson and Burns, 2007), find initial forest cover (absolute) reduces the predicted percentage change in forest cover (deforestation). Using the same data source, Shandra *et al*. (2009) find that forest cover increases the predicted percentage change in forest cover, albeit insignificantly, while Rudel (1994) shows that forest cover significantly increases predicted deforested area (absolute). The other choice is to use rates of deforestation, normally defined in terms of forest loss as a percent of forest area averaged over a period of time, either linearly or using the compound interest law (FAO, 1995; Puyravaud, 2003). The latter is more appealing – at least theoretically – and normally used. None of these approaches controls for potential bias attributed to different sizes across countries (or sub-national units).

Alternatively deforestation may be expressed relative to total land area (of the country or sub-national unit), rather than relative to the forest area. This approach is considered for two reasons: First controlling the change in forest cover (or deforested area) relative to the total area of the country lessens the bias which arises from countries having different forest areas relative to total land area. That is, a country with vast forest cover is more likely to experience larger deforestation in absolute terms than a country with small forest cover. On the other hand, the rate of change in forest cover as a share of the country's total land area is likely to be lower in a country with vast forest cover, but higher in a country with small forest cover. This has implication for the robustness of the regression estimates.[7]

Second, this kind of quantification offers some analytical advantages to test the forest transition (FT) hypothesis. Since the FT theory is intended to explain deforestation at country level (Rudel *et al*., 2005; Angelsen, 2008), change in forest cover is better analyzed relative to overall competing land use changes in the country (Barbier *et al*., 2010). Indeed, the FT theory is about changes in forest stock relative to land area, so regressing forest cover as a share of total land area on the rate of deforestation offers a suitable approach to test the FT hypothesis.

The drawback with this definition is that it does not take into account the natural or original forest cover of the country. Unfortunately, reliable data on this are not available. To deal with this in the case of countries or sub-national units with no current deforestation we generate a deforestation dummy variable. This deforestation dummy in addition to historical deforestation together control for initial forest stock conditions (Burns *et al*., 2003).

We estimated a set of models, with an increasing number of predictors. The explanatory variables included differ in the global, Brazil, Vietnam and Indonesia analyses due to availability of data. The models are summarized in Table 5-1.

[7] More specifically, when using the standard definition of deforestation rates, the variance of the error terms were strongly correlated with forest cover.

Table 5-1 Models for predicting deforestation

Variables	Model I	Model II	Model III	Model IV	Model V
Historical deforestation	X	X	X	X	
Trend in historical deforestation	X	X	X	X	X
Forest cover (squared) and GDP		X	X	X	X
Agricultural GDP share and prices			X	X	X
Other factors				X	X

We start with a simple model which only uses historical deforestation and a trend factor. This corresponds to the simplest suggestion in the climate negotiations, and in some proposals on how to set reference levels, e.g. the way the Amazon fund sets the reference level for the Brazilian Amazon.

The second model is based on FT logic: at early stages of the FT (represented by countries with high forest cover) deforestation is likely to be higher than the historical level. At later stages, the situation reverses. These are the most commonly advocated national circumstances and therefore Model 2 is relevant to the question posed by Meridian (2009) about how to adjust reference levels. We also include GDP per capita, which might also be a proxy for the stage in the forest transition (negative sign expected), but may be given other interpretations as well, e.g. reflecting high demand for agricultural and forest products (positive sign), high opportunity costs of inputs (like labour) in forest clearing (negative sign) or better governance and capacity to contain illegal deforestation (negative sign).

The third model includes some of the drivers of deforestation, related to the agricultural sector. This includes the overall reliance of agriculture (share of GDP) and agricultural prices.

The fourth model has a comprehensive list of explanatory factors which are commonly included in deforestation regression models, including a set of political variables. Finally, the fifth model is the same as the fourth, except that historical deforestation is excluded. The comparisons between the results of models IV and V can illustrate how much of the historical deforestation is captured by the other variables considered.

In addition to using rates of deforestation as share of land area, we estimate several other models where we use deforestation in absolute terms. The same approach reported in Table 5-1 is adopted. These estimations are aimed at demonstrating how sensitive the FT hypothesis is to different forms of quantification. However, the selection of main results depends on how well historical deforestation correlates with current deforestation. This is described in detail in later discussions. Finally, with some countries (or sub-national units) expected to have minimal (or zero) deforestation rates, we estimate a tobit model (Tobin, 1958) in addition to OLS to test the sensitivity of results. The tobit model measures not only the likelihood that deforestation will occur in a country (or sub-national unit) given its initial conditions of forest stock and/or other prevailing economic factors, but also measures the intensity of deforestation activities.

5.5 Global model

5.5.1 Data sources and sampling

Country level panel data come from online databases of Food and Agriculture Organization (FAO), World Bank, International Monetary Fund (IMF) and United Nations (Population Division). The data, accessed as of August 2011, cover the past two decades (1990 – 2010) on forest area and other economic related variables for the 2000 – 2010 periods. The sample includes countries in the three regions: Africa, Asia and Latin America. The larger share of the sample is included in FAO's country classification of least developed and developing countries, the remaining being countries assumed to be transitional countries.[8] The overall sample consists of 124 countries (see Appendix A6 Country sample). We excluded countries with missing information on key variables, countries with constant forest area in more than one year (indicating poor quality data), and countries with less than 10,000 ha of forest area in 1990. The final sample used in analysis consists of 65 countries.

The forest cover data and deforestation 1990-2010 are from FAO's Forest Resource Assessments (FRA). Annual deforestation rates for 2000 - 2009 are calculated using FAOSTAT data, which are largely based on FRA.

Forest cover measured as the area under both natural and planted forests is used to calculate forest stock and annual deforestation rate. Forest stock is calculated as the share of country land area. Annual deforestation rate is defined as forest loss between two periods and expressed as a percentage of country land area. We define deforestation rate as a positive value. That is, a positive value means loss of forest cover from period t_1 to t_2. We calculate historical deforestation – as a reference level – for the 1990 – 2000 period. Then "current annual" deforestation rate is calculated for the period 2000 – 2010.

Economic related variables that require brief explanation include crop price index and governance. The crop price index is defined as the measure of change in major crop prices for a given country in response to crop exports. It is calculated using FAO data as follows:

[8] These include Algeria, Argentina, Brazil, Cayman Islands, Chile, China, Colombia, Costa Rica, Ecuador, El Salvador, French Guiana, Guatemala, Mayotte, Mexico, Panama, South Africa and Vietnam.

$$CPI_{ct} = \frac{\sum_{i=1}^{n} p_{cit}\theta_{cit}}{n} \quad \textbf{(3)}$$

Where CPI_{ct} is the crop price index for country *c* in period *t*. P_{cit} is the average international market price for crop group *i* (cereals, pulses, oil crops and sugar (sugar cane and sugar beets)). *n* is the number of crop groups. θ_{cit} is the share of country *c*'s total exports for crop group *i* weighted with export share of crop group *i* for 2000. θ_{cit} allows us to control for effective cross-country comparisons unbiased by the scale differences in crop exports. Increasing θ_{cit} implies increased crop prices which in turn are an incentive for a country to expand its agricultural land area. CPI_{ct} thus reflects agricultural commodity price fluctuation, taking into account the composition of the country's agricultural export.

We use four indicators of governance measured in units ranging from -2.5 to 2.5, with higher values corresponding to better governance outcomes (Kaufmann *et al*., 2009; 2010). These indicators include: voice and accountability capturing citizens' perceptions on government selection, freedom of expression and association; political stability and absence of violence capturing perceptions on government destabilization; regulatory quality capturing perceptions on government's ability to formulate and implement policies regulating private sector development; and control of corruption capturing perceptions on the extent to which public power is exercised for private gain.

Other variables are Gross Domestic Product (GDP) per capita (current prices in US$) collected from International Monetary Fund (IMF), agricultural GDP (as a percentage of national GDP) from World Bank, and population density from United Nations (Population Division).

Table 5-2 Descriptive statistics and bivariate correlations

The mean and standard deviation columns are self-explanatory. The columns headed 1 to 14 give pairwise Pearson correlations).

	Mean (N=650)	Standard deviation	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Deforested area (1000ha)	114.7	329.1	1.000													
2. Deforested area (% of land)	0.187	0.226	0.220	1.000												
3. Historical deforestation (deforested area for 1990 – 2000 period as % of land)	0.227	0.281	0.206	0.888	1.000											
4. Historical deforestation (deforested area for 1990 – 2000 period (1000ha))	150.0	407.1	0.889	0.184	0.328	1.000										
5. Deforestation dummy=1 if no deforestation, 0 otherwise	0.235	0.425	-0.193	-0.461	-0.402	-0.202	1.000									
6. Lag of forest stock[c] (share of	0.316	0.213	0.272	0.411	0.419	0.281	-0.176	1.000								

land)																
7. GDP per capita	1810.2	2081.2	0.158	-0.079	-0.010	0.156	0.047	0.059	1.000							
8. Agricultural GDP (% of national GDP)	21.7	13.8	-0.098	0.105	0.036	-0.101	-0.130	0.010	-0.651	1.000						
9. Crop price index[C]	15262.2	266075.2	-0.018	-0.044	-0.043	-0.019	0.077	-0.034	0.019	-0.049	1.000					
10. Population density[C]	0.862	1.338	-0.115	-0.112	-0.087	-0.097	0.176	-0.215	-0.168	0.009	0.008	1.000				
Governance indicators																
11. Control of corruption	-0.579	0.560	0.026	-0.255	-0.201	-0.014	0.360	-0.096	0.394	-0.399	0.090	-0.089	1.000			
12. Regulatory Quality	-0.505	0.608	0.054	-0.117	-0.045	0.041	0.215	-0.112	0.450	-0.482	0.024	0.016	0.735	1.000		
13. Political Stability	-0.582	0.804	0.010	-0.016	-0.016	-0.061	0.249	0.063	0.345	-0.327	0.076	-0.167	0.652	0.534	1.000	
14. Voice and accountability	-0.568	0.736	0.177	0.099	0.168	0.157	-0.071	0.075	0.373	-0.333	0.076	0.008	0.608	0.742	0.495	1.000

5.6 Regression results

The bivariate Pearson correlations (or Pearson's r) in Table 5-2 show that high deforestation rates are strongly correlated with high rates of historical deforestation and the share of forest stock, but less correlated with the share of agricultural GDP, population density and governance indicators. The correlation between annual deforestation and historical deforestation expressed as percentage of total country land area does not change even when expressed in absolute terms (Pearson's r = 0.89).

This finding may overestimate the significance of the result because current deforestation for many countries is simply estimated as an extrapolation of previous estimates. This would bias the result so as to exaggerate the significance of historical deforestation in explaining current deforestation. The global results should therefore be viewed together with the three country analyses. This bias is likely to be smaller for the other variables included in the regressions. In the final discussion and conclusion we therefore put more emphasis on the country level results which are based on better quality data.[9]

Turning to Table 5-3, the results of the first model show that historical deforestation has a strong predictive power on current deforestation, with a coefficient of 0.72: an increase in historical deforestation of 0.1 percent units (e.g. from 0.50 to 0.60 %) increases expected deforestation in current period by 0.072 percent units. The trend variable is positive and significant in this model but becomes insignificant when more explanatory variables are included. Also, from this model, one observes that historical deforestation alone explains about 88% of the variance in current deforestation (R^2 = 0.877).

The inclusion of forest stock and income (GDP per capita) in model (2) barely increases the explanatory power. The forest stock coefficients are statistically significant in models (2) and (5), but become weak in models (3) and (4). Since we have included historical deforestation, the interpretation is the impact of forest cover on a *change in deforestation compared to the historical level*. The relative sign of the linear and squared coefficients indicates an inverted U-shaped relationship, and model (2) suggests that for forest covers below 60% of country land area the relationship is negative. When we exclude historical deforestation but include other variables in model (5); the relationship is negative only when forest cover is 51% of country land area. Overall, this result lends support to the forest transition (FT) theory (Rudel *et al*., 2005; Angelsen, 2008), which suggests that countries with initially large forest cover are more likely to clear forests continuously up to the lowest forest cover area after which forest regrowth and reforestation start.

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9 For reasons of data quality, we also eliminated some countries from the analysis, cf. above discussion on data used.

Table 5-3: Determinants of country level deforestation 2000-2010

	M1	M2	M3	M4	M5
Historical deforestation (ref. period 1990 – 2000) (%)	0.719***	0.660***	0.654***	0.639***	
	(0.028)	(0.033)	(0.032)	(0.033)	
Trend variable	0.006***	0.002	0.000	0.001	0.003
	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)
Deforestation dummy =1 if deforestation=0, 0 otherwise	-0.041***	-0.059***	-0.066***	-0.067***	-0.180***
	(0.007)	(0.008)	(0.008)	(0.010)	(0.015)
Lagged forest stock (share of land area)		0.168***	0.100**	0.119**	0.894***
		(0.044)	(0.043)	(0.043)	(0.099)
Lagged forest stock squared (share of land area)		-0.140**	-0.059	-0.115*	-0.882***
		(0.061)	(0.061)	(0.061)	(0.132)
log of GDP per capita		0.001	-0.000	-0.004**	-0.013**
		(0.001)	(0.001)	(0.002)	(0.004)
Agriculture, value added (% of GDP)			0.003***	0.004***	0.008***
			(0.001)	(0.001)	(0.001)

Agriculture, value added (% of GDP) squared			-0.000***	-0.000***	-0.000***
			(0.000)	(0.000)	(0.000)
Crop price index			-0.003**	-0.001	-0.001
			(0.001)	(0.001)	(0.002)
Population density				0.002	-0.001
				(0.002)	(0.005)
Governance indicators					
Control of corruption				-0.022**	-0.099***
				(0.010)	(0.019)
Regulatory quality				-0.001	0.001
				(0.013)	(0.027)
Political stability (no violence)				0.035***	0.071***
				(0.009)	(0.011)
Voice & accountability				-0.027**	-0.007
				(0.009)	(0.014)
Regional dummies					
Latin America (com-pared to Africa)				0.043**	0.149***
				(0.018)	(0.026)
Asia (compared to Africa)				-0.023**	0.010

				(0.011)	(0.017)
Wald Chi square value	1535.6***	3212.7***	3910.9***	5945.8***	1119.6***
R^2	0.877	0.882	0.888	0.895	0.670
Number of observations	650	650	650	650	650

***, **, * indicate significance levels at 1%, 5%, 10% respectively. Figures in parentheses are panel corrected standard errors.

As expected, we find mixed relationships of forest stock on deforestation when we use absolute terms of deforested area Table 5-3. This suggests that the evidence of the FT hypothesis is sensitive to the model specification, and we return to this point in section 4.6.

Income per capita is (GDP) negatively related to the deforestation rate, that is, higher income implies lower deforestation (i.e. a downward adjustment of historical deforestation). Similar relationships have been found in earlier studies (Ehrhardt-Martinez, 1998; Jorgenson, 2006; Jorgenson and Burns, 2007). Thus, this is in line with the forest transition logic, assuming income is an indicator of the stage in the forest transition.

Model (3) attempts to include the agricultural sector as a possible explanation of deforestation. The explanatory power of the model (as measured by R^2) and magnitude of the coefficient related to historical deforestation almost remain the same as in Model 2. The crop price index is significant and negative in model (3) but insignificant in models (4) and (5), which might be due to the small variation across countries as many agricultural commodity prices move in tandem. The share of agricultural GDP is highly significant and positive in the same models[10]. Countries dominated by agriculture (high share of agricultural GDP) tend to have higher deforestation rates initially, but such countries are likely to have lower deforestation rates when agricultural income contributes a larger share to national GDP. This suggests that higher agricultural income, for example, in the form of intensification of agricultural production, reduces pressure on forest.

The inclusion of population and governance/policy related variables increases the explanatory power to about 90% and some of the variables are statistically significant. Control of corruption and 'voice and accountability' reduce deforestation rates. This seems consistent with efforts to control illegal logging. Contrary to many popular views, political stability and absence of violence in general can increase deforestation, although it fits well with the observation that instability and violence are destructive for economic activities, including deforestation.

The gradual inclusion of forest stock and economic growth related factors appears to have a slight effect on the coefficient of historical deforestation rate (reduces from 0.719 to 0.654), but inclusion of population and governance variables reduces it to 0.639. Historical deforestation is short of being a 1:1 predictor of current deforestation. Adding new variables affects the predictive power slightly (R^2).

A final observation concerns the difference between model (4) and (5), i.e., how the results change when the main predictor – historical deforestation – is left out. The predictive power drops to 67%, which is reasonable, but many of the variables significant in model (4) remain so in model (5). Forest stock coefficient increases in magnitude, and the significance of an inverted-U relationship remains.

[10] The coefficient on the squared term is significantly negative, indicating an inverted U-shaped relationship, but the turning point is well outside the data range.

5.7 Regression analysis by country

We turn to the application of regression techniques to individual countries.

5.7.1 Brazil

Data sources

Focus on Brazil is justified by the country's large forest area and significant deforestation rates, as well as its position in REDD+ policy discussions and implementation. Another reason to focus on Brazil is the availability of good quality data on deforestation in the Amazon region (approximately 50% of the country, and the region with most forests) and socio-economic characteristics at the sub-national (municipal) level. It is the largest contiguous forest region in the world with time series data on deforestation. However, no time series data are available on regeneration, which restricts our analysis to the downward slope of the forest transition curve.

Our analysis relies mostly on publicly available data from the Brazilian Environmental Agency (Ibama), IPEA (Applied Economics Research Institute), INPE (National Spatial Research Institute), and also from Imazon (Amazon Institute of People and the Environment). We have data on 719 municipalities comprised of yearly observations on area deforested, remaining forest stock, population and GDP as well as one time observations on road density. Descriptive statistics for the variables included in the analysis are presented in Table 5-4 below. Many initiatives aim to decrease deforestation by changing policies, for example, land tenure reform and regulatory measures, rather than direct payments to landowners. This means that impacts are broader, that there will be broad participation in REDD+ across regions, and that effectiveness of nation-wide policies are harder to measure through regression analysis, where variation within the sample is key.

