Payments for Forest Ecosystem Services: Global and Local Assessments of Costs and Benefits

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CHAPTER 2 ▪

The Economic Costs of Avoided Deforestation in the Developing World: A Meta-Analysis[1]

Summary

This meta-analysis aims to identify the key factors governing the economic costs of avoided deforestation in developing countries. To this end, data were collected from 32 primary studies published between 1995 and 2012, yielding 277 observations. Results show that unit costs depend significantly on cost features like estimation methodology, inclusion or exclusion of cost components, carbon accounting method, area size, alternative land uses and beneficiaries, time horizon, and the continent in which the forest protection scheme is implemented, but also factors like the share of agriculture in a nation's economy play a significant role in explaining unit costs. In future studies, greater attention needs to be paid to additional cost components like transaction costs and the presence of the co-benefits of avoided deforestation.

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2.1 INTRODUCTION

The avoidance of deforestation has major potential as a means of tackling global climate change (IPCC, 2000; Houghton, 2005; Stern, 2006; Nabuurs *et al.*, 2007; Eliasch, 2008). The most important reason for this is that deforestation is one of the largest sources of anthropogenic greenhouse gas emissions (Nabuurs *et al.*, 2007). According to Houghton (2005), deforestation accounts for a quarter of all such emissions. Secondly, deforestation can be avoided at relatively modest cost compared with alternative carbon emission abatement measures in other economic sectors. What makes avoided deforestation economically competitive is that no new technology is required to facilitate action and opportunity costs are likely to be low, since deforestation occurs mainly in tropical developing countries (Sedjo *et al.*, 1995; van Kooten *et al.*, 2004; Hope and Castilla-Rubio, 2008).

In his review of 29 regional empirical studies, Boucher (2008) found that the costs of reducing emissions from deforestation (RED) in developing countries compare favourably to parallel costs in fossil fuel sectors and are lower than current carbon prices in the European Union's Emissions Trading Scheme (ETS). Besides reducing carbon emissions, avoided deforestation also delivers other benefits, such as biodiversity conservation and watershed and soil quality protection (Sedjo *et al.*, 1995; Chomitz and Kumari, 1998; Ebeling and Yasué, 2008; Stickler *et al.*, 2009; World Bank, 2011; Strassburg *et al.*, 2012). In this respect, RED avoids the drawbacks of other forestry-related options to reduce emissions, such as afforestation and reforestation, which tend to favour monoculture over the preservation of exotic species (Brown *et al.*, 2008). In practice, however, taking these additional benefits into account may well increase transaction costs, while the extent to which RED can deliver co-benefits is very much context-dependent (Ebeling and Yasué, 2008; Strassburg *et al.*, 2012).

Until now, the costs of reducing carbon emissions in the forestry sector have been systematically reviewed using mainly qualitative approaches (Sedjo *et al.*, 1995; Chomitz and Kumari, 1998; van Kooten *et al.*, 2004; Ebeling and Yasué, 2008; Stickler *et al.*, 2009; World Bank, 2011). To our knowledge, there are only two studies in which such a review has been based on quantitative meta-regression models. van Kooten *et al.* (2004) initially reviewed 55 studies, followed by van Kooten *et al.* (2009), who examined 68 studies covering a wide range of literature published between 1989 and 2007. These meta-analyses are helpful in synthesizing the empirical findings of a large number of studies, as they quantify and explain the costs of various types of forestry activities on a global scale in developed and developing countries, including avoiding deforestation, afforestation, reforestation and more general forest management. Given the breadth of these two existing meta-analyses in both the developed and developing world, however, they allow for less detailed investigation of relevant issues in a specific context, for instance the costs and co-benefits of RED in developing countries. The present study performs a new meta-analysis, the main objective of which is to assess and explain the relationships between the unit cost of avoided deforestation and its main driving factors in developing countries, which have continued to witness large-scale deforestation over the past decade (FAO, 2010). Besides presenting an update of existing studies up to and including 2012, the meta analysis presented here builds on the two earlier meta-analyses by including new variables, with the aim of further explaining the observed variation in the cost estimates of avoided deforestation. These new variables relate to factors 'internal' to the studies themselves, such as inclusion of additional cost components like transaction costs, co-benefits of forest conservation, alternative land uses and beneficiaries of non-forested land uses, and 'external' factors taken from sources outside the studies, such as past and current deforestation rates in the study area and the share of agriculture in Gross Domestic Product (GDP), as an indicator of an economy's dependence on agriculture and corresponding influence on opportunity costs.