The data on deforestation and forest stock are available on a yearly basis from 2000 to 2009 inclusive. This enables us to use average annual deforestation for the period from 2000 to 2004 as an index of historical deforestation and use it to predict deforestation for each year in the period 2005-2009. This reference period is constrained by data availability and is not intended to pre-judge negotiated outcomes under UNFCCC or elsewhere. Simple statistics in Table 5-4 show that the mean annual deforestation rate was 0.34% for 2005 -2009 period compared to 1.5% for the reference level (2000 – 2004). Since we measure deforestation rate as a share of total national land area, this means the non-forest land use area expanded fairy rapidly by 1.5% in the reference period compared to 0.34% annually for the 2005 – 2009 period.

Table 5-4: Descriptive statistics and bivariate Pearson correlations

	Mean (N=650)	Standard deviation	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Deforested area (sq. km)	17.7	56.4	1.000												
2. Deforested area (% of land)	0.34	0.65	0.443	1.000											
3. Historical deforestation (deforested area for 2000 – 2009 period (sq. km))	45.4	95.2	0.755	0.259	1.000										
4. Historical deforestation (deforested area for 2000 – 2009 period as % of land)	1.47	3.21	0.030	0.134	0.366	1.000									
5. Deforestation dummy=1 if no deforestation, 0 otherwise	0.252	0.434	-0.183	-0.300	-0.237	-0.069	1.000								

6. Lag of forest cover (sq. km)	4230.9	12467.2	0.330	-0.055	0.303	-0.103	-0.192	1.000							
7. Lag of forest cover (share of land)	0.281	0.308	0.279	0.107	0.278	-0.090	-0.461	0.564	1.000						
8. GDP for 2000 (Reals)	99802.6	656377.9	0.021	-0.018	0.025	-0.008	-0.050	0.028	0.059	1.000					
9. Cattle & agricultural GDP for 2000 (Reals)	14294.2	21298.1	0.446	0.127	0.486	-0.004	-0.207	0.126	0.077	0.111	1.000				
10. Dummy for good soil = 1, 0 otherwise	0.481	0.500	0.121	0.158	0.140	0.131	-0.162	-0.082	-0.042	-0.033	0.058	1.000			
11. Population density (# of people per sq. km)	23.87	131.37	-0.043	0.004	-0.042	0.090	0.032	-0.055	-0.066	0.274	-0.035	-0.059	1.000		
12. Official roads in 2000 (km)	20.6	38.6	0.089	0.007	0.062	-0.036	-0.046	-0.033	-0.060	0.300	0.302	0.025	0.021	1.000	
13. Unofficial roads in 1997 (km)	393.1	695.8	0.619	0.170	0.649	-0.037	-0.247	0.270	0.235	0.063	0.687	0.109	-0.075	0.245	1.000

5.7.1.1 Regression results

Similarly to the approach taken for global data analysis, we first do bivariate Pearson correlations (Table 5-4). Absolute historical deforestation correlates highly with annual deforestation by about 76% compared (column 1), compared to only 13% when we use annual percentage rates deforestation and historical deforestation (column 2).

Table 5-5 shows the results for the different models. In Model 1, the estimated elasticity of historical deforestation is 0.66, indicating that according to this model, for every 1% increase in a municipality deforestation rate in the historical period 2000-2004, there is a 0.66% increase in deforestation in the period 2005-2009. The trend variable indicates that deforestation decreases per year and the results are consistent in all models.

Model (2) includes historical deforestation as well as forest stock and GDP. The elasticity of historical deforestation drops to 0.46, and there is an inverted-U relationship with forest stock, shown by a positive linear term and a negative quadratic term. The inverted-U relationship continues to hold in models (3) through (5), with the turning point changing only slightly from 61% in model (4) to 62% in model (5), well above the one in the global model.[11] GDP is positive and significant in model 2, but consistently negative and significant in model (3) through model (5), which include explicitly the contribution to GDP from cattle and agriculture. In model (3), we include agricultural related variables. An increase agricultural and cattle GDP increases deforestation significantly. This is expected as increased demand for agricultural and grazing land may lead to encroachment on forest land. Likewise, municipalities with good soils suitable for agriculture are associated with high deforestation rates. The change of sign in the GDP coefficient which agriculture is included explicitly may indicate a negative contribution (i.e. a decrease in deforestation) from non-agricultural activities collectively, though this might not be true for all municipalities individually.

Table 5-5 Determinants of municipality level deforestation in Brazil (2005-2009)

	M1	M2	M3	M4	M5
Log of historical deforestation (2000 – 2004)	0.656*** (0.012)	0.461*** (0.018)	0.402*** (0.018)	0.395*** (0.018)	
Trend variable	-0.035*** (0.010)	-0.136*** (0.011)	-0.141*** (0.010)	-0.136*** (0.010)	-0.145*** (0.011)
Deforestation dummy =1 if deforestation=0, 0 otherwise	-0.235*** (0.042)	-0.372*** (0.046)	-0.396*** (0.045)	-0.373*** (0.044)	-0.773*** (0.040)
Lagged forest stock (share of land area)		2.560*** (0.279)	2.416*** (0.269)	2.180*** (0.253)	4.756*** (0.255)

[11] The turning point is found by considering the two coefficients of the forest stock and forest stock squared variable, and at which level of the forest stock the sum of the positive linear and the negative squared effect turn from being positive to negative.

Lagged forest stock squared (share of land area)		-2.095*** (0.287)	-1.610*** (0.279)	-1.800*** (0.266)	-3.826*** (0.285)
Log of GDP in Reals for year 2000		0.051*** (0.005)	-0.132*** (0.015)	-0.034* (0.018)	-0.130*** (0.020)
Log of GDP from cattle and agri-culture in Reals in 2000			0.215*** (0.018)	0.117*** (0.020)	0.280*** (0.022)
Dummy for good soil=1, 0 otherwise			0.206*** (0.031)	0.237*** (0.031)	0.348*** (0.034)
Log of popula-tion density (number of peo-ple per sq. km)				-0.125** (0.013)	-0.081*** (0.014)
Log of official roads in 2000 (km)				0.021** (0.009)	0.018* (0.010)
Log of unofficial roads in 1997 (km)				0.039*** (0.007)	0.076*** (0.008)
Chi square value	8607.4***	11612.3***	12480.5***	13607.7***	9646.7***
R^2	0.793	0.814	0.822	0.831	0.789
Number of observations	3595	3595	3595	3595	3595

***, **, * indicate significance levels at 1%, 5%, 10% respectively. Figures in parentheses are panel corrected standard errors.

Model (4) includes several other potential circumstances that could be relevant to the determination of RLs. This model includes the explanatory variables in model (3) as well as policy variables and other socioeconomic factors that have been discussed in the literature to have important influences on deforestation. Here we see that the elasticity of historical deforestation further decreases to 0.40. The relationships for all variables and their significance levels hold as they do in models (2) and (3), except for GDP. Municipalities with high population density have lower deforestation rates. This finding is consistent with earlier work in southern parts of Brazil where increasing population is resulting in increasing rates of rural-urban migration and expansion of forest cover (Baptista, 2008). On the other hand, increased road network of both official and unofficial roads increases deforested area significantly. Increased road network improves market access of both forest and agricultural products all of which accelerate deforestation activities.

Model (5) is the same as model (4), except that it omits historical deforestation. This is similar to most econometric models estimated to assess the causes of deforestation. We note that several coefficients change in magnitude when comparing models (4) and (5), but qualitatively remain the same. More specifically, coefficients are usually bigger in this specification as compared to the results in model (4), indicating that historical deforestation absorbs the effects of the other covariates. The R^2 only drops from 0.83 to 0.79 when historical deforestation is omitted.

5.7.2 Indonesia

5.7.2.1 Data

Indonesia is experiencing high rates of deforestation and forest degradation (Mather, 2007) and forms a good case study area to identify the causes of deforestation. Figure 3 shows the extent of deforestation and forest degradation in Indonesia for the period we study (2000 – 2009).

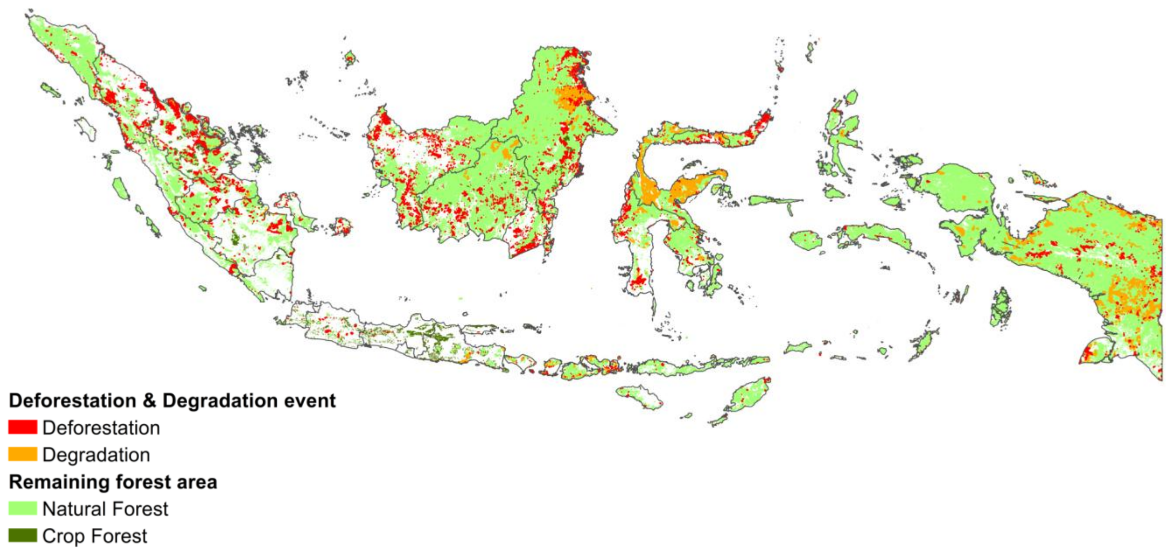


Figure 3: Deforestation and degradation in Indonesia between 2000 – 2009.

Unlike other datasets, annual deforestation data were not available to us for Indonesia. We use forest stock data from 371 districts for the years 2000, 2003, 2006 and 2009 obtained from the Ministry of Forestry (MOFOR). Other data for different years like protected zone areas (2005), GDP (2006), commercial plantations (2005) among others also come from MOFOR. Road density is calculated based on the data from Indonesian Statistical Center (BPS). We use the average of deforested area for 2000 – 2003 period as historical deforestation and the dependent variable is average of deforested area for the 2006 – 2009 period. Table 5-6 shows descriptive statistics and bivariate correlations for selected key variables.

Table 5-6：Descriptive statistics and bivariate Pearson correlations

	Mean (N=371)	Standard deviation	1	2	3	4	5	6	7	8	9	10	11
1. Deforested area (2006-2009) (ha)	6820.2	28665.4	1.000										
2. Deforested area (2006-2009) (% of land)	0.823	1.736	0.385	1.000									
3. Historical deforestation (deforested area for 2000-2003) (ha)	2803.1	8633.0	0.446	0.164	1.000								
4. Historical deforestation (deforested area for 2000-2003) (% of land)	0.589	2.940	0.009	-0.005	0.369	1.000							
5. Deforestation dummy=1 if no deforestation in 2003-2006, 0 otherwise	0.367	0.483	-0.162	-0.159	-0.234	-0.123	1.000						
6. Forest stock in 2006 (ha)	269614.3	712283.6	0.689	0.116	0.375	-0.011	-0.257	1.000					
7. Forest stock in 2006 (% of land)	30.2	25.4	0.219	0.210	0.230	-0.006	-0.448	0.556	1.000				
8. District GDP per capita in 2006 (million IDR)	14.3	29.7	0.001	0.013	0.055	0.008	0.028	0.044	0.014	1.000			
9. Agricultural GDP as % of district GDP	31.4	19.0	0.091	0.092	0.078	-0.054	-0.324	0.198	0.436	-0.332	1.000		
10. Population density per sq. km	1081.9	2349.1	-0.105	-0.172	-0.140	-0.055	0.395	-0.164	-0.431	0.145	-0.525	1.000	
11. Road density (km/ha) (%)	0.213	0.192	-0.169	-0.157	-0.170	0.053	0.470	-0.283	-0.466	0.038	-0.355	0.434	1.000

The results in Table 5-6 show that deforestation in Indonesia is increasing, from 0.6% in 2000-2003 to 0.8% in 2006-2009. Because of the stronger relationship observed, based on the bivariate correlations in columns (1) and (2), for the modelling we chose to use absolute terms rather than rates of deforestation and historical deforestation and Table 5-6 reports the results.

Table 5-7: Determinants of province level deforestation 2006-2009

	M1	M2	M3	M4	M5
log historical deforestation	0.934*** (0.035)	0.324*** (0.057)	0.310*** (0.058)	0.259*** (0.056)	
Deforestation dummy =1 if no deforestation, 0 otherwise	1.310*** (0.285)	-1.410*** (0.388)	-1.632*** (0.401)	-0.541 (0.441)	-1.096** (0.427)
Forest stock (share of land)		0.121*** (0.178)	0.082*** (0.023)	0.075*** (0.022)	0.091*** (0.023)
Forest stock squared (share of land)		-0.001*** (0.0002)	-0.001** (0.0002)	-0.001** (0.0002)	-0.001** (0.0002)
log of district GDP per capita (million IDR)		0.740*** (0.141)	0.706*** (0.138)	1.507*** (0.190)	1.855*** (0.194)
Agricultural GDP as a % of district GDP			0.051* (0.026)	0.116*** (0.028)	0.136*** (0.029)
Agricultural GDP as a % of district GDP squared			-0.001 (0.000)	-0.001** (0.000)	-0.002*** (0.000)
Population density per sq. km				-0.428*** (0.085)	-0.549*** (0.084)
Road density (km/ha) (%)				-2.042** (0.908)	-1.358 (0.962)
F – value	352.5***	250.5***	185.2***	185.6***	171.7***
R^2	0.599	0.759	0.764	0.787	0.771
Number of observations	371	371	371	371	371

***, **, * indicate significance levels at 1%, 5%, 10% respectively. Figures in parentheses are robust standard errors.

5.7.2.2 Regression results

From Table 5.7, consistent with the other results, model (1) shows that historical deforestation significantly explains the current (or future) deforestation. That is, historical deforestation alone explains about 60% of the variation in deforestation rates among Indonesian districts. A 1% increase in previous deforestation causes a about 0.9% increase in current deforestation. Model (1) also shows that districts with no deforestation initially are likely to have positive deforestation rates in future. However, this finding does not hold when we include more variables in models (2) through (5).

The inclusion of forest stock and district GDP (Model 2) reduces the magnitude of the estimated dependence on historical deforestation substantially and slightly increases the explanatory power, and these effects remain the same in models (3) and (4). The coefficient on historical deforestation drops from 0.93 in model (1) to 0.26, and the explanatory power increases from 60% to 79% when we add proxy variables for economic growth and forest stock in model (4). Even when we drop historical deforestation in model (5), the explanatory power remains as high as 77%. Two implications can be drawn from these results: One, historical deforestation is not the only major factor influencing deforestation rates in the districts of Indonesia. Secondly, historical deforestation in Indonesia appears, as is to be expected, to capture the effects of other variables. Other important factors explaining high deforestation rates in districts of Indonesia include: Districts with large forest stocks experience high deforestation rates, which start declining only when the forest cover reduces to about 63 – 70% of land area as evidenced by the inverted-U relationship in models (2) and (5). However, districts with high population densities have lower deforestation rates possibly such districts are progressing towards urbanization and industrialization. This is somewhat supported by lower deforestation rates in districts with high road density, an indicator increasing urbanization.

Districts with high GDP have high deforestation rates, which can be explained in several ways, e.g. market access affecting both the GDP and deforestation rates. Increased share of agricultural GDP significantly accelerates deforestation rates, but further increases in agricultural revenues may also slow down deforestation rates as producers operate on intensive margin. The robustness of our findings is supported by the satellite imagery results as shown in **Error! Reference source not found.**. It shows the drivers of deforestation for the time period 2000-2009. Expansion of subsistence agriculture is a major driver of deforestation (34%), followed by commercial agriculture (32%) and aquaculture (3%). Large areas deforested and still open land constitutes 18%, and only 11% of deforested area has been reforested or regenerated. This includes crop forests like oil palm or pulpwood plantations.

5.7.3 Vietnam

5.7.3.1 Data

Like Brazil, Vietnam has good data on annual deforestation by province. The data came from General Statistics Office of Vietnam (GSO) and the Forest Department (KIEMLAM) under the Directorate of Forests[12]. In general, the data cover land use, forest area and other economic related variables for the period 1995 – 2010. Annual deforestation for the 1995 – 2010 and economic related variables for the period 2005 – 2009 are from GSO, while forest cover area data for the period 2005 – 2009 come from (KIEMLAM). Table 5-8 reports descriptive statistics and bivariate correlations.

Forest stock is calculated as a share of forest cover in a given province. Results in Table 5-8 show that correlation between annual deforestation and historical deforestation expressed as percentage of provincial land area is 0.697 compared to 0.480 when annual deforestation and historical deforestation are expressed in absolute terms. Historical deforestation is calculated as average forest loss for the 1995 – 2004 period and expressed as a percentage of provincial land area. As with global data, we choose to use rates of annual deforestation and historical deforestation in the regression analyses.

Table 5-8 reports several other specifications where we use different transformations of deforestation and forest stock to test the robustness of FT hypothesis. We were unable to obtain data on Gross Domestic Product (GDP) at province level. We instead use GDP per capita and the percentage of GDP contributed by agriculture, forestry and fishing at national level. The other variables, population density and the volume of passengers carried by road, are at province level. Due to missing data, we use data from 61 provinces out of 64 provinces that constitute Vietnam.