This chapter is structured as follows. Section "Methodology" presents the methodology of our meta-analysis. In Section "Data description" we describe in detail the data set employed in the metaregression model. The main results derived from the meta-analysis and their economic implications are discussed in Section "Estimated meta-regression model". Section "Conclusion" concludes the article.

2.2 METHODOLOGY

Meta-analysis is the statistical evaluation of the findings of empirical studies, and is a useful tool for extracting information from large amounts of data in order to provide quantitative underpinning for a more comprehensive assessment (Glass *et al.*, 1981). It is a means of synthesizing the results of multiple studies examining the same phenomenon through identification of a common effect, which is then explained using regression techniques in a meta-regression model (Nelson and Kennedy, 2009). It enables researchers to explain differences in the outcomes of individual studies in terms of differences in underlying assumptions and standards of design or measurement (Wolf, 1986). As such, meta-analysis is an important extension of and supplement to more qualitative analysis. It is widely recognized that the extensive and growing body of literature on environmental valuation and environmental impacts has become difficult to interpret and that there is a need for research synthesis techniques, in particular statistical meta-analysis, to aggregate information and insights (Stanley, 2001). In addition to identifying consensus in results across studies, meta-analysis is also of interest as a means of transferring results from existing studies to new ones.

The dependent variable in the meta-regression analysis presented here is the net present value of the cost of forest conservation, measured in 2005 US dollars (US$) per tonne of carbon. In theory, the costs of avoided deforestation consist of four main components: opportunity costs, start-up costs, on-going costs and transaction costs (Eliasch, 2008; Sohngen, 2009; World Bank, 2011). Opportunity costs are the benefits foregone by not choosing the next best alternative: in the case of non-forested land use, for example, the foregone revenues from sales of agricultural commodities or timber. In this study, the opportunity costs consist of the one-off benefits accruing from prior logging, where trees are first removed from the land (site preparation) and sold in the market (rather than 'slash and burn'), followed by the annual benefits of alternative land uses such as commercial logging, cropping or animal farming. As pointed out in the literature, opportunity costs arising from alternative land uses should be treated as the minimum payment required for rainforest conservation rather than as a proxy for total costs (Wertz-Kanounnikoff, 2008; Grieg-Gran, 2009). Start-up costs are costs incurred at the beginning of a project, such as the investment sum required for implementing a conservation project. On-going costs consist of the expenditures needed to maintain and manage the project, and usually include management, operation and maintenance costs. Transaction costs are generally characterized as any other unaccounted information costs, and typically consist of monitoring, enforcement and administration costs (McCann *et al.*, 2005). Compared with the opportunity, start-up and on-going costs, transaction costs are usually the least visible and least easily measurable cost item. In this case, transaction costs relate more specifically to the development and implementation of contracts for carbon sequestration in the different forest conservation projects.