[12]The online data were accessed as of October, 2011 from www.gso.gov.vn and www.kiemlam.org.vn

Table 5-8 :Descriptive statistics and bivariate Pearson correlations

	Mean (N=650)	Standard deviation	1	2	3	4	5	6	7	8	9	10	11
1. Deforested area (ha)	41.5	170.1	1.000										
2. Deforested area (% of land)	0.019	0.117	0.962	1.000									
3. Historical deforestation (deforested area for 1995 – 2004 period (ha))	98.2	170.5	0.480	0.318	1.000								
4. Historical deforestation (deforested area for 1995 – 2004 period as % of land)	0.026	0.057	0.736	0.697	0.723	1.000							
5. Deforestation dummy=1 if no deforestation, 0 otherwise	0.415	0.494	-0.206	-0.137	-0.371	-0.292	1.000						
6. Lag of forest cover (1000 ha)	211.82	208.9	-0.050	-0.111	0.148	-0.119	-0.206	1.000					
7. Lag of forest cover (share of land)	0.297	0.199	0.010	-0.062	0.284	-0.019	-0.239	0.817	1.000				
8. National GDP per	14.38	3.43	-0.035	-0.039	0.008	0.007	0.141	0.034	0.049	1.000			

capita													
9. Agriculture, forestry and fishing as % of national GDP	20.96	0.67	0.040	0.020	0.006	0.005	0.029	0.014	0.028	0.480	1.000		
10. Population density (persons/ha)	0.005	0.007	-0.023	0.016	-0.149	0.044	0.025	-0.456	-0.536	0.015	0.005	1.000	
11. Volume of passengers carried by road (million persons)	23.46	64.65	-0.065	-0.045	-0.138	-0.101	0.106	-0.196	-0.279	0.056	0.022	0.635	1.000

5.7.3.2 Regression results

Results from model (1) estimate that historical deforestation explains about 51% of the variation in future (or current) annual deforestation in Vietnam. Comparing model (1) with models (2) through (4), the addition of other variables appears to cause little variation in predicted future deforestation. Including forest stock and other variables such as GDP, population density and road network, increases the explanatory power by only about 2%. That is, R^2 increases from 50% in model (1) to 52% in model (3). This is consistent with results obtained using Global and Brazil data indicating that historical deforestation plays a significant role in explaining futures deforestation, or captures the influence of other variables.

Unlike Global and Brazil data, the coefficient on historical deforestation in the Vietnam data is larger than unity. Model (1) shows that amongst Vietnamese provinces a 1% increase in historical deforestation increases annual deforestation by 1.5%. This is consistent with the observation below that provinces with large forest cover clear more forests initially before embarking on reforestation.

The coefficient of historical deforestation remains the same when we include forest stock and economic growth indicators (GDP) in model (2), population density and road network in model (3). In particular, the inclusion of economic indicators appears to have no effect on the coefficient of historical deforestation. Similarly, model (4) shows that with exclusion of economic growth indicators, the coefficient on historical deforestation in models (3) and (4) remains fairly similar. This is expected since we use national instead of province data for GDP and the percentage of GDP contributed by agriculture, forestry and fishing.

The other key result we observe in Vietnam data is the relationship between annual deforestation and forest stock. Consistent with Global and Brazil data, we find an inverted-U relationship between deforestation rate and forest stock, but with turning points well below 50% forest cover. That is, provinces with large forest cover are more likely to clear more forests initially before embarking on reforestation activities.

We were able to obtain data on reforestation through plantations in Vietnam. For comparison and to check robustness, we regressed the reforestation rate on similar variables included in the deforestation models. Reforestation is defined negatively and expressed as a percentage of provincial land area. We report results in model (6). We observe opposite relationships: provinces with lower historical deforestation rates are less likely to carry out reforestation activities, which is in line with a hypothesis that forest scarcity encourages forest planting. Provinces with large forest stocks have less incentive to establish forest plantations.

Table 5-9: Determinants of province level deforestation 2005-2009

	M1	M2	M3	M4	M5	M6 (reforestation)
Historical deforestation (1995 – 2004) (% of land)	1.459*** (0.406	1.471*** (0.413)	1.484*** (0.416)	1.464*** (0.409)		-0.269*** (0.053)
Trend variable	-0.008** (0.003)	0.015 (0.020)	0.015 (0.020)	-0.006** (0.003)	0.003 (0.004)	
Deforestation dummy =1 if no deforestation, 0 otherwise	0.017** (0.007)	0.017** (0.007)	0.014** (0.006)	0.011* (0.006)	-0.031** (0.013)	-0.035** (0.013)
Lagged forest stock (share of land area)		0.132** (0.060)	0.122* (0.064)	0.067 (0.041)	0.260** (0.111)	-0.401*** (0.101)
Lagged forest stock squared (share of land area)		-0.253** (0.102)	-0.250** (0.105)	-0.189** (0.073)	-0.463** (0.207)	0.351* (0.182)
log of national GDP per capita		-0.129 (0.132)	-0.131 (0.132)			
Agric., forestry and fishing as a percentage of national GDP		0.013 (0.014)	0.013 (0.014)			
Population density (persons/ha)			-0.867* (0.527)	-1.177* (0.631)	1.036** (0.520)	-4.459*** (1.117)
log of volume of passengers carried by road (mill persons)			0.005** (0.002)	0.004* (0.002)	-0.001 (0.002)	0.013*** (0.004)
Chi square value	13.0**	19.7**	20.5**	18.1**	12.9**	520.4***
R^2	0.506	0.516	0.518	0.515	0.052	0.609
Number of observations	301	301	301	301	301	270

***, **, * indicate significance levels at 1%, 5%, 10% respectively. Figures in parentheses are panel corrected standard errors.

The results on population density and road network are interesting. Population density is negatively associated with deforestation rate. *A priori*, one might expect an increase in population density to accelerate deforestation as the demand for agricultural and settlement land increases. However, the finding is consistent in Global and Brazil data, which further validates our results and consistency with earlier work that populated countries like Vietnam have increased forest plantations (Mather, 2007; Rudel, 2009). The result may also reflect a simple correlation, namely that population densities tend to be lower in high forest areas (Sunderlin et al. 2008). An increase in the volume of passengers carried by road is positively associated with increased deforestation, a similar result obtained in Brazilian data.

Model (5) underscores the relative significance of historical deforestation in explaining the annual deforestation. Exclusion of historical deforestation reduces the explanatory power from about 51% to 5%. This suggests that historical deforestation captures a number of factors that drives deforestation (beyond those included in the regression analysis), and possibly also that deforestation process have there are evolving with time, with the relative roles of different factors changing.

5.8 Discussion, conclusions and some implications

Before turning to general discussion, we summarize the key findings from the four datasets analyzed. We used the similar model specification described earlier for each dataset (Global, Brazil, Vietnam and Indonesia). We only consider variables directly related to forestry and economic growth. This helps to see which variables are robust across the countries and between the global and the country data sets. The selected core variables are presented in Figure 5 and include historical deforestation as a percentage of land, forest stock as a percentage of land area, national GDP per capita, agriculture, forestry and fishing as a percentage of national GDP, population density as persons/ha, and an estimate of road use by millions of passengers carried by road. Historical deforestation and forest stock appear to be rather robust predictors. The other indicators considered mostly have the same sign, the most notable exception being that for Indonesia the GDP is positively correlated with deforestation, rather than negatively for the other countries. This may reflect the high value of agricultural commodities obtainable from deforested land in Indonesia. Population density is perhaps surprisingly found to be negatively correlated with deforestation, perhaps because of its association with increasing urbanization with greater reliance on non-forest resources.

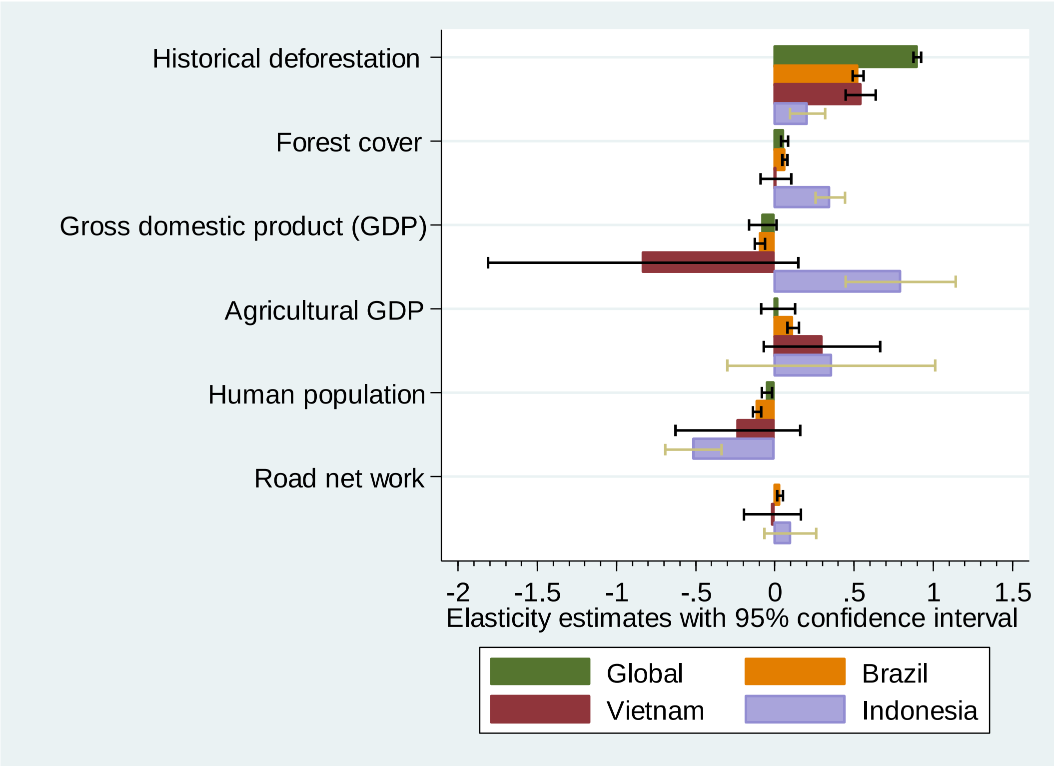


Figure 4. Selected predictors of deforestation in Global, Brazil, Vietnam and Indonesia datasets.

Note: All variables are in logarithmic form

Irrespective of data quality and the unit level of analysis (national or sub-national units), historical deforestation is positively correlated with the rate of future deforestation. Historical deforestation should therefore be a key variable to consider when setting REDD+ reference levels. Given the literature on spatial dependencies in deforestation (Laurance et al., 2001; Soares-filho et al., 2006), it is perhaps surprising that this effect is not even larger. Other than results from Vietnam, the coefficient on historical deforestation is consistently less than unity. For Vietnam exclusion of historical deforestation as an explanatory variable in the deforestation model makes the explanatory power drop by 70%, indicating the presence of causal relationships not captured adequately by the other variables considered. This was not the case with results obtained from global data or for Brazil and Indonesia; in these cases exclusion of historical deforestation had a marginal effect on the model explanatory power. Unlike Brazil, where forest transition is still in its infant stages in much of the Amazon (Baptista and Rudel, 2006; Walker, 2012), and Indonesia, which is experiencing high deforestation rates (Mather, 2007), Vietnam has gone through a noticeable forest transition period (Meyfroidt and Lambin, 2008). Thus, the significant drop we observe in the model explanatory power when we exclude historical deforestation from the regression may be because Vietnam is on a different part of the FT curve.

Despite the importance of historical deforestation in predicting future deforestation, we note that the coefficient (elasticity) of historical deforestation decreases as more variables are included. This indicates that historical deforestation is not a perfect predictor of deforestation, and draws the attention to other underlying causes of deforestation. In particular, we find evidence attesting to the forest transition (FT) theory, although some of these results are sensitive to how one measures deforestation and forest stock, and the variables included. FT is associated with a wide range of interdependent economic, political and institutional processes in agriculture and forestry (Mather, 1998; Mather et al., 1999), thus to relate it in simple ways to factors such as forest cover and income is challenging.

Figure 6 elaborates on the impact of how deforestation and forest cover are measured. Figure 6 shows how forest stock relates to deforestation, using two different approaches. When measuring both deforestation and forest stock in absolute terms, we observe linear relationships as evidenced in left panel of Figure 6. This is largely due to what we might call a “big country effect”: Large countries (or sub-national units in the country regressions) also tend to have larger areas of deforestation (in absolute terms), and this produces an almost linear relationship between forest cover and deforestation.

On the other hand, measuring both deforestation and forest stock as share of land area, the FT pattern is exposed. From Figure 6, it is easy to identify the country’s location along the FT curve. We believe this is the more appropriate formulation of the model, and it avoids the “big country effect” in the analysis.

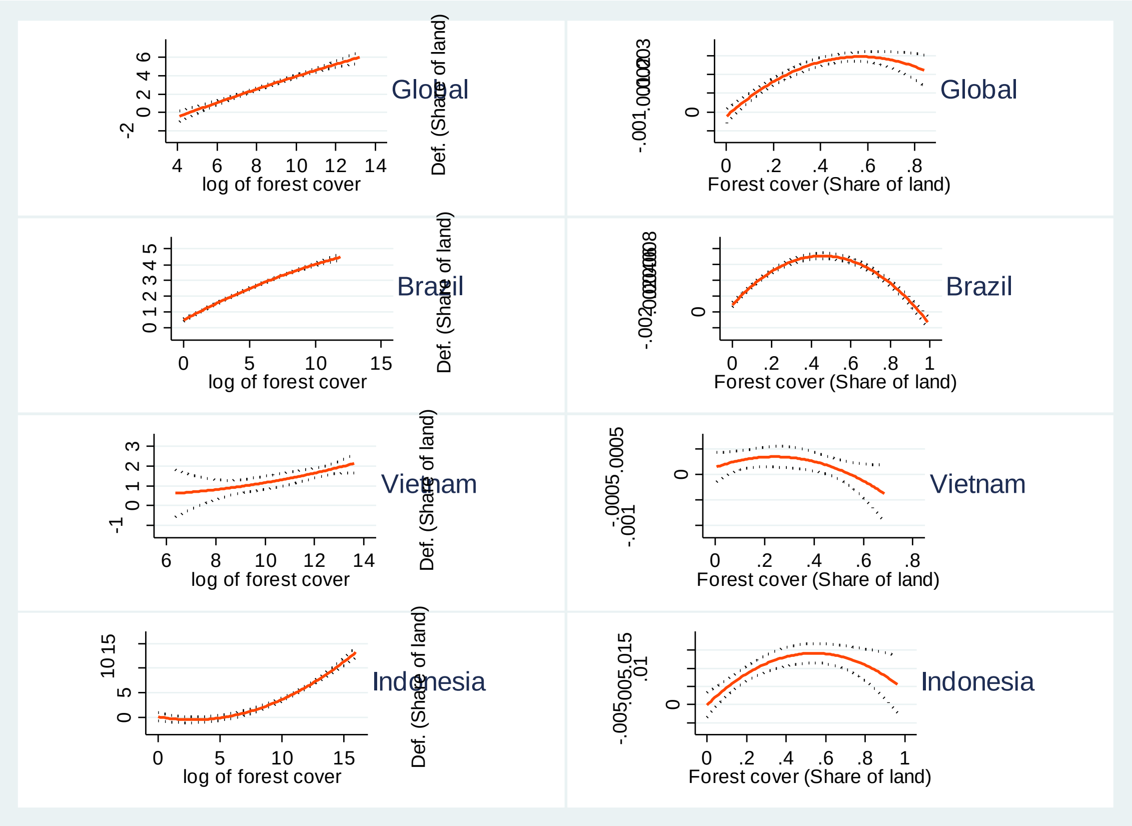


Figure 5. Quadratic prediction of deforestation on forest cover. Dotted lines show 95% confidence interval and solid lines show predicted deforestation

Other national or sub-national circumstances can have implications for deforestation that differ between countries. For example, we find that income (GDP) is associated with lower deforestation rates in global and Brazil data analyses, but associated with higher deforestation rates in Indonesia, although in the Brazilian case higher agricultural share of GDP is associated with higher deforestation. This suggests that in the case of Indonesia activities that increase GDP put more pressure on forests than is the case for Brazil. This may be related to the high value of commodities such as palm oil, or the occurrence of resources such as coal in forested areas. There is some evidence in the global analysis that whereas an increase agricultural GDP as a share of total GDP initially increases deforestation rates, as the share increases further deforestation rate declines. This implies that BAU in countries whose economic growth depends heavily on agriculture would eventually reduce deforestation rates, though forest cover might by then have been considerably reduced.

The negative relationship between population density and deforestation rates is consistent with the preceding discussion. This relationship is generally consistent across a number of model specifications, particularly those obtained from country case studies (Brazil, Vietnam and Indonesia), although in a few cases a positive relationship between population density and deforestation rate was observed. Countries in the process of industrialization are more likely to have high rates of rural-urban migration and hence farmland abandonment for reforestation. But countries far from industrialization process may accelerate agricultural production by expansion into forest areas. This is further supported by the reduction in deforestation rates associated with increased road density (an indicator of increased access to markets and urbanization) in Indonesia, but contradicted by an opposite relationship observed in Brazil. As earlier mentioned, in Brazil deforestation is mainly driven by capital intensive activities and hence increased road density amounts pressure on these capital intensive activities and so is increased deforestation rate.

Finally the quality of governance in a country has also mixed relationships: countries with better mechanisms to control corruption and oversee good accountability are likely to have lower deforestation rates. Perhaps surprisingly, other things being equal the global data suggest that countries with political stability are associated with high deforestation rates, a finding consistently gaining ground in empirical literature (Ehrhardt-Martinez *et al*., 2002; Marquart-Pyatt, S. 2004; Shandra *et al*., 2009).

We summarize our main findings in this section as follows:

Historical deforestation is the key single variable to predict future deforestation and explains most of the current variation across countries and sub-national units. Countries or regions experiencing high rates of deforestation in the recent past are more likely to have high levels of current and future deforestation rates. However, the coefficients in most cases are below one, suggesting that a simple extrapolation can be misleading, and that other factors might also be considered, especially as with one exception in the present study these can account for much of the variance even without inclusion of historical deforestation in the model specification.

Evidence of the **forest transition (FT)** hypothesis is observed. The FT hypothesis suggests that some high forest cover-low deforesting countries are experiencing accelerating rates of deforestation, while other countries with high deforestation rates experience decreasing rates of forest cover loss. However, the robustness of FT theory depends on the way forest stock is quantified: FT theory is supported when forest stock is measured relative to the total land area, but contradictory results emerge when forest stock is measured in absolute terms. This underscores the description of FT as a wide set of interdependent and context-specific economic, political and institutional processes in agriculture and forestry, where a regular global pattern is harder to detect.

A number of **other national circumstances** were tested, but with findings across the four different data sets and for different models that depend on circumstances. For example, the impact of income (GDP per capita) varies across countries. Countries with a high dependence on agriculture, as measured by the sector’s share of GDP, are generally observed to have high deforestation rates, but eventually deforestation tends to decline as agricultural income increases. Population density is found to have different relationships with high deforestation rates, and the same is true for a set of governance variables tested.

The different relationships of national circumstances may be – in part – be explained by the quality of data used, and that the interrelations of economic, political, cultural and institutional differ across countries, which points to the benefit of using national level rather than global analysis to predict deforestation rates. Given constraints in data availability and quality, the analyses suggest that past deforestation rates and possibly also share of forest cover are the best general predictors of future deforestation, although the relationships observed are often understandable in terms of underlying causality and understanding improves as data accumulate.

6 Costs of REDD+

This chapter is based on a literature review on the potential costs of setting up REDD+ programmes in Cameroon, Vietnam, Indonesia and Brazil. A data collection framework was used that considers opportunity costs, implementation costs, and transaction costs that may arise during different phases of REDD+ implementation in the respective countries.

6.1 An overview on issues related to REDD+ cost estimation

Estimating the costs of REDD+ is not straightforward. This is reflected by the wide range of existing cost estimates for REDD+ implementation. The Stern Review (2006) presents estimates that the opportunity costs of avoiding deforestation range from USD 3 billion to USD 15 billion, resulting in carbon prices of USD 1 to USD 5 $tCO2e^{-1}$. The Stern Review used a macroeconomic modelling approach, based on meta-analyses of results from different models. The Eliasch Review (2008) used a global partial equilibrium model to predict farmers' land-use decisions in response to different carbon prices, and estimated that USD 17 to USD 33 billion yr-1 would be needed to reduce emissions of the forest sector by 50% with average carbon prices of up to USD 15 $tCO2e^{-1}$. A wide variation of cost estimates is also found in studies that have been produced at regional, national or local levels. One reason for this difference in cost estimates is that studies differ in their focus on who bears the costs of REDD+, consider different cost categories, or make different assumptions on how REDD+ programs would be implemented (Bond et al., 2009).

Costs are incurred by buyers and sellers of REDD+ action. Since stakeholders incur different costs, for any cost calculation it is essential to determine whose costs are in the focus of interest. Costs can be divided according to who bears them, and may include costs of individual actors, countries, government agencies, international donors or buyers in a carbon market. Individual actors, e.g. landholders who consider joining a REDD+ program, will focus on the costs of their participation, especially if a land-use change is required that affects their current income. Countries with a potential for REDD+ will be interested in knowing more about the costs of implementing REDD+ programs on the ground, while international donors might seek guidance on where and how to best allocate funds in order to achieve cost-effective emission reductions and other co-benefits from REDD+. In this study, the focus is mainly on costs incurred by suppliers of REDD+ credits.

Cost categories may include opportunity costs, implementation costs and transaction costs. Opportunity costs are the most widely considered category and can be defined as forgone economic benefits from the best alternative land use (Lubowski, 2008). A comparison of 29 opportunity cost estimates from three different continents finds average costs of USD 2.51 $tCO2e^{-1}$, indicating that land-use activities on deforested or degraded forest land often have a low profitability. The cost estimates range from less than zero (meaning that an agricultural activity is generating a loss) to USD 13.34 tCO_2e^{-1} (Boucher, 2008). Few studies adopt a comprehensive approach to estimating REDD+ that includes all opportunity costs and other costs. As a result, calculations of payments based on existing REDD+ estimates are likely to underestimate total costs. Products or services that do not have a market price are usually not considered in opportunity cost calculations, but might nevertheless be of great value for rural communities or households. In addition, if the demand for food cannot be met by alternative local production because land has been set-aside for REDD+, deforestation might be shifted to other areas. To avoid leakage, measures might be needed to address this unmet demand which will result in higher costs than opportunity cost calculations suggest (Fisher et al., 2011). Grieg-Gran (2006) presents a comprehensive list of factors that affect opportunity costs of REDD+, including site quality and climatic conditions, suitability of forest land for alternative uses, underlying carbon density estimates, scale of operation, distance to markets and commodity prices. The selected methodology and underlying assumptions for opportunity cost calculation will have an important impact on the results. Factors to be considered include the chosen land-use modelling method, discount rate and time horizon, the proportion of deforested land that is associated with low, average and high return land uses, and assumptions made with regard to additionality and leakage. Opportunity costs nevertheless probably have the largest share of the total costs of REDD+, assuming that countries and/or individual actors are to be paid for forgone benefits of deforestation (Olsen and Bishop, 2009).

The costs of actually implementing and running an REDD+ programme are often neglected. This is partly because estimates of these costs can only be speculative as long as full details on how an REDD+ programme will operate are not known (Grieg-Gran, 2008). Implementation costs are the costs of actions carried out to achieve REDD+ and include, for example, capacity building for institutions that are involved in MRV, the costs of preventing illegal logging, or costs related to the issuance of land titles to land users as an incentive to invest in land use practices that contribute to REDD+ (Pagiola and Bosquet, 2009). Studies of REDD+ implementation costs show significant economies of scale, i.e., large programmes have lower implementation costs per unit of emission reduction or removal compared to smaller programmes (Olsen and Bishop, 2009). Based on a preliminary assessment, the Meridian Institute (2009) estimated the costs for REDD+ readiness and implementation for a 50% global reduction in forest emissions to be in the range of USD 15 to USD 35 billion yr-1. Table 6-1 presents cost range estimates for a list of activities a country might have to carry out to reach REDD+ readiness. Estimates cover a five-year planning horizon and are based on country estimates and on data from development aid activities.

Table 6-1 Cost range estimates for achieving REDD+ readiness (in USD) based on Hoare et al. (2008) in: Meridian Institute (2009)

Action	Cost range estimate
Strategy development	200,000 – 1,000,000
Establishment of relevant infrastructure	700,000 – 1,500,000
Stakeholder consultation	150,000 – 2,000,000
Pilot testing	250,000 – 500,000
Establishment of baseline, monitoring system, and inventory	1,000,000 – 6,610,000
Land-tenure reform	4,000,000 – 20,000,000
Land-use planning and zoning	1,750,000 – 10,000,000
Capacity building for implementation activities	1,750,000 - 10,000,000
Forest policy and legislation reform	300,000 – 1,000,000
Tax reform (e.g. removal of subsidies/tax incentives)	300,000 – 1,000,000
Standards and guidelines	50,000 – 1,000,000
Enforcement of planning and environmental requirements	500,000 – 2,000,000
Independent monitoring	1,000,000 – 5,000,000
NGO capacity building	100,000 – 1,000,000
Effective juridical system	500,000 - 5,000,000
Institutional reform	600,000 - 14,000,000
Treasury reform	500,000 – 5,000,000
Establishment of ability to process and manage issuance of payments to project beneficiaries	100,000 – 5,000,000
Total	13,750,000 – 91,610,000

Transaction costs are the costs that arise in the process of connecting buyers and sellers of emission reductions and/or removals (Lubowski, 2008), and include, for example, the costs incurred in running the the MRV associated with REDD+ activities.

The list of factors that affect the costs of REDD+ and that should ideally be considered in cost calculations is much longer. The way in which REDD+ targets are achieved will affecy the costs of emission reductions and removals. The budgetary costs to a government implementing REDD+ will differ according to whether reductions are to be achieved by targeted payments, a protected area without targeted payments, an extensive PES program not specifically targeted on REDD+, or an agricultural intensification programme. The costs also depend on the policies and measures chosen to implement REDD+ and on the ambition to reduce emissions. REDD+ costs will also vary with regard to the financing mechanism selected for REDD+, i.e. whether payments will be channelled through a direct compliance carbon market mechanism, a market-linked system such as auctions, a voluntary market or contributions, or through international public sources (e.g. bilateral or multilateral aids). As an example of these costs, For a REDD+ program in the Brazilian Amazon, the national and project-level implementation costs were estimated at USD 0.58 $tCO2e^{-1}$, once the programme would be fully established after a 10-year implementation phase (Nepstad et al., 2007).

The brief overview on issues related to REDD+ cost estimation shows that there is no single answer to the question on how much it will cost to implement REDD+ on the ground. Stakeholders bear different costs and follow different interests; countries' forest ecosystems have different potentials to remove CO_2 from the atmosphere and to store carbon in biomass; and many details on how the international REDD+ framework will ultimately look are still unknown. What is possible at present is the estimation of cost ranges for REDD+ implementation scenarios that are based on existing data and on current assumptions. Assumptions can be replaced by evidence from the ground, once the implementation of REDD+ action advances. The mix of existing data and assumptions necessary to fill gaps will depend on each countries stage in the process of REDD+ implementation. The cost estimates presented here make no attempt to correct for different assumptions on discount rate or other macroeconomic variables; the data have been taken from the sources referenced and are compared on the basis that the authors were taking account of representative conditions.

6.2 Approach for REDD+ cost estimation

This section presents the approach applied in this study to estimate the costs of implementing REDD+ action in Cameroon, Vietnam, Indonesia and Brazil. A literature review was undertaken to compile available data on REDD+ costs. Sources of information were peer reviewed articles, Readiness Plan Idea Notes (R-PIN), REDD+ Readiness Preparation Proposals (R-PP), UN-REDD+ Programme documents, and reports provided by the Informal Working Group on Interim Finance for REDD+ (IWG-IFR). Where possible, available data were grouped according to their cost category, considering opportunity, implementation and transaction costs as defined in the previous section.

Data were further organised within the framework of a phased approach for REDD+. The proposed phases consist of (1) initial REDD+ readiness and confidence building, (2) full readiness and designing of an REDD+ financing mechanism, and (3) operating of a REDD+ financing mechanism (UN-REDD Programme, 2009). Countries are supposed to move from receiving financing for the development of national REDD+ strategies (Phase I), to receiving support and incentives for the implementation of those strategies based on defined performance indicators (Phase II), to results-based payments based on quantified changes in GHG emissions and removals (Phase III) (Meridian Institute, 2009).

Some additional costs are available in Table A5 that are not country-specific but provide estimates of costs for e.g. institutional reform, land-tenure reform etc.

6.3 Costs by country

6.3.1 Brazil

6.3.1.1 Expected REDD+ program activity costs in Brazil

Brazil is neither a member of the UN-REDD, nor of the FCPF. Documents like R-PINs and R-PPs that are important sources of information to estimate REDD+ readiness costs are therefore not available for Brazil. However, several studies estimate the costs of developing REDD+ programmes in the country or focus on the costs of certain elements of such programmes. Nepstad et al. (2007) calcu-late the costs of developing a REDD+ program for the Brazilian Amazon and estimate that the ten-year program would cost approximately USD 531 million, including expenses for monitoring, forest management and protection, and payments for emissions reductions.

Depending on the drivers of deforestation, estimated opportunity costs for Brazil vary widely. Nepstad et al. (2007) estimate that it would cost about USD 1.49 $tCO2e^{-1}$ to reduce deforestation by 100% while 94% percent of projected levels of deforestation could be avoided at a carbon price of USD 0.76 $tCO2e^{-1}$. Vera Diaz and Schwartzmann (2005) estimate the cost of eliminating deforestation to be USD 5.44 $tCO2e^{-1}$ with soybeans and USD 2.34 $tCO2e^{-1}$ without soybeans.

There is a risk associated with using the costs of a low value driver in estimating costs and therefore devising levels of payment. If the drivers change over time, the low cost driver could be replaced by a high value driver, making the basis of payment estimates inappropriate for the new circumstances.

Table 6-2 Opportunity cost estimates for deforestation drivers in Brazil

Activity (Deforestation driver)	Opportunity cost estimates (USD ha^{-1})	
	Low	High
Timber logging	24	2378
Commercial agriculture	461	1924
Small scale agriculture	2	332
Mining	n.a.	n.a

Source: Adapted from Olsen and Bishop (2009)

The following overview of opportunity costs is based on Olsen and Bishop (2009). Small scale and traditional **cattle ranching** generates annual profits between USD 2 to USD 332 ha^{-1} while medium and large scale ranching, extensive ranching and improved pasture are more profitable at USD 461 to USD 1033 ha^{-1}. **Soybean production** is highly profitable at between USD 1027 and USD 1924 ha^{-1}. Agricultural production in more remote Amazonas is based on more varied production of food crops, fruits, fibres and some cash crop production (coffee). The profitability of **subsistence crops** is low with manioc and rice (USD 2 ha^{-1}) and perennials and bananas (USD 2 ha^{-1}) the least profitable.

The opportunity costs for **tree plantations** (USD 2 378 ha^{-1}) and for coffee and rubber are also relatively high. However, the land area used for tree plantations and tree crops is very small, accounting for only one percent of land use. Returns to one-off timber harvesting vary significantly from USD 24 ha^{-1} in low productivity forest in Amazonas to USD 1 435 ha^{-1} in high productivity forest in the Amazon. Vera Diaz and Schwartzmann (2005) estimate returns of almost USD 1 700 ha^{-1} for high productivity logging followed by ranching versus less than USD 450 ha^{-1} for logging low productivity forest followed by ranching, based on information from Ecuador. Stumpage fee estimates from Brazil are lower than in Ecuador[13].

6.3.2 Cameroon

Expected REDD+ program activity costs in Cameroon

In Cameroon, sources of finance for REDD+ come from developed country organisations and governments (for example, DANIDA, KfW, GTZ, EU, DFID), multilateral organisations (for example, GEF, World Bank FCPF) and NGOs. Once a R-PP (Readiness Preparation Proposal under the FCPF) has been submitted and accepted by the FCPF, Cameroon will be eligible to an additional USD 3.4

[13] See Grieg-Gran 2006 and Grieg-Gran 2008

million for the implementation of its R-PP (REDD Countries Database, 2011). A total of USD 93 million are committed to Cameroon for REDD+ implementation, of which approximately USD 13 million are to be forwarded between 2010 and 2012 (see Appendix: Voluntary REDD+ Database, 2011).

An overview of potential expenditures for REDD+ readiness activities is given in Table 6-3. To date, activities have been undertaken in: research and development, REDD+ pilot projects, reinforcement of capacities (IPCC, 2007; FAO, 2008; FCPF, 2008; UNFCCC, 2009). Elements such as the development of an MRV system might be realized within the transnational Congo Basin forest conservation efforts. The integration of Cameroonian REDD+ investments in existing efforts to realize REALU in the whole Congo Basin will be crucial in Phase II.

Table 6-3 Overview of cost estimates for REDD+ activities and opportunity costs in Cameroon

Phase	REDD+ Activity	Costs (USD)	Temporal and spatial reference	Type	Source
1	**REDD+ Strategy Development***				
1	Research and development	1,500,000	2010 - ?, Cameroon	IC	Cameroon R-PIN, 2008
1	Reinforcement of capacities	6,000,000	2010 - ?, Cameroon	IC	Cameroon R-PIN, 2008
1	**Pilots and other activites**				
1	REDD+ pilot projects	3,000,000	2010 - ?, Cameroon	IC	Cameroon R-PIN, 2008
1	**MRV:** **data collection, planning and design of monitoring system**				
1	Forest survey	896,676			
1	Field component of a national forest monitoring programme	185,105	2008, Cameroon	IC	FAO, 2008 cited in UNFCCC, 2009
1,2	**Institutional Reform**	Not available, see appendix[14]			
1,2	**Land Tenure Reform**	Not available, see appendix			
1,2	**Land Use Planning**	Not available, see appendix			
1,2	**Juridical Reform**	Not available, see appendix			
1,2	**Treasury Reform**	Not available, see appendix			
1,2	**Support Services**	Not available,			

[14] Apendix A5 gives generalised (not country specific) cost estimates.

		see appendix			
	MRV: data collection, emission change monitoring				
2,3	Forest carbon monitoring system, Tier 3 IPCC	1,034,246	First year, Cameroon	TC[2], IC	Hardcastle and Baird, 2008
3	Forest carbon monitoring system, Tier 3 IPCC	389,478	Annually, Cameroon	TC, IC	Hardcastle and Baird, 2008
3	Cost of administering a payment scheme	8,296,000 -18,665,000	Annually, Cameroon	TC	Grieg-Gran, 2008
	Driver-specific opportunity costs relevant to REDD+ activities				
	Oil palm after forest	1,500 ha^{-1}	Cameroon	OC[3]	Swallow et al. 2007
	Oil palm after short fallow	950 ha^{-1}	Cameroon	OC	Swallow et al. 2007
	Extensive cocoa without fruit sales	450 ha^{-1}	Cameroon	OC	Swallow et al. 2007
	Average of land use change 1984-2001 at Akok and Awae study sites	11 - 22 $tCO2e^{-1}$	Cameroon	OC	Swallow et al. 2007
	Oil palm	6 $tCO2e^{-1}$	Cameroon	OC	Minang et al., 2011
	Extensive cocoa gardens with fruit	7 $tCO2e^{-1}$	Cameroon		Minang et al., 2009
	Extensive cocoa gardens in the jungle	3,50 $tCO2e^{-1}$	Cameroon		Minang et al., 2010
	Cacao Gardens: shaded intensive cocoa system with fruit trees	11,00 $tCO2e^{-1}$	Cameroon	OC	Minang et al., 2011
	Mixed crops, shifting cultivation	2,50 $tCO2e^{-1}$	Cameroon	OC	Minang et al., 2011

[1]IC = Implementation costs; [2]TC = Transaction costs; [3]OC = Opportunity costs

Table 6-4 Opportunity cost estimates for deforestation drivers in Cameroon

Activity (Deforestation driver)	Opportunity cost estimates	
	Low	High
Timber logging	n.a.	n.a.
Commercial agriculture	450 USD ha^{-1}	1500 USD ha^{-1}
Small scale agriculture	4 USD ha^{-1}	n.a.
Mining	n.a.	n.a.-
Average land use change opportunity costs	11 USD tCO_2e^{-1}	28.00 USD tCO_2e^{-1}

Sources: (Swallow, van Noordwijk et al., 2007; Robiglio, Ngendakumana et al., 2010; Minang, van Noordwijk et al., 2011; Swallow, 2011)

Opportunity cost data found in secondary literature come from bottom-up studies. Opportunity costs of avoiding emissions from the conversion of natural forest to **small scale agricultural land use** range from USD 4 to USD 10 for intensive cocoa system with fruit trees and are USD 4 for mixed crops that are planted in shifting cultivation food production systems (Minang, van Noordwijk et al., 2011). The profitability of **commercial agricultural land uses** ranges from USD 450 to USD 1 500 per hectare,. Farm sizes in the reviewed studies range from 5-80 hectares (Swallow, 2011). The average land use change opportunity costs of one ton carbon emissions ranges from USD 11 to USD 28, depending on the discount rate (Swallow et al., 2007, Robiglio, 2007).