Finally, any benefit resulting from avoided deforestation is also of importance in considering the net costs of conservation. Benefits may accrue to different groups who rely on and value environmental services, including watershed services such as irrigation or drinking water supply, soil protection, and timber and non-timber revenues from sustainable forest management. The monetary value of the benefits derived from these services can be subtracted from the costs of forest conservation to derive the net present value of the unit costs of avoided deforestation, as formulated in Eq. (2.1):

$$NPV_{cost\ of\ avoided\ deforestation} = \sum \frac{\frac{C_t - B_t}{(1+r)^t}}{CER} \tag{2.1}$$

where *NPV* is the net present value, *C* are the total costs (per hectare), *B* are the benefits of avoided deforestation or conservation (per hectare), *CER* is the carbon emission reduction (per hectare), *t* is a time index and *r* is the discount rate. Costs and benefits are measured in monetary terms and carbon emission reduction in tonnes. As can be seen from Eq. (2.1), the effect of the discount rate on cost increases exponentially the further into the future the costs occur, while carbon density, i.e. the amount of carbon stored per hectare of land, is inversely correlated to the cost: at the same total cost, forested land with a higher carbon density will exhibit lower unit costs (per tonne of carbon).

The discounted cost of avoided deforestation in Eq. (2.1) as the dependent variable is regressed on a number of possible explanatory factors, as shown in Eq. (2.2), relating to (i) the cost estimate (Cost), (ii) the carbon storage capacity of the forest and other co-benefits (Carbon), (iii) alternative non-forested land uses and beneficiaries (Nonforest), and (iv) other location- or region-specific factors (Other), such as the country in which the forest is located, the average deforestation rate in the particular country and the share of agriculture in the country's GDP.

$$y_{ij} = \sum \beta X_{ij} = \beta_0 + \beta^{CO} Cost_{ij} + \beta^{CA} Carbon_{ij} + \beta^{NF} Nonforest_{ij} + \beta^{OT} Other_{ij} + \omega_{ij} \tag{2.2}$$

In Eq. (2.2), y_{ij} is the vector of net present values of the cost of avoided deforestation i from study j, X_{ij} is the design matrix of corresponding regressors consisting of the four aforementioned categories of explanatory factors and β is the vector of associated effect estimators. The superscript indicates to which group of regressors the estimated coefficient belongs. β_0 is the intercept and ω_{ij} is the vector of residual terms, which are assumed to be normally distributed with mean zero and variance σ^2.

Regression analysis is typically employed in meta-analysis, with specialised variations being used to address methodological and econometric issues (Nelson and Kennedy, 2009). Performing a successful analysis involves a number of challenges (Johnston and Rosenberger, 2010). These include the difficulties of ensuring commensurability across data sets, the variation in methods and approaches because the experiments are not controlled, limited data sets and inadequate methods of analysis (Smith and Pattanayak, 2002). The choice of a meta-regression model has to take due account of data heterogeneity, heteroscedasticity and otherwise correlated observations (Nelson and Kennedy, 2009). Heterogeneity in the primary data occurs because studies have different characteristics, are based on different populations, and vary in design and methods. Standard approaches to address heterogeneity are to include suitable regressors in the analysis or conduct a series of random draws from the data set using a random effect size model (Nelson and Kennedy, 2009). Heteroskedasticity occurs when the variances across samples are non-constant, for reasons such as differences in sample size and estimation procedures. A standard approach for addressing heteroskedasticity is to weight the observations, preferably with greater focus on observations with lower variance (Nelson and Kennedy, 2009). Correlation within and between primary studies can occur when a number of split samples are generated from a single study or when the same data set is used for more than one prediction model. Methods to address this include selecting only one sample from each study, using hierarchical regression techniques or applying random effects panel data corrections (Nelson and Kennedy, 2009).

For this study, a number of regression models were estimated to assess the robustness and stability of the impacts of the explanatory factors. The selection of models was based on those presented in the existing literature (van Kooten *et al.*, 2004, 2009) and the outcomes of statistical tests of the models' underlying distributional assumptions. In order to account for correlated effect size estimates, i.e. cross-sectional correlations between multiple observations from the same or different studies, both within-study and between-study error variance was factored into the regression model. Making the errors depend on explanatory factors and including them in the random part of the model allows a random-effects regression model to be estimated. The error becomes a composite matrix including the stochastic disturbances associated with the fixed and random effects in the model's design matrix. This is shown in Eq. (2.3).

$$y_{ij} = \beta_0 + \beta^{CO}Cost_{ij} + \beta^{CA}Carbon_{ij} + \beta^{NF}Nonforest_{ij} + \beta^{OT}Other_{ij} + \varepsilon_{ij} + \mu_j \quad (2.3)$$

In Eq. (2.3), ε_{ij} is the residual associated with the slope parameter β (indicating within-study variation) and μ_j that associated with the intercept β_0 (indicating between-study variation). The error terms ε_{ij} and μ_j are identically and independently normally distributed with mean zero and variance of σ_e^2 and σ_u^2, respectively.

2.3 DATA DESCRIPTION

The main literature sources for our meta-analysis were peer-reviewed articles available from the Webs of Science, followed by studies found in published books and reports. The meta-analysis is therefore somewhat biased towards the inclusion of published studies. There are certain well-documented disadvantages associated with the inclusion of published literature only. At the same time, peer review can also be considered an important quality indicator of the studies included in the meta-analysis. We were unable to find much other, 'grey' literature, i.e. unpublished studies. Only one study was included from the cited previous literature reviews (Makundi and Okiting'ati, 1995)[2]. The meta-analysis presented here is hence based on a new database of primary studies, including studies carried out after publication of the two existing meta-analyses (van Kooten *et al.*, 2004, 2009) between 2005 and 2012, when the proposal of reduction of emissions from deforestation and degradation (REDD) resurfaced on the political agenda.

The resultant database comprises a total of 32 studies, published between 1995 and 2012, yielding 227 observations in total. The studies included in the meta-analysis are listed in Table 2.1, together with the mean and median unit costs found in each study. The number of observations (Nobs) per study varies between 1 and 32, with an average of 7 and with half of the studies producing 4 observations per study (median value). In the meta-regression model, control will be included for the fact that most studies produced multiple cost estimates. About one third of the studies (11) presented a single cost estimate. As presented in Table 2.1, main factors accounting for the multiplicity of observations in each primary study include variations in alternative land uses, discount rate, area size and carbon density.

[2] Because the excluded studies do not match our selection criteria, i.e. they neither focus on avoided deforestation activities nor are they projects in developing countries.

Oversampling between primary studies was carefully checked and found to have no impact on the final results[3]. The use of data extrapolation in the primary studies, for example applying national-scale data to local-scale cases, was also found to have no impact[4].

The cost of avoided deforestation is measured in 2005 US$ per tonne of carbon (referred to in this paper as the unit cost in order to distinguish it from total costs). While most studies provide explicit information on cost estimates, this was not readily available in all cases and the unit cost was then calculated indirectly based on the data and information provided in the study in question. For instance, some studies present separate information on the cost per hectare (US$/ha) and the carbon stock per hectare (tC/ha), so the former had to be divided by the latter to obtain the required unit cost. Costs were originally measured in US$ in all the studies and there was therefore no need to convert different currencies into a common denominator based on Purchasing Power Parity (PPP). Unit costs were converted to the same price level year (2005 US$) by applying the appropriate price inflation index (source: http://data.worldbank.org). As expected, a relatively high mean discount rate, about 9% per annum, was used across the different studies in this developing country context where the annual economic growth rate (and hence the opportunity costs of capital) is relatively high. The average time horizon used to estimate the NPV of the unit costs was just over 30 years.

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[3] Only a few studies used carbon density estimated by others for studies that are also included in our analysis. Coomes *et al.* (2008) and Potvin *et al.* (2008) used Kirby (2005)'s carbon density while Grieg-Gran (2009) and Börner and Wunder (2008) employed Houghton (2005)'s carbon density. Regarding the (opportunity) costs of avoided deforestation, the cost estimates in almost all cases were based on multiple sources and adapted to match the economic situation of the study area. In some cases estimates for opportunity costs or other cost components were adopted from other studies. Potvin *et al.* (2008) employed Grieg-Gran's estimate for transaction costs. Ruslandi *et al.* (2011) adopted Venter *et al.* (2009)'s price for oil-palm plantations. Given the frequent use of observations from Grieg-Gran's (2009) study, we re-ran the models with the exclusion of the 28 observations from this study and found that the main results stayed the same. Oversampling occasionally occurred in a limited number of observations, but this did not have any major impact on the results of this meta-analysis.