Forestry tax incomes in 2005 amounted to about USD 24 million (MINEFI, 2006). The figure can be used as one indicator for the role of the sector for national development. Household spending data is available for the **fuelwood and charcoal**, which comprise the largest market for forest products, especially in terms of volume of felled trees (Essama-Nssah and Gockowski, 2000). Each urban household spends an average of USD 55 to USD 59 per year for fuelwood and charcoal, amounting to some USD 65–70 million spent by 1.3 million urban households (Topa, Karsenty et al., 2009).

6.3.3 Indonesia

Expected REDD+ program activity costs in Indonesia

An independent review of REDD+ and global climate change funds found USD 2.9 billion committed to Indonesia (as of early 2010) (Wood, 2010). Table A3 provides details regarding the donors and partnerships.

Indonesia currently seeks external support in the following areas (FCPF, 2009):

- Methodologies for determining RL;
- analysis on financial aspects of REDD+ (readiness), potential markets for REDD+, and MRV issues which will affect REDD+ implementation;
- capacity building at all levels, access to data/information and technology transfer;
- identification of specific on the ground investment opportunities and other activities with a potential for emission reductions and sustainable development.

Underlying causes of Indonesian land-use change emissions include agricultural expansion in the context of a land-use planning framework that favours it, timber extraction and migration to the forest frontiers. The lack of REDD+ implementation capacities is an obstacle for forest conservation (FCPF, 2009). The findings from the first report of the Indonesian-Norwegian Partnership emphasise the following (Caldecott, Indrawan et al., 2011):

- Focus in the REDD+ development in Indonesia should be on the quality of processes rather than exclusively on outputs and dates;
- The disbursement of existing funds should be dependent on project documentation and compliance with agreed schedules;
- An extension of the start-up phase (Phase I) should be considered.

With regard to phase I of REDD+ implementation, cost estimates are available for activities related to REDD+ strategy development, pilot projects and MRV (see Table 6-5).

Phase II activities such as data collection for MRV and activity change monitoring have started in Indonesia. Cost estimates for payment processing, institutional reform, land tenure reform, land use planning, juridical reform, treasury reform and support services are available. The reform cost estimates are based on Delphi panel results, i.e. they present an estimate of the likelihood of occurrence based on expert judgement. Cost estimates for some MRV elements are also available, including data collection, activity change monitoring, design of a monitoring and evaluation framework, emission change monitoring and forest carbon monitoring.

Table 6-5: Overview of cost estimates for REDD+ activities and opportunity costs in Indonesia

Phase	REDD+ Activity	Costs (USD)	Temporal and spatial reference	Type	Source
1	**Stakeholder Consultation**	**n.a.**			
		No specific costs available			
1	**REDD+ Strategy Development**				
	Assessment of land use, forestry policy and governance	138,000	2011-2013, Indonesia	IC	Indonesia R-PP, 2009
	Develop REDD+ strategy options	2,200,000	2011-2013, Indonesia	IC	Indonesia R-PP, 2009
	Social and environmental impact assessment	600,000	2011-2013, Indonesia	IC	
	Design of REDD+ implementation framework	2,300,000	2011-2013, Indonesia	IC	Indonesia R-PP, 2009
1	**Capacity building**				
	National readiness management arrangements	713,000	2011-2013, Indonesia	IC	Indonesia R-PP, 2009
1	**MRV: planning and design**				
	Design a monitoring system	6,475,000	2011-2013, Indonesia	IC	Indonesia R-PP, 2009
	Development of a reference scenario	6,153,000	2011-2013, Indonesia	IC	Indonesia R-PP, 2009
1,2	**Institutional Reform**	No specific costs available[15]			
1,2	**Land Tenure Reform**	No specific costs available			
1,2	**Land Use Planning**	No specific costs available			
1,2	**Juridical Reform**	No specific costs available			

[15] Appendix A5 contains generalised, not country specific, cost ranges for these areas.

1,2	**Treasury Reform**	No specific costs available			
1,2	**Support Services**	No specific costs available			
	MRV: data collection, emission change monitoring				
2,3	Forest carbon monitoring system (Tier 3 IPCC)	1,997,000	First year, Indonesia	IC	Hardcastle and Baird, 2008
3	Forest carbon monitoring system (Tier 3 IPCC)	666,000	Annually, Indonesia	TC, IC	Hardcastle and Baird, 2008
3	**Cost of administering a payment scheme**	70,551,000- 158,740,000 (Administration costs over a 30 year period, based on an annual lower bound of US$ 4ha^{-1} and upper bound of US$ 9 ha^{-1})	Annually, Indonesia	TC	Grieg-Gran, 2008
	Driver specific opportunity cost				
	Agriculture commercial (est. 54% cause of def.)	3.24 – 21.54 tCO2e^{-1}	Annual, Indonesia -various vegetation types (e.g. forest, peat land)	OC	Zen et al 2005 (in Vermeulen and Goad 2006); Olsen and Bichop, 2009 (four different assumptions); Grieg-Gran, 2008; Butler et al. 2008; Indonesia R-PP,

					2009
		3,340 – 9,630 ha^{-1}	Annual, Indonesia -various vegetation types (e.g. forest, peat land)	OC	Olsen and Bichop, 2009 (four different assumptions)
	Agriculture local shifting (est. 20% cause of def.)	0.48 - 1.35 ha^{-1}	Annual, Sumatra, SE Asia – various local agricultural activities (e.g. upland rice, cassava, fuel wood, small scale shifting, small scale rubber)	OC	Tomich et al. 2005; Robledo and Blaser, 2008; Indonesia R-PP, 2009
		296.75 (39) ha^{-1} (without small scale palm)	Annual, Sumatra, SE Asia – various local agricultural activities (e.g. upland rice, cassava, fuel wood, small scale shifting, small scale rubber)	OC	Grieg-Gran, 2008
	Timber/logging (est. 99% cause of degr.)	0 - 1,120.00 ha^{-1}	Annual, Sumatra, SE Asia, Indonesia (e.g. Indonesian pulp sector, commercial logging, illegal logging)		Robledo and Blaser, 2008; Tomich et al 1998; Pirard, 2008
		2.13 (0.3) – 4.78 $tCO2e^{-1}$	Annual, Sumatra, SE Asia, Indonesia (e.g. Indonesian pulp sector, commercial logging, illegal logging)	OC	Tomich et al. 2005

Table 6-6 Opportunity cost estimates for deforestation drivers in Indonesia

Activity (Deforestation driver)	Opportunity cost estimates (USD ha^{-1})	
	Low	High
Timber logging	0	1200
Commercial agriculture	3	3000
Small scale agriculture	0.5	296
Mining	n.a.	n.a.

Sources: (Tomich, van Noordwijk et al., 1998; Tomich, Cattaneo et al., 2005; Zen, Barlow et al., 2005; Butler and Laurance, 2008; Grieg-Gran, 2008; Pirard, 2008; Robledo and Blaser, 2008; FCPF, 2009; Olsen and Bishop, 2009)

Mining is thought to present the most profitable economic activity in Indonesia. Land-use change from forest to other land uses due to **urban expansion** is also assumed to be very profitable. There were no estimates of the opportunity costs of mining[16] in Indonesia in the published literature, at the time of writing this study.

Opportunity cost estimates of forest conservation in areas suitable for **commercial agriculture** can range from USD 3 up to USD 3,000 ha^{-1} (Zen, Barlow et al., 2005; Butler and Laurance, 2008; Grieg-Gran, 2008; Olsen and Bishop, 2009). The large difference between the upper and lower estimate can be explained by the different assumptions regarding the suitability of alternative areas for agricultural development, as well as the difference in value of large-scale commercial agriculture as compared to small scale farming. With regards to commercial agriculture, several studies assume that the current carbon price levels in different compliance and voluntary schemes cannot compete with the profitability of oil palm plantations in Indonesia (Sandker, Suwarno et al., 2007; Butler, Koh et al., 2009; Sheil, Casson et al., 2009). However, commercial agricultural expansion is possible and profitable on degraded land. Strategic land use planning to integrate agricultural development and climate change mitigation goals, the reallocation of concessions, and the strengthening of forest conservation attempts could lead to REDD+ without significantly reducing agricultural opportunities (Koh and Ghazoul, 2010).

Opportunity costs estimates for **small scale agriculture** are lower although the range is huge, from USD 0.48 to USD 296.75 ha^{-1} (Tomich et al., 1998; Grieg-Gran, 2008; Robledo and Blaser, 2008; FCPF, 2009). Where smallholders use their land to cultivate oil palms, higher opportunity cost occur compared to areas of shifting cultivation or cassava plantations. The present carbon price levels enable REDD+ investors to buy out small scale forest dwellers in Indonesia. Hence, REDD+ in areas dominated by smallholder agriculture leads to significant social, ethical and environmental (leakage) concerns (Brown, Seymour et al., 2008; Minang, van Noordwijk et al., 2010; Wood, 2010). Therefore the international REDD+ debate has turned to the discussion on social and environmental safeguards.

[16] The annual national earnings from mining could be considered as a proxy for the opportunity costs of mining, In such a case the GDP from mining could be used as an indicative figure, divided by the area of land used for mining. Such an estimate would not differentiate between the income to different actors in the mining industry though, and therefore might be too broad an estimate to really indicate opportunity costs to the landowners.

Existing REDD+ projects in Indonesia and the scientific community try to address this issue with the design of fair benefit distribution systems. In general, further careful investigation of how smallholder land is valued is necessary. The existing approach only uses the value of yield per hectare, underestimating the full value of small-scale agricultural land, including social elements.

Opportunity costs estimates for **timber and logging** operations range from USD 0 to USD 1 200 ha^{-1} (Tomich, van Noordwijk et al., 1998; Pirard, 2008; Robledo and Blaser, 2008). Their occurrence and magnitude is subject to the same discussion as opportunity costs of commercial agriculture. Timber plantations and sustainable forest management on afforested degraded land could lead to REDD+ successes in Indonesia without foregoing the benefits of the wood and wood product sector. Pirards (2008) study on opportunity costs of the Indonesian pulp and paper sector gives very valuable insights regarding the reasons why opportunity cost estimates vary between zero and thousands of Dollars in Indonesia (Pirard, 2008): strategy matters. A good development plan that takes different sectoral developments into account and focuses on land use changes with net GHG benefits, helps to reduce the costs of REDD+. However, any activity is dependent on its implementation by stakeholders and their respective transaction costs.

6.3.4 Vietnam

Expected REDD+ program activity costs in Vietnam

Vietnam's R-PP and other REDD+-relevant documents indicate substantial investments in activities related to stakeholder consultation, the development of a national REDD+ strategy and a MRV system. Table 6-7 provides an overview of actual and potential costs of the REDD+ readiness and the other phases. Vietnam is quite advanced regarding the set-up of its institutional framework and the enhancement of national REDD+ management capacities. Some funds are needed to strengthen existing capacities and to further develop an REDD+ enabling political framework.

Table 6-7 Overview on cost estimates for REDD+ activities and opportunity costs in Vietnam

Phase	REDD+ Activity	Costs (USD)	Temporal and spatial reference	Type	Source
1	**Stakeholder Consultation**	950,000	2011-2013, Vietnam	IC	Vietnam R-PP, 2011
1	**REDD+ Strategy Development**				
1	Assessment of land use, forestry policy and governance	235,000	2011-2013, Vietnam	IC	Vietnam R-PP, 2011
1	Development of REDD+ strategy options	1,870,000	2011-2013, Vietnam	IC	Vietnam R-PP, 2011
1	Social and Environmental Impact	198,000	2011-2013, Vietnam	IC	Vietnam R-PP, 2011
1	National readiness management arrangements	756,000	2011-2013, Vietnam	IC	Vietnam R-PP, 2011
1	**MRV: planning and design, design of a monitoring system**				
1	Design of a monitoring system	3,160,000	2011-2013, Vietnam	IC	Vietnam R-PP, 2011
1,2	**Institutional Reform**	Not available, see Appendix[17]			
1,2	**Land Tenure Reform**	Not available, see Appendix			
1,2	**Land Use Planning**	Not available, see Appendix			
1,2	**Juridical Reform**	Not available, see Appendix			
1,2	**Treasury Reform**	Not available, see Appendix			
1,2	**Support Services**	Not available, see Appendix			
1	**MRV**				

[17] Appendix A5 contains generalised, not country specific, cost ranges for these areas

1	Design of a monitoring and evaluation framework	230,000	2011-2013, Vietnam	IC	Vietnam R-PP, 2011
1	RL development	1,000,000	2011-2013, Vietnam	IC	Vietnam R-PP, 2011
1	Design of a REDD+ implementation framework	460,000	2011-2013, Vietnam	IC	Vietnam R-PP, 2011
2,3	Forest carbon monitoring system (Tier 3, IPCC)	477,000	First year, Vietnam	IC	Hardcastle and Baird, 2008
2,3	Forest carbon monitoring system (Tier 3, IPCC)	110,000	Annually, Vietnam	TC, IC	Hardcastle and Baird, 2008
3	**Cost of administering a payment scheme**				
	Driver-specific opportunity costs of REDD+	Not available			
	Opportunity cost of avoided tropical deforestation	Not available			
	Value of agricultual produce (mainly industrial perennial crops)	55,000,000 - 70,000,000	Annually, Vietnam	OC	UN REDD 2010
	Coffee and rubber plantations	224.10 $tCO2e^{-1}$	NPV,Vietnam	OC	Hoang et al., 2010

Table 6-8 Opportunity cost estimates for deforestation drivers in Vietnam

Activity (Deforestation driver)	Opportunity cost estimates ($USD\ ha^{-1}$)	
	Low	**High**
Timber logging	50*	1300**
Commercial agriculture	n.a.	1600
Small scale agriculture	n.a.	400***
Mining	n.a.	n.a.

*Net present value (NPV) of natural forest with a lifecycle of 50 years; **NPV of planted forest (*Acacia mangium,* 7 years old); ***NPV of shifting cultivation

Sources: Hoang et al. (2010), van Noordwijk (2009) in Hoang et al. (2009)

An opportunity analysis carried out using data from Dak Nong province indicated that about 80% of emissions linked to economic benefits do not exceed USD 5 tCO_2e^{-1}. The highest carbon abatement costs resulted from natural forest conversion to coffee and rubber plantations with costs up to USD 224.10 tCO_2e^{-1} (Hoang et al., 2010).

With regard to **commercial agriculture**, rubber is one of Vietnam's most important agricultural export crops, with a net profit per hectare of about USD 1600. Due to the high profitability of rubber production, the government plans to expand rubber areas in the country (Hoang et al., 2010). The expansion will take place on current agricultural land with low economic returns, derived from household agricultural production, unused land, and poor quality forest under the "production forest" category. A loose definition of "poor quality forest" is responsible for deforestation in many parts of the country (Hoang et al., 2010).

The export of **wood furniture,** mainly to Europe, Japan and North America, is another important source of income for Vietnam, which reached a value of USD 2.4 billion in 2007; a ten-fold increase since 2000. The increase is possible almost entirely because of growth in imports of roundwood and sawnwood, mainly from Laos, Myanmar and Cambodia. The domestic demand for furniture, **paper and pulp** is also high (Mayfroidth and Lambin, 2009).

6.4 Summary

This chapter summarises the results of a literature review on potential costs of REDD+ programmes for Cameroon, Vietnam, Indonesia and Brazil. Opportunity costs, implementation costs, and transaction costs that may arise during different phases of REDD+ implementation were considered. The review focused on estimates of the costs of REDD+ programmes at the country level.

Information on costs was mainly taken from bottom-up studies, although input from larger modelling exercises was also considered. The data from bottom-up studies spread over wide ranges, especially for opportunity costs. These ranges make it difficult to come up with cost estimates for REDD+ activities. The ranges reflect the uncertainty with regard to how REDD+ programmes will operate, the current lack of data in many REDD+ countries and the lack of common methodologies for estimating REDD+ programme costs. The ranges of cost data also illustrate that it may be difficult to devise a solid evidence base for payments under a REDD+ framework.

The study indicates a data collection framework that could be used as guidance on REDD+ activities and cost categories that should be included in cost calculations to obtain a complete overview on potential costs. The use of a common data collection framework and methodology for cost estimates would allow a comparison the costs of REDD+ programmes of different countries, particularly as these are further developed in the future.

The costs presented in this report are country specific, but they may be able to provide some guidance for countries with similar circumstances, e.g. a similar forest cover and stage of REDD+ implementation, where local data are not available.

7 Financial incentive benchmarks (FIB) for REDD+

The financial incentive benchmark (FIB), sometimes referred to as the crediting or payment baseline, is conceptually in this report the basis for rewarding countries, projects or other entities for successful REDD+ efforts. The payment for a given time period is defined by: (emissions - FIB) x carbon price. The simplest option is to set FIB = RL (which we have previously defined as the BAU baseline). There are, however, several considerations that suggest that this might not be optimal. The approach taken is that the RL is the starting point for arriving at a FIB, but that these considerations could lead to a significantly lower FIB, as illustrated in the example at the end of the chapter.

7.1 Additionality

The idea of additionality as applied to funding has widespread support in REDD+ negotiations. The concept has, however, different meanings and can also be applied at different scales (Meridian Institute, 2011). A strong formulation of additionality is that *all* international funding should be for mitigation efforts additional to those which would have been undertaken without it, i.e. FIB ≤ RL. A weaker formulation is that the realised emissions, after REDD+, should be lower than the BAU scenario, i.e. emissions < RL. Weak additionality applied to groups of countries might also imply that some REDD+ funding is for emission reductions that are not additional, but seen as a whole REDD+ is additional. A further implication of weak additionality is that we might have FIB > RL, which - if REDD+ credits are traded in a carbon market – could imply paying for an increase in emissions, or paying in the absence of any reductions at all. In the following, we will mainly refer to the additionality in the strong version, i.e. a requirement that *FIB ≤ RL*.

As discussed in Meridian (2011), additionality can be applied at different scales. *National additionality* implies setting FIB ≤ RL emissions for each participating country. *Aggregate additionality* implies that the sum of FIBs for participating countries in a REDD+ mechanism should be below the sum of their RLs. *Global additionality* also considers emissions from non-participating countries, and potential international leakage. For the purposes of this report, the concept of national additionality is most relevant. This would automatically imply aggregate additionality, but not necessarily global additionality. However, it would seem unreasonable if participating REDD+ countries were held responsible for increases in emissions in other countries.

7.2 Participation constraints, expected gain and leakage

Bali Action Plan assumes that REDD+ will be based on voluntary participation and positive incentives (UNFCCC, 2007). This might be interpreted as a *expected gain* principle, i.e., the REDD+ countries should have a positive net benefit from any REDD+ agreement it enters, with:

Net benefits (REDD+ rent) = Total international REDD+ transfers - total costs of REDD+

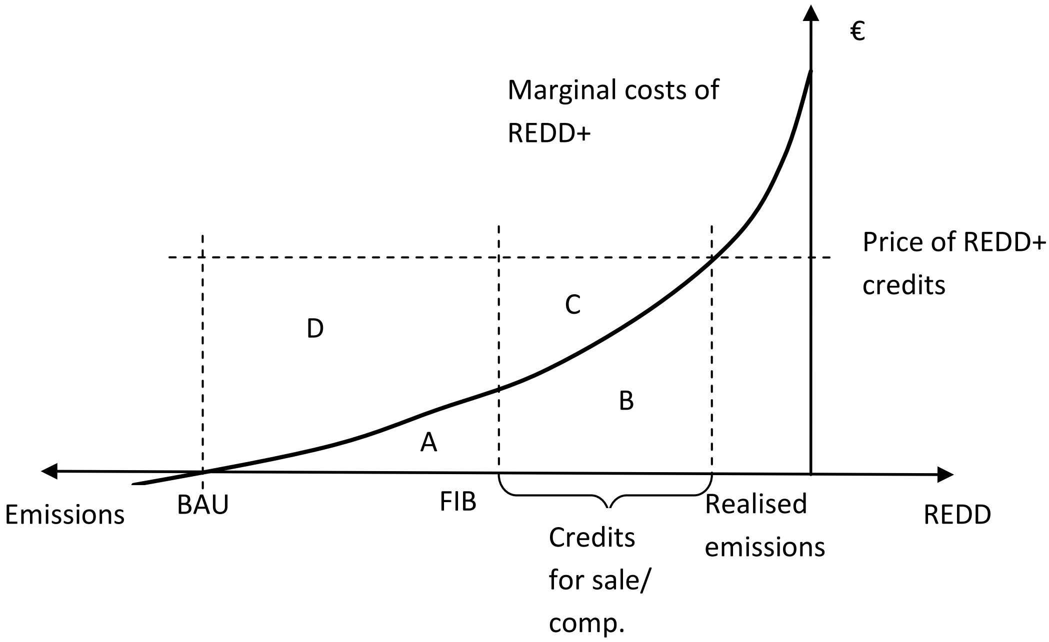
This principle is at times interpreted as setting FIB equal to the RL, but FIB can be below the RL and still be compatible with an expected gain principle, as illustrated in Box 5.1. The reason is that initial reductions are cheap, and setting FIB = RL will make REDD+ countries earn large rents (transfers are higher than costs). FIB can be set lower, as long as the REDD+ rent earned on the reductions below the FIB is sufficiently high to cover the costs of the initial reductions.

A key question is how large the FIB must be in order for the country to expect a positive net gain. If the marginal cost curve is linear, and a country is paid for at least 50% of the emissions reductions (with emission reduction being defined as the difference between the actual emissions and the RL) there will be a net gain. But costs curves are typically convex, thus the FIB can be set further to the right, i.e. payments can be less than 50% of the realised REDD+, and the country still benefits.

Minimising international leakage (displaced emissions) is linked to participation, i.e. successful REDD+ intervention in one country should not lead to higher emissions in other countries due to, for example, logging or agricultural companies moving across the border. In the simple logic displayed in Box 1, the way to avoid this is to ensure that all potential REDD+ countries will benefit from participation.

Figure 6 Illustration of different principles for setting financial incentive baselines (FIB)

Box 1. The first three considerations (additionality, ensuring maximum participation through epectation of gain and effectiveness) are illustrated by the figure below. The marginal costs of reducing deforestation and degradation start at zero in the RL (i.e. the BAU scenario), and they increase as reductions become more costly (e.g. increasingly profitable alternative land uses are being excluded or being re-organised, say by increasing agricultural productivity). Given an international price for REDD+ credits, the country will reduce emissions up to the point where the marginal costs equal the price, which will determine the realised emissions. The price might be the credit price in a carbon market or the agreed price in a bilateral agreement (such as USD 5 per tCO_2 in the agreements between Norway and Brazil or Guyana). The total cost of these reductions is equal to the area A + B. A financial incentive baseline (FIB) is given, and the country receives revenue from selling REDD+ credits for reductions beyond the FIB, i.e. equal to the area B + C. Thus, the country's net gain equals C – A. If the FIB is set equal to RL, the country will gain the area C + D.



The four principles discussed in the text can be summarized as follows, listed in the order of strength in the way of setting lower FIBs

- Additionality (weak): Realised emissions < RL
- Additionality (strong): FIB ≤ RL
- *Participation (expectation of gain* requirement*): FIB set such that A ≤ C*
  The REDD+ rent from the reductions below the FIB (area C) is least sufficiently large to cover the costs of the initial reductions (A) for which there is no international payment.
- *Maximize effectiveness of the transfer payment, given participation constraint: FIB set such that A = C*
  For a given amount of funding, this will ensure that the payment received (B+C) just covers the costs of the emissions reductions (A+B).

7.3 Effectiveness and efficiency

Following an increasingly accepted terminology, we define *effectiveness* of a policy as the absolute level reductions of GHG emissions (measured in tCO_2e) in a country, while *efficiency* refers to the costs per emission reduction units (tCO_2e/USD). Concern for effectiveness is closely linked to the idea of "environmental integrity", i.e. achievement of sufficient emissions reductions to avoid dangerous climate change as required by the UNFCCC.

Setting FIB has implications for effectiveness and efficiency, but the link depends on the design of the REDD+ mechanism. We consider three stylized cases. Further, as discussed earlier in this report, cost can refer to different things. In this sub-section we adopt a narrow interpretation of costs as the payment by the buyers of REDD+ credits. Effectiveness is therefore interpreted as the volume of emission reductions stimulated directly (in response to the payment) and indirectly (to reach the FIB) by a REDD+ payment at a given FIB. Efficiency is interpreted as effectiveness divided by costs.

Case 1: Fixed demand. This system implies that an upper limit is set on the number of REDD+ credits that can enter the carbon market. A proposal for such a system was considered in the 2009 discussion on climate legislation in the United States, i.e. the idea that US companies could use REDD+ up to a fixed overall limit to achieve their assigned GHG emission caps. As REDD+ was considered a cheap offset mechanism, this cap was expected to be binding. A tighter FIB will increase the emission reduction by the same amount of tCO2e, thus there is a certain gain in effectiveness. The change in efficiency is uncertain, as both the price and the emissions reductions will increase.[18]

Case 2: REDD+ Fund. In this system a fund with a fixed amount of money is assigned to buy REDD+ credits.[19] This might be a reasonable approximation of the international REDD+ system over the short-medium term, where different national and multinational funds such as the Norwegian International Climate and Forest Initiative are being set up. Although used for different purposes, some of these, such as Norway's bilateral agreement with Brazil and with Guyana are close to this stylized case. Many analyses (eg Borner and Wunder, 2008) find that the curve is relatively flat initially, before it rises. Thus, effectiveness gain from a tighter FIB can be expected to be large for relatively small funds. Since the amount of money allocated to REDD+ is fixed, the effectiveness and efficiency criteria are equivalent in this case.

Case 3: Carbon market. The third system is one where REDD+ credits are made fully fungible in a carbon market. We assume first that the carbon market price is fixed, i.e. the amount of REDD+ credits brought to the market is too small to affect the price (demand assumed to be perfectly elastic). While this might be a reasonable approximation in initial phases, where many countries lack the MRV systems necessary to participate, a key argument for bringing REDD+ credits into the markets is that they can supply large amount of comparatively cheap emissions reductions. Yet this fixed price assumption is often applied in some models and options assessment (e.g. Busch et al). Under this assumption, the emissions reductions are only determined by the carbon price, and changes in FIBs have no impact on the realised emissions and therefore effectiveness. It should, however, increase efficiency as the costs of achieving these reductions are smaller.

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[18] Since demand is constrained, and markets therefore do not clear, the REDD credit price could be anywhere between the MC of REDD, and the carbon price in, say, a US carbon market. If we assume that REDD countries are paid a price equal to MC, we can conclude that the price will increase when RLs are set tighter.

[19] A fund may not necessarily have a fixed amount of money available, but a fixed amount for REDD+ credit purchases is assumed here to discuss this stylized case. In real life, the finance may be added based on good results.

Overall, this suggests that we often have a trade-off between (i) generous FIBs to ensure participation and net gains to poor countries, and (ii) effectiveness and efficiency. The maximum emissions reductions is achieved by setting RLs such that the REDD+ rent is minimized (as close to zero as possible), and the REDD+ funds are just enough to pay for the domestic costs of emission reductions. This does not consider the role of rent in encouraging participation.

A conclusion from the discussion so far in this chapter, and as illustrated in Box 5.1, is that the principle of additionality (even in its strongest form) is a weak one compared to a requirement about maximum effectiveness. Additionality (strong version) only requires FIB is not set higher than BAU, while effectiveness says it should be set well below BAU. Thus strong additionality should be considered a minimum requirement, while efficient use of funds and maximising climate impact are argumants for going further in reducing FIB, consistent with maintaining participation. In the example illustration at the end of the chapter, we apply the principle of effectiveness (and efficiency) of REDD+ funding.

7.4 Payment for costs incurred

A consideration related to the effectiveness argument is that international payments should cover the net costs of a country in terms of forgone benefits from forest conversion and unsustainable uses (opportunity costs) and transaction costs related to the implementation of REDD+. Fig 7 shows that this implies that FIB set such that A=C. For a given amount of funding, this will ensure that the payment received (B+C) just covers the costs of the emissions reductions (A+B), less any own action undertaken by the country which is considered more below.

Thus, at the limit, the principle of "Payment for costs incurred taking own action into account" is identical to "maximize effectiveness", and would imply no REDD+ rent for the country. However, setting the FIB such that this is achieved is only one of several possible options to maximize effectiveness. We briefly review these options in Table 7-1. Three criteria are used to assess the five options listed: (i) the incentives provided to the country, and thereby the overall reductions achieved; (ii) the information requirements, e.g. about the REDD+ potential and associated costs, and (iii) how uncertainty is handled, e.g. about opportunity costs or changes in external factors such as global agricultural commodity prices.

Table 7-1 Options to maximize effectiveness of a given REDD+ transfer[20].

[20] These different FIB approaches could be chosen to reflect different national circumstances or based on e.g. income per capita

Option	Elaboration	Incentives (overall reductions)	Information requirements	Risk handling
1.Stricter FIB	Might include a safety margin to account for uncertainty	Good; correct incentives on the margin (does not affect overall reductions)	Medium - high	Countries adjust efforts based on new information, but may opt out if costs seriously underestimated (& FIB set tightly)
2.Lower price	Set price per tCO_2e below the marginal rate	Incentives on the margin reduced; less emissions reductions	Low	Aim to set the price to control risks both of excessive rent and underestimating costs
3.Differentiated payment	Example: corridor approach, with higher payment per tCO_2e the larger the reductions are	Good, payment mimics the MC curve	High, must know differentiated costs	Would need interaction to incorporate new information
4.Sub-FIB s	Sub-FIBs for areas or sectors (drivers) A version of the option above	Good, as above	High, detailed information about costs	Would need interaction to incorporate new information
5.Fixed contract	A deal about fixed reductions and fixed payment (based on estimated costs)	Uncertain; must include conditions target under-/over-achieved	High	Poor, REDD+ countries assume high risk.

Based on the three criteria, a system of differentiated payments (option 3, and partly also option 4) appears attractive. It provides strong incentives (at the margin) and handles risk relatively well. As a drawback, the informational requirements are high, and costs should be split disaggregated by area, actor, and sector. Aggregate costs estimates are needed in option 1 (stricter FIB) and 5 (fixed contract), but these must to some extent be based on such detailed information (although the level of precision could be lower). We return to option 3 below. The least attractive appears to be lowering the carbon price (2) or a fixed contract (5). The fixed contract option must also include elements from the other options to cover situations where achieved emissions reductions are not achieved (or overachieved). It may, therefore in practice be similar to either options 1 or 2.

Overall, a system of differential payments, for example, in the form of a corridor approach, or a system of stricter FIBs, seems to be the systems that best meet the three criteria.

7.5 FIBs to reflect a fair benefit and cost sharing

The considerations discussed so far do not differentiate between countries, except for the differences reflected in REDD+ costs. Differences in opportunity costs of REDD+ is an argument for setting FIBs differently in order to achieve maximum effectiveness. Some have noted the potentially perverse distributional effects of these: countries with low opportunity costs tend to be poorer (low agricultural productivity and poverty are related), with the implication, based on cost arguments alone, that REDD+ transfers should be lower too.

There are other, normative, arguments for adjusting FIBs, to let some countries receive an REDD+ rent and/or other countries not be fully paid for the REDD+ costs. For example, middle-income countries (with high forestry emissions) should be expected to shoulder some of the REDD+ costs themselves. Differentiation among non-Annex I countries is politically sensitive. However, the Durban Platform approved by COP17 (UNFCCC, 2011) states that all parties should take on commitments ("... a protocol, another legal instrument or an agreed outcome with legal force under the Convention applicable to all Parties").

This issue has been reflected in the REDD+ discussion: (1) Should REDD+ be considered as an international payment for environmental services system (IPES), i.e. Annex I countries paying non-Annex I countries in full for REDD+, or (2) Should REDD+ become part of an international agreement where middle income non-Annex I countries assume legally binding emission targets for REDD+, either for REDD+ separately or as part of their Nationally Appropriate Mitigation Actions (NAMAs)? In the latter case, REDD+ could become part of a global cap and trade (CAT) system.

The arguments for a differentiation among REDD+ countries fall into several categories:

1. Differences in capabilities: While capabilities cover several dimensions, e.g. governments' capacity to monitor forest stocks and implement REDD+ policies, the predominant suggestion is to use income (GDP) per capita as a proxy for capabilities.

2. Differences in responsibilities: Some argue that countries' commitments and the burden-sharing should be based on how much countries currently emit, or the accumulated historical emissions. Another line of argument is linking responsibilities to capabilities, i.e. that higher income means assuming higher responsibility in terms of covering the costs of climate mitigation.

3. REDD+ transfers for development and adaptation: A third line of argument is that REDD+ should enable economic development of poor countries, and enable a low-carbon development path. REDD+ transfers should therefore go beyond covering the REDD+ costs. Similarly, poor countries are most vulnerable to climate change, and mitigation and adaptations need to be linked.

Thus there are at least three possible ways to operate the benefit and cost sharing principle:

(i) income per capita,

(ii) emissions (current or accumulated),

(iii) individual assessments of capabilities and needs.

Using per capita income as a factor for differentiation might be, politically, one way of differentiating across countries. One early proposal in the debate (e.g. by Coalition for Rainforest Nations) was to include a *development adjustment factor* (DAF) in reference level setting. A costs sharing factor, based on the country's income per capita, is therefore included as an element in the example illustration at the end of this chapter.

7.6 Dealing with uncertainty

Setting RLs and FIBs and is uncertain due to several factors. First, estimating BAU has several inherent uncertainties: the future values of drivers of deforestation and degradation are not known, e.g. the prices of palm oil and soy beans, and the relationship between such drivers and the agricultural land expansion into forests are uncertain.

Second, the costs of avoided deforestation and degradation are uncertain, e.g. the agricultural income that could have been obtained from cleared land (output prices and technologies). Third, the effectiveness of the REDD+ policies implemented is not fully known, e.g., how farmers will respond to particular incentives aimed to constrain forest clearing.

Some of the consequences of getting RLs and FIBs wrong have already been discussed under effectiveness and efficiency. Depending on the effect on FIB, setting RLs too high risks over-payment and reduced effectiveness, and potentially also no additionality with the risk of 'hot air' in a market based system.

Setting RLs and FIBs too low risks under-payment, and potential drop-out by some countries if the participation constraint is no longer met. This increases the potential for international leakage, which also will undermine the effectiveness and credibility of the system.

A system for RL and FIB setting should therefore take the uncertainty into account, both for reasons of effectiveness (and efficiency), and also to get a 'fair risk sharing' between the countries. Several options have been proposed in the literature, and are briefly discussed in Table 7-2 .

Table 7-2 Options to deal with uncertainty in RL and FIB setting

Option	Elaboration	Pros	Cons
1.*Ex-post* adjustment	Formula agreed, final level set when parameters (e.g. agric. prices) are known	Predictable, and politically robust	Hard to establish the formula.
2.Corridor approach	Gradually increasing payments within a corridor.	Flexible, payments could mimics MC curve	Political acceptance a challenge
3.Stepwise approach	Estimated level multiplied by an uncertainty or conservativeness factor (<1), based on assessment of data quality	May allow participation earlier than would otherwise be the case. Incentivises countries to produce better data.	Lower rate of payment for countries with poor data. Does not address uncertainties in drivers
4.Renegotiations	Renegotiate based an initial agreement	Flexible, can incorporate unforeseen factors	Political gaming
5.Insurance	Could design insurance contract based approaches in 1 and 2.	Well developed markets for insurance	Probably expensive, complex formula

One major proposal in the REDD+ debate is the suggestion of an *ex-post* adjustment of the RL (and hence FIB), initially proposed as the "Compensated Successful Efforts" by Combes Motel et al. (2009). Deforestation pressures in, for example, the Brazilian Amazon are closely linked to the profitability of cattle and soy bean production, and adjusting RLs based on the prices of these commodities should better reflect the true BAU scenario, and therefore better measure the real emissions reductions.

Another approach is the Stepwise approach, presented earlier in the report. An adjustment factor is introduced to reflect the degree of uncertainty of the emissions and RL estimates. This addresses of the problems of uncertainty linked to emissions estimates and may increase participation, and incentivise improvements in data quality.

Two other options to deal with uncertainty are contract renegotiation or insurance, but these have not so far been explored in the context of REDD+ RLs.

The corridor approach was proposed by Schlamadinger et al (2005). This recognises that any point estimate of the RL is uncertain. A discount factor is therefore introduced, where deeper emissions reductions get an increasingly lower discount factor (i.e. higher payment). The approach defines an interval (corridor) around the point estimate of the RL, with the discount factor increasing from 0 to 1 (no to full payment) within this interval. Thus REDD+ countries will (so long as they are within an agreed uncertainty range of the FIB) get some payment even if they are unlucky and face strong deforestation drivers, making the policies less successful than anticipated in reducing deforestation. On the other hand, a donor country will, as a result of the discount factor, not make full payments in the opposite case, i.e. deforestation is reduced for other reasons than successful REDD+ policies.

The corridor approach is illustrated by the following example. Assume the best guess for the FIB (based on a best guess BAU baseline and any other considerations) is that annual emissions from deforestation are 0.5% of the forest carbon stock. These are uncertain, and an interval from 0.7 to 0.3% is identified (say the 95% interval) for the FIB. The following scheme can then be agreed on:

Emissions above 0.7%: no payment
Emissions between 0.7-0.6%: 20% payment
Emissions between 0.6-0.5%: 40% payment
Emissions between 0.5-0.4%: 60% payment
Emissions between 0.4-0.3%: 80% payment
Emissions below 0.3%: 100 % payment

Further, as already noted, the payment scheme will tend to mimic the marginal cost curve, and hence contribute to higher effectiveness.

The corridor approach has, to our knowledge, not been applied in any agreements so far. One reason might be that few agreements actually are in place using this Phase III approach of emissions based payments. Uncertainty may also not be explicitly acknowledged. Finally, there is a fear of making agreements too complex, although conceptually the approach is rather simple, particularly compared to the many other complexities involved in designing and measuring a system of emissions based payments. The corridor approach may therefore be an idea worth pursuing.

8 Concluding remarks

This study's analysis of available data suggests that, whilst historical deforestation rates are the most important single predictor of business-as-usual deforestation, including other socio-economic variables in regression analysis increases the amount of variance explained, and in three out of the four countries analysed in detail, the other variables by themselves can explain most of the variance that is explained by historical deforestation. For one country analysed this is not the case, although the reasons for this are not clear. This suggests that consideration of specific causal factors (in addition to the general expectation based on historical deforestation rates) is likely to increase understanding of the drivers of deforestation and hence of reference levels. Because of data limitations these results do not include consideration of degradation. The results are nevertheless suggestive enough to encourage further investigation, to broaden the scope to more countries using existing data sources, and, as suitable data become available, to include degradation and eventually other REDD+ activities.

The study distinguishes between reference levels as a business-as-usual projection and financial incentive benchmarks as the agreed level below which international incentive payments would be made. The text uses the abbreviation RL exclusively in the former sense, and FIB exclusively in the latter. Although a formulaic approach is unlikely to succeed in setting FIBs, the study provides arguments from international equity and environmental and economic effectiveness and efficiency why FIBs should not necessarily equal RLs.

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Appendix A

Appendix A contains information on REDD+ funding from the Voluntary REDD+ database. Source: http://reddplusdatabase.org/ Difference from the sum per country given in the list and the sum of funds reported by donor countries in the text can be explained by rounding to million US$ in the voluntary REDD+ database overview per country and the different time spans under consideration . In the text the total incoming funding per country calculated by the voluntary REDD+ database project team is given.

A1 Brazil (Voluntary REDD+ Database, 2011)

Table A1 - 1 Voluntary REDD+ Database, 2011

Timespan	Funder	Recipient	US $ million
2008-2009	Germany	Brazil	$15
2008-2012	Germany	Brazil	$30
2008-2009	Germany	Brazil	$14
2008-2009	Germany	Brazil	$6
2008-2008	Germany	Brazil	$3
2008-2009	Germany	Brazil	$2
2008-2012	Germany	Brazil	$3
2008-2009	Germany	Brazil	$5
2009-2012	Germany	Brazil	$4
2009-2012	Germany	Brazil	$9
2008-2012	Japan	Brazil	$27
2008-2009	GEF - Global Envir...	Brazil	$10
2010-2012	GEF - Global Envir...	Brazil	$18
2008-2009	GEF - Global Envir...	Brazil	$5
2008-2009	GEF - Global Envir...	Brazil	$7
2010-2010	United States of A...	Brazil	$4
2010-2010	United States of A...	Brazil	$1
2010-2013	Germany	Brazil	$5
2010-2015	Germany	Brazil	$4
2008-2009	Brazil	Brazil	$100
2010-2010	France	Brazil	$2
2009-2010	Norway	Brazil	$49

		Sum	$323

INCOMING FUNDING, 2008 - 2009	
$400.83M	Reported by Brazil
$216.64M	Reported by others

A2 Cameroon

Table A2 REDD Funding to Cameron (VRD, 2011)

Timespan	Funder	Recipient	US $ million
2008-2009	Germany	Cameroon	$1
2008-2012	Germany	Cameroon	$2
2008-2015	WCS - Wildlife Con...	Cameroon	$0
2010-2012	Cameroon	Cameroon	$27
2010-2012	FCPF - Forest Carb...	Cameroon	$0
2010-2012	FCPF - Forest Carb...	Cameroon	$36
2010-2012	GEF - Global Envir...	Cameroon	$4
2010-2012	GEF - Global Envir...	Cameroon	$2
2010-2012	GEF - Global Envir...	Cameroon	$8
2010-2012	GEF - Global Envir...	Cameroon	$5
2008-2009	FCPF - Forest Carb...	Cameroon	$3
2010-2012	FCPF - Forest Carb...	Cameroon	$5
2010-2011	France	Cameroon	$0
		Sum	$93

INCOMING FUNDING, 2010 – 2012		
$0.0M	Reported by Cameroon	
$13.37M	Reported by others	

Source: http://reddplusdatabase.org/ Difference form the sum per country given in the list and the sum of funds reported by donor countries in the text can be explained by rounding to million US$ in the voluntary REDD+ database overview per country and the different time spans under consideration . In the text the total incoming funding per country calculated by the voluntary REDD+ database project team is given.

A3 Indonesia

Table A3 REDD Funding to Indonesia (VRD, 2011)

Timespan	Funder	Recipient	US $ million
2008-2012	Australia	Indonesia	$28
2010-2012	Australia	Indonesia	$28
2008-2009	Germany	Indonesia	$29
2008-2009	Germany	Indonesia	$11
2008-2011	Germany	Indonesia	$2
2008-2015	United Kingdom	Indonesia	$29
2007-2012	Australia	Indonesia	$9
2010-2012	WCS - Wildlife Con...	Indonesia	$0
2008-2009	Indonesia (National Programme)	Indonesia	$6
2008-2015	UN-REDD Programme	Indonesia	$6
2008-2012	CI - Conservation ...	Indonesia	$9
2011-2014	Finland	Indonesia	$5
2008-2012	Japan	Indonesia	$31
2008-2012	Japan	Indonesia	$29
2008-2015	TNC - The Nature C...	Indonesia	$5
2010-2013	ITTO - Internation...	Indonesia	$1
2008-2009	GEF - Global Envir...	Indonesia	$5
2008-2009	GEF - Global Envir...	Indonesia	$8
2008-2009	GEF - Global Envir...	Indonesia	$4
2008-2009	FCPF - Forest Carb...	Indonesia	$3
2010-2012	FCPF - Forest Carb...	Indonesia	$5
2010-2010	United States of A...	Indonesia	$6
2010-2010	United States of A...	Indonesia	$5
2010-2010	United States of A...	Indonesia	$2
2010-2010	United States of A...	Indonesia	$20
2010-2010	United States of A...	Indonesia	$2
2010-2015	Germany	Indonesia	$4
2008-2012	Germany	Indonesia	$1
2009-2011	Germany	Indonesia	$1
2009-2012	Germany	Indonesia	$10

2010-2011	ITTO - Internation...	Indonesia	$0
2009-2011	Germany	Indonesia	$1
2010-2010	Norway	Indonesia	$31
		Sum	$336

INCOMING FUNDING, 2008 - 2009	
$157.6M	Reported by Indonesia
$314.93M	Reported by others

Source: http://reddplusdatabase.org/ Difference form the sum per country given in the list and the sum of funds reported by donor countries in the text can be explained by rounding to million US$ in the voluntary REDD+ database overview per country and the different time spans under consideration . In the text the total incoming funding per country calculated by the voluntary REDD+ database project team is given.

For the Indonesian case in addition to the voluntary REDD+ database information is available from (Wood, 2010):

Table A3 Donors to REDD+ in Indonesia (Wood, 2011)

Multilateral and bilateral donors in REDD+ and associated GCC programs in Indonesia (May 2010)1			
Country/ Institution	Program	Value (commitment)	Notes
United Nations (UNDP, UNEP, FAO)	UNREDD	5.644 million USD	combination of policy support and demonstration activity [70]
World Bank	Forest Carbon Partnership Fund (FCPF) – Readiness Fund	3.6 million USD	technical support
World Bank	Forest Investment Program (FIP)	80 million USD	allocated, but disbursement not yet decided
International Tropical Timber Organisation (ITTO)2	REDD-environmental services program (REDDES)	814,590 USD	demonstration activity [90, 85, 86]
Australia	Indonesia- Australian Forest Carbon Partnership	61 million USD (70 million AUD)	2007-2012, demonstration activities and technical support [90]
France	Climate Change Program Loan	800 million USD [07]	budget support loan (co-funding Japan)
Germany	FORCLIME, Merang REDD pilot, policy development, etc	48.19 million USD (32.34 million euro)	2009-2016, demonstration activities and technical support [90]
Japan	Forest Preservation Program (grant) and Climate Change Program Loan (budget support loan)	751 million USD loan, 11 million USD grant [17]	forest monitoring and reforestation support, climate change mitigation loan (co-financing

			France)
Norway	Norway-Indonesia REDD+ program	1 billion USD	3 phase grant linked to policy reform, strategy development, and emissions reductions
United Kingdom	Multistakeholder forestry program (part REDD+) and Fast Start Facility	84 million USD (55 million UKP)	5 years technical assistance to national government and selected regions [90, 51]
South Korea2	Korea-Indonesia Joint Program on Adaptation and Mitigation of Climate Change in Forestry	5 million USD	2008 – 2013, afforestation/ reforestation and REDD+ [31, 90, 92]
United States of America2	Indonesia Forest and Climate Support Project (IFACS)	around 30 million USD	demonstration activities and forest management activities

This table does not include NGO and private sector initiatives, although one of these, TNC's Bureau Carbon Project has been recognised as an official demonstration activity [105]
ITTO, USA and South Korea were are not analysed further in this report because South Korea and ITTO are only involved in single pilot projects, and the USA has yet to commit climate funds to Indonesia, although a program is in the process of tender.

The study identifies approximately $ 2.9 billion committed funding in association with multilateral and bilateral donors in REDD+ and associated Global Climate Change (GCC) programs in Indonesia.

A4 Vietnam

Table A4 REDD+ Funding to Vietnam (VRD, 2011)

Timespan	Funder	Recipient	US $ million
2008-2015	UN-REDD Programme	Vietnam	$4
2009-2012	Finland	Vietnam	$5
2009-2010	Finland	Vietnam	$0
2010-2012	Finland	Vietnam	$0
2008-2009	Japan	Vietnam	$23
2008-2009	Japan	Vietnam	$81

2010-2012	FCPF - Forest Carb...	Vietnam	$36
2008-2009	FCPF - Forest Carb...	Vietnam	$3
2010-2012	FCPF - Forest Carb...	Vietnam	$5
2010-2013	Germany	Vietnam	$1
2010-2015	Germany	Vietnam	$10
2010-2010	United States of A...	Vietnam	$0
		Sum	$168

INCOMING FUNDING, 2005 - 2014	
$0.0M	Reported by Vietnam
$124.14M	Reported by others

Source: http://reddplusdatabase.org/ Difference form the sum per country given in the list and the sum of funds reported by donor countries in the text can be explained by rounding to million US$ in the voluntary REDD+ database overview per country and the different time spans under consideration . In the text the total incoming funding per country calculated by the voluntary REDD+ database project team is given.

A5 General costs

For some phases of REDD+ implementation, only general country costs are available, and these are provided below. These costs come from the information given by a Delphi panel of experts:

Table A5 General estimates of Costs for REDD+ implementation

Phase	REDD+ Activity		Temporal and	Type	Source

		Costs (USD)	spatial reference		
1,2	**Institutional Reform**	13,000,000 – 14,000,000	Likely national cost (low-high Delphi expert panel estimate) any country	IC	IWG-IFR, 2009
1,2	**Land Tenure Reform**	> 21,000,000	Likely national cost (low-high Delphi expert panel estimate) any country	IC	IWG-IFR, 2009
1,2	**Land Use Planning**	4,500,000 - 10,000,000	Likely national cost (low-high Delphi expert panel estimate) any country	IC	IWG-IFR, 2009
1,2	**Juridical Reform**	> 4,500,000	Likely national cost (low-high Delphi expert panel estimate) any country	IC	IWG-IFR, 2009
1,2	**Treasury Reform**	> 4,500,000	Likely national cost (low-high Delphi expert panel estimate) any country	IC	IWG-IFR, 2009
1,2	**Support Services**	4,500,000 - 10,000,000	Likely national cost (low-high Delphi expert panel estimate) any country	IC	IWG-IFR, 2009

A6 Country sample

A6 Table 1 Country Sample

Country	Missing data	Suspicious data	Forest area < 10,000ha	Country	Missing data	Suspicious data	Forest area < 10,000ha
Afghanistan		x		Jordan		x	
Algeria				Kazakhstan			
Angola				Kenya			
Anguilla			x	Kyrgyzstan			
Antigua and		x		Lao People's DR			

Barbuda							
Argentina				Lesotho	x		
Armenia				Liberia			
Aruba			x	Madagascar			
Azerbaijan		x		Malawi			
Bahamas		x		Maldives			x
Bahrain			x	Mali			
Bangladesh				Mauritania			
Barbados			x	Mauritius	x		
Belize				Mayotte	x		
Benin				Mexico			
Bhutan				Mongolia			
Bolivia				Montserrat			x
Botswana				Morocco			
Brazil				Mozambique			
British Virgin Islands			x	Myanmar			
Burkina Faso				Namibia			
Burundi				Nepal		x	
Cambodia				Netherlands Antilles			x
Cameroon				Nicaragua			
Cape Verde				Niger			
Cayman Islands		x		Nigeria			
Central African Republic				Pakistan			
Chad				Panama			
Chile				Paraguay			
China				Peru			
Colombia				Philippines			
Comoros	x			Puerto Rico			
Congo				Rwanda			
Costa Rica				St Kitts and Nevis		x	
Cuba				St Lucia		x	
Côte d'Ivoire				St Vincent & the Grenadines	x		
DR Congo				Sao Tome and Principe		x	

Djibouti			x	Senegal			
Dominica	x			Seychelles		x	
Dominican Republic		x		Sierra Leone			
Ecuador				Somalia			
Egypt				South Africa		x	
El Salvador				Sri Lanka			
Equatorial Guinea				Sudan			
Eritrea				Suriname		x	
Ethiopia				Swaziland			
French Guiana				Syrian Arab Republic			
Gabon		x		Tajikistan		x	
Gambia				Timor-Leste			
Georgia				Togo			
Ghana				Trinidad and Tobago			
Grenada		x		Tunisia			
Guatemala				Turkmenistan		x	
Guinea				Uganda			
Guinea-Bissau				United Republic of Tanzania			
Guyana		x		United States Virgin Islands	x		
Haiti				Uzbekistan			
Honduras				Venezuela			
India				Vietnam			
Indonesia				Yemen		x	
Iraq		x		Zambia			
Jamaica	x			Zimbabwe			

Countries marked with “x” were dropped

Appendix B

Appendix B contains more detail behind the data displayed in Chapter 5 which presents the regression analysis.

Table B 1 Determinants of country level deforestation 2000-2010

	M1	M2	M3	M4	M5
Rates of def., historical def., estimated with OLS-PCSE					
Historical deforestation (%)	0.733***	0.696***	0.695***	0.666***	
Lagged forest stock (share)		0.155***	0.084*	0.065	0.830***
Lagged forest stock squared (share)		-0.118*	-0.036	-0.047	-0.774***
R^2	0.873	0.876	0.881	0.889	0.628
Rates of def., historical def. estimated with tobit model					
Historical deforestation (%)	0.768***	0.757***	0.756***	0.707***	
Lagged forest stock (share)		0.152**	0.070	-0.005	0.917***
Lagged forest stock squared (share)		-0.095	-0.001	0.036	-0.876***
Absolute terms of def. & historical def. (not in logs) estimated with OLS-PCSE					
Historical deforestation (absolute)	0.722***	0.712***	0.711***	0.718***	
Lagged forest stock (share)		-179.263**	-181.017**	-353.229***	-320.308*
Lagged forest stock squared (share)		315.800***	312.018***	491.820***	940.467**
R^2	0.813	0.816	0.816	0.833	0.239
Absolute terms of def. & historical def. (in logs) estimated with OLS-PCSE					
log of historical def. (absolute)	0.942***	0.946***	0.942***	0.927***	
Lagged forest stock (share)		-0.287	-0.527*	-0.298	2.479**
Lagged forest stock squared (share)		0.638**	0.930**	0.501	-0.511
R^2	0.975	0.975	0.975	0.976	0.816
Number of observations (all models above)	650	650	650	650	650
Rates of def., historical def., data averaged over periods by country estimated with OLS					
Historical deforestation (%)	0.780***	0.719***	0.715***	0.681***	
Lagged forest stock (share)		0.156	0.106	0.098	0.972**

Lagged forest stock squared (share)		-0.127	-0.073	-0.101	-0.981**
R^2	0.890	0.895	0.898	0.906	0.664
Absolute terms of def. & historical def, data averaged over periods by country estimated with OLS					
log of historical deforestation (absolute)	0.949***	0.935***	0.935***	0.931***	
Lagged forest stock (share)		-0.200	-0.362	-0.040	4.103
Lagged forest stock squared (share)		0.463	0.626	0.119	-3.227
R^2	0.978	0.978	0.979	0.979	0.826
Number of observations (for last 2 panels)	79	79	79	79	79

***, **, * indicate significance levels at 1%, 5%, 10% respectively. The explanatory variables included in the models M1 – M5 are same as those in Table 3, except deforestation dummy is excluded, and models using averaged data over periods exclude the trend variable. *def.* denotes deforestation. "share" refers to forest cover as a ratio of forest area to country area. Details of these results are available on request.

Table B 2 Determinants of municipality level deforestation 2005-2009 (Brazil)

	M1	M2	M3	M4	M5
Absolute terms of def., historical def. (in logs) estimated with OLS-PCSE					
log of historical deforestation (absolute)	0.676***	0.500***	0.446***	0.425***	
lagged forest stock (share)		2.998***	2.884***	2.494***	5.974***
lagged forest stock squared (share)		-2.459***	-2.012***	-2.088***	-4.843**
R^2	0.791	0.810	0.818	0.828	0.775
Absolute terms of def., historical def. (ALL other variables not in logs) estimated with OLS-PCSE					
Historical deforestation (absolute)	0.456***	0.438***	0.401***	0.353***	
lagged forest stock (share)		14.701	-6.837	-14.028	21.014
lagged forest stock squared (share)		2.071	27.546*	31.422**	4.387
R^2	0.614	0.621	0.633	0.651	0.477
Rates of def., historical def. estimated with OLS-PCSE					
Historical deforestation (%)	0.041***	0.030***	0.024***	0.011**	
lagged forest stock (share of land)		-0.991***	-0.889***	-0.545***	-0.454**
lagged forest stock squared (share of land)		0.506***	0.455***	0.297***	0.253***
R^2	0.153	0.275	0.305	0.333	0.331
Absolute terms of def., historical def. (in logs) estimated with OLS-PCSE					
log of historical deforestation (absolute)	0.676***	0.517***	0.464***	0.467***	
log of lagged forest stock (absolute)		-1.338***	-1.332***	-1.254***	-1.294**
log of lagged forest stock squared (absolute)		0.711***	0.716***	0.648***	0.753***
R^2	0.791	0.808	0.814	0.823	0.763
Rates of def., historical def., estimated with OLS-PCSE					
Historical deforestation (%)	0.041***	0.020***	0.017***	0.009**	
lagged forest stock (share)		2.635***	2.372***	2.439***	2.476***
lagged forest stock squared (share)		-2.881***	-2.520***	-2.321***	-2.349**
R^2	0.153	0.348	0.359	0.374	0.373
Absolute terms of def., historical def. (ALL other variables not in logs) estimated with OLS-PCSE					
Historical deforestation (absolute)	0.456***	0.434***	0.391***	0.346***	
lagged forest stock (absolute)		0.001***	0.001***	0.001***	0.001***
lagged forest stock squared (absolute)		-0.000	-0.000	-0.000	-0.000
R^2	0.614	0.625	0.637	0.653	0.487
Absolute terms of def., historical def. estimated with Tobit model					
log of historical deforestation (absolute)	0.789***	0.646***	0.589***	0.538***	
lagged forest stock (share)		4.402***	4.253***	3.690***	7.970***
lagged forest stock squared (share)		-3.673***	-3.201***	-2.946***	-6.255**
Rates of def., historical def. estimated with Tobit model					
Historical deforestation (%)	0.047***	0.029***	0.026***	0.016***	
lagged forest stock (share)		4.291***	3.927***	3.690***	3.747***
lagged forest stock squared (share)		-4.320***	-3.821***	-3.216***	-3.258**

Number of observations (all models above)	3595	3595	3595	3595	3595

***, **, * indicate significance levels at 1%, 5%, 10% respectively. All explanatory variables (including their respective transformations unless otherwise stated) included in the models M1 – M5 are same as those in Table 5, except we exclude deforestation dummy and models using averaged data over periods exclude the trend variable. Details of these results are available on request.

Table B 3 Determinants of municipality level deforestation 2005-2009 (Brazil) - continued

	M1	M2	M3	M4	M5
Absolute terms of def, historical def. (in logs), data averaged over periods by municipality estimated with OLS					
log of historical deforestation (absolute)	0.683***	0.530***	0.469***	0.442***	
lagged forest stock (share)		3.447***	3.360***	3.008***	6.96
lagged forest stock squared (share)		-2.969***	-2.502***	-2.561***	-5.7
R^2	0.859	0.873	0.883	0.893	0.84
Rates of def., historical def., data averaged over periods by municipality estimated with OLS					
Historical deforestation (%)	0.062***	0.018***	0.016**	0.008	
lagged forest stock (share)		2.878***	2.624***	2.621***	2.65
lagged forest stock squared (share)		-3.155***	-2.806***	-2.511***	-2.5
R^2	0.150	0.554	0.571	0.596	0.59
Absolute terms of def., historical def. (in logs), data averaged over periods by municipality estimated with tobit					
log of historical deforestation (absolute)	0.682***	0.607***	0.540***	0.491***	
lagged forest stock (share)		4.413***	4.298***	3.814***	8.25
lagged forest stock squared (share)		-3.851***	-3.338***	-3.070***	-6.6
Rates of def., historical def., data averaged over periods by municipality estimated with tobit					
Historical deforestation (%)	0.060***	0.023***	0.020**	0.011*	
lagged forest stock (share)		3.680***	3.378***	3.212***	3.25
lagged forest stock squared (share)		-3.878***	-3.461***	-2.905***	-2.9
Number of observations (all models above)	719	719	719	719	719
Absolute terms of def., historical def. (in logs), data averaged by year and state estimated with OLS					
log of historical deforestation (absolute)	0.850***	0.702***	0.495**	2.137***	
lagged forest stock (share)		2.195	6.235**	-9.984	5.59
lagged forest stock squared (share)		-2.194	-5.924**	3.358	-3.5
R^2	0.958	0.961	0.968	0.980	0.96
Rates of def., historical def., data averaged by year and state estimated with OLS					
Historical deforestation (%)	0.181***	0.113**	0.083**	0.594***	
lagged forest stock (share)		1.242**	0.703	-1.277	0.79
lagged forest stock squared (share)		-1.510**	-0.477	-0.984	0.16

R^2	0.524	0.718	0.746	0.814	0.76
Absolute terms of def., historical def. (in logs), data averaged by year and state estimated with tobit					
log of historical deforestation (absolute)	0.853***	0.719***	0.511**	2.142***	
lagged forest stock (share of land)		2.289	6.290**	-9.805*	5.88
lagged forest stock squared (share of land)		-2.247	-5.955**	3.215	-3.7
Rates of def., historical def., data averaged by year and state estimated with tobit					
Historical deforestation (%)	0.185***	0.116**	0.086**	0.575***	
lagged forest stock (share)		1.188**	0.696	-1.079	0.97
lagged forest stock squared (share)		-1.447**	-0.450	-0.970	0.13
Number of observations (for models in last four panels	45	45	45	45	45

Table B 4 Determinants of province level deforestation 2005-2009 (Vietnam)

	M1	M2	M3	M4	M5
Rates of def., historical def., excluding squared term of forest stock estimated with OLS-PCSE					
Historical deforestation (%)	1.424***	1.429***	1.453***	1.457***	
Lagged forest stock (share)		-0.028	-0.044**	-0.041*	0.017
R^2	0.502	0.505	0.510	0.509	0.019
Rates of def., historical def., estimated with OLS-PCSE					
Historical deforestation (%)	1.424***	1.428***	1.453***	1.443***	
Forest stock (share)		0.128**	0.115*	0.076*	0.240**
Forest stock squared (share)		-0.265**	-0.257**	-0.212**	-0.406**
R^2	0.502	0.512	0.516	0.514	0.037
Rates of def., historical def. estimated with tobit					
Historical deforestation (%)	1.685***	1.738***	1.721***	1.676***	
Forest stock (share)		0.214**	0.255**	0.032	0.222
Forest stock squared (share)		-0.261*	-0.297*	-0.034	-0.217
Absolute terms of def. & historical def. (not in logs) estimated with OLS-PCSE					

Historical deforestation (absolute)	0.486***	0.528***	0.526***	0.529***	
Forest stock (share)		162.748	166.424	223.021**	286.219**
Forest stock squared (share)		-479.230*	-479.215*	-547.117**	-391.355
R^2	0.275	0.304	0.304	0.302	0.060
Absolute terms of def. & historical def. (in logs) estimated with OLS-PCSE					
log of historical deforestation (absolute)	0.574***	0.545***	0.533***	0.561***	
Forest stock (share)		-0.926	-2.001	-0.663	5.325***
Forest stock squared (share)		2.349	3.498	1.750	-2.217

Table B 5: **Determinants of province level deforestation 2006-2009 (Indonesia)**

	M1	M2	M3	M4	M5
Absolute terms of def. & historical def. (plus ALL other variables not in logs) estimated with OLS					
Historical deforestation (absolute)	1.572*	0.759***	0.685**	0.677**	
Forest stock (absolute)		-0.007	-0.011**	-0.012**	-0.009
Forest stock squared (absolute)		0.000***	0.000***	0.000***	0.000***
R^2	0.235	0.774	0.788	0.790	0.757
Absolute terms of def. & historical def. (plus ALL other variables in logs) estimated with OLS					
log of historical defor-estation (absolute)	0.946***	0.359***	0.335***	0.231***	
log of forest stock (abso-lute)		0.463	3.454***	6.777***	9.351***
log of forest stock squared (absolute)		-0.041	-1.466**	-3.196***	-4.439***
R^2	0.582	0.767	0.772	0.799	0.786

Absolute terms of def. & historical def., (in logs), forest stock as share of land estimated with OLS					
log of historical deforestation (absolute)	0.946***	0.390***	0.389***	0.277***	
log of forest stock (absolute)		12.973***	10.419***	7.996***	10.428***
log of forest stock squared (absolute)		-9.415***	-7.025**	-6.870**	-8.600***
R^2	0.582	0.749	0.752	0.786	0.767
Absolute terms of def. & historical def. (in logs) estimated with tobit					
log of historical deforestation (absolute)	0.906***	0.537***	0.539***	0.304***	
Forest stock (share)		0.168***	0.183***	0.143***	0.178***
Forest stock squared (share)		-0.001***	-0.001***	-0.001***	-0.002***
Absolute terms of def. & historical def. (in logs) estimated with tobit					
log of historical deforestation (absolute)	0.049	-0.019*	-0.020*	-0.018	
Def. dummy =1 if no def., 0 otherwise	0.456**	-0.287	-0.254	0.164	0.185
Forest stock (share)		4.019***	4.599***	4.252***	4.227***
Forest stock squared (share)		-3.777**	-4.255**	-4.682**	-4.646**
R^2	0.027	0.259	0.260	0.297	0.296
Rates of def. & historical def., estimated with OLS					
Historical deforestation (%)	0.051	-0.013	-0.015	-0.022*	
Forest stock (share)		4.360***	5.080***	4.056***	3.996***
Forest stock squared (share)		-4.007***	-4.609***	-4.483**	-4.409**
R^2	0.006	0.254	0.257	0.296	0.295

Rates of def. & historical def., estimated with tobit					
Historical deforestation (%)	-0.014	-0.036	-0.044	-0.075**	
Forest stock (share)		0.075***	0.110***	0.086***	0.084***
Forest stock squared (share)		-0.001***	-0.001***	-0.001***	-0.001***
Number of observations (all models above)	371	371	371	371	371
Absolute terms of def. & historical def. (in logs), data averaged by province estimated with OLS					
log of historical deforestation (absolute)	1.060***	0.314**	0.294**	0.286**	
Forest stock (share)		0.076*	-0.004	-0.0004	0.017
Forest stock squared (share)		-0.001	0.000	-0.000	-0.000
R^2	0.933	0.982	0.985	0.986	0.981
Absolute terms of def. & historical def. (in logs), data averaged by province estimated with tobit					
log of historical deforestation (absolute)	1.060***	0.341**	0.314**	0.303**	
Forest stock (share)		0.074*	-0.001	0.0001	0.019
Forest stock squared (share)		-0.001	-0.000	-0.0001	-0.000
Number of observations (two panels above)	29	29	29	29	29
Rates of def. & historical def., data averaged by province estimated with OLS					
Historical deforestation (%)	0.247	-0.108	-0.126	-0.143**	
Forest stock (share)		0.030	0.055	0.024	0.013
Forest stock squared		-0.000	-0.001	-0.001	-0.000

(share)					
R^2	0.077	0.518	0.527	0.667	0.650
Number of observations	30	30	30	30	30

Table B 6 Determinants of province level deforestation 2006-2009 (Indonesia)

	M1	M2	M3	M4	M5
Absolute terms of def. & historical def. (plus ALL other variables not in logs) estimated with OLS					
Historical deforestation (absolute)	1.572*	0.759***	0.685**	0.677**	
Forest stock (absolute)		-0.007	-0.011**	-0.012**	-0.009
Forest stock squared (absolute)		0.000***	0.000***	0.000***	0.000*
R^2	0.235	0.774	0.788	0.790	0.757
Absolute terms of def. & historical def. (plus ALL other variables in logs) estimated with OLS					
log of historical deforestation (absolute)	0.946***	0.359***	0.335***	0.231***	
log of forest stock (absolute)		0.463	3.454***	6.777***	9.351*
log of forest stock squared (absolute)		-0.041	-1.466**	-3.196***	-4.439*
R^2	0.582	0.767	0.772	0.799	0.786
Absolute terms of def. & historical def., (in logs), forest stock as share of land estimated with OLS					
log of historical deforestation (absolute)	0.946***	0.390***	0.389***	0.277***	
log of forest stock (absolute)		12.973***	10.419***	7.996***	10.428

log of forest stock squared (absolute)		-9.415***	-7.025**	-6.870**	-8.600*
R^2	0.582	0.749	0.752	0.786	0.767
Absolute terms of def. & historical def. (in logs) estimated with tobit					
log of historical deforestation (absolute)	0.906***	0.537***	0.539***	0.304***	
Forest stock (share)		16.815***	18.332***	14.349***	17.834
Forest stock squared (share)		-12.396***	-13.665***	-14.604***	-17.436
Absolute terms of def. & historical def. (in logs) estimated with tobit					
log of historical deforestation (absolute)	0.049	-0.019*	-0.020*	-0.018	
Def. dummy =1 if no def., 0 otherwise	0.456**	-0.287	-0.254	0.164	0.185
Forest stock (share)		4.019***	4.599***	4.252***	4.227*
Forest stock squared (share)		-3.777**	-4.255**	-4.682**	-4.646*
R^2	0.027	0.259	0.260	0.297	0.296
Rates of def. & historical def., estimated with OLS					
Historical deforestation (%)	0.051	-0.013	-0.015	-0.022*	
Forest stock (share)		4.360***	5.080***	4.056***	3.996*
Forest stock squared (share)		-4.007***	-4.609***	-4.483**	-4.409*
R^2	0.006	0.254	0.257	0.296	0.295
Rates of def. & historical def., estimated with tobit					

Historical deforestation (%)	-0.014	-0.036	-0.044	-0.075**	
Forest stock (share)		7.529***	11.044***	8.613***	8.424**
Forest stock squared (share)		-6.244***	-9.338***	-9.652***	-9.425*
Number of observations (all models above)	371	371	371	371	371
Absolute terms of def. & historical def. (in logs), data averaged by province estimated with OLS					
log of historical deforestation (absolute)	1.060***	0.314**	0.294**	0.286**	
Forest stock (share)		7.587*	-0.414	-0.038	1.717
Forest stock squared (share)		-6.993	0.380	-0.571	-1.726
R^2	0.933	0.982	0.985	0.986	0.981
Absolute terms of def. & historical def. (in logs), data averaged by province estimated with tobit					
log of historical deforestation (absolute)	1.060***	0.341**	0.314**	0.303**	
Forest stock (share)		7.359*	-0.047	0.013	1.851
Forest stock squared (share)		-6.802	-0.067	-0.695	-1.895
Number of observations (two panels above)	29	29	29	29	29
Rates of def. & historical def., data averaged by province estimated with OLS					
Historical	0.247	-0.108	-0.126	-0.143**	

deforestation (%)					
Forest stock (share)		2.989	5.459	2.389	1.350
Forest stock squared (share)		-3.469	-5.863	-4.673	-3.506
R^2	0.077	0.518	0.527	0.667	0.650
Number of observations	30	30	30	30	30

Appendix C

Figure 7 Data on forest sources and Predicted deforestation

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