[4] Studies where original cost data on national scale were applied to a local case (and vice versa) are Butler *et al.* (2009), Grieg-Gran (2009), Silva-Chávez (2005), Ravindranath *et al.* (2001) and Potvin *et al.* (2008), of which most observations relate to Grieg-Gran (2009). We re-ran the models with the exclusion of this study (Grieg-Gran, 2009) and found that the main results stayed the same.

In those cases where insufficient data or information was available, either for the dependent or independent variables in the regression analysis, authors were contacted and asked for their help. The explanatory variables used previously in the studies by van Kooten *et al.* (2004, 2009) are highlighted in bold in Table 2.2 and include regional and national scope, soil carbon, carbon density and discount rate. Hence, compared to these previous analyses, several variables included in the analysis presented here are new. It should be noted that although opportunity cost was included as an explanatory variable in van Kooten *et al.* (2004, 2009) too, it was treated as an additional cost component in their studies besides investment and implementation costs and not always accounted for in the studies included in the meta-analysis. Opportunity cost in our study is a main component of the unit cost and reported in all study observations.

Table 2.1 Overview of studies selected for inclusion in the meta-analysis

Study	Nobs	Varying factor	Mean cost ($/tC)	Median cost ($/tC)	Country/ Continent	Scale	Cost component	Method	Co-benefits
Bellassen and Gitz (2008)	1		10.45	10.45	Cameroon	National	OC	Averaging	No
Blaser and Robledo (2007)	12	Alternative land use	9.22	10.27	Africa, SE Asia, Latin America	Regional	OC	Averaging	No
Boer (2001)	1		4.18	4.18	Indonesia	National	Start-up and on-going costs	Modelling	No
Börner and Wunder (2008)	5	Alternative land use & area size	16.65	11.70	Brazil	Local	OC, start-up and on-going costs	Option ranking	No
Butler *et al.* (2009)	1		72.16	72.16	Indonesia	Local	OC, start-up and on-going cost	Option ranking	No
Coomes *et al.* (2006)	2	Alternative land use	6.16	6.16	Panama	Local	OC, and on-going costs	Averaging	No
Diaz and Schwartzman (2005)[a]	6	Alternative land use	4.05	3.41	Brazil	National	OC	Averaging	No
Grieg-Gran (2009)	28	Alternative land use, carbon density & area size	8.01	7.10	> 6 countries[c]	National	OC and transaction costs	Averaging	No
Fisher *et al.* (2011)	2	Alternative land use	119.39	119.39	Malaysia	Local	OC	Averaging	No
Fisher *et al.* (2011)	1		29.92	29.92	Tanzania	National	OC and on-going costs	Averaging	No
Irawan *et al.* (2011)	30	Alternative land use & discount rate	28.88	15.40	Indonesia	Local	OC	Averaging	No

Kindermann *et al.* (2008)[b]	6	Carbon density & area size	58.59	48.22	Africa, SE Asia, Latin America	Regional	OC	Modelling	Yes (timber)
Kremen *et al.* (2000)	6	Discount rate & time horizon	19.40	16.89	Madagascar	Local	OC and on-going costs	Averaging	Yes (eco-tourism)
Lasco *et al.* (2001)	1		0.70	0.70	Philippines	National	Start-up and on-going costs	Modelling	No
Makundi and Okiting'ati (1995)	1		13.46	13.46	Tanzania	National	Start-up cost	Averaging	No
Nepstad *et al.* (2007)	4	Alternative land use	5.16	5.12	Brazil	National	OC	Averaging	Yes (timber)
Nepstad *et al.* (2009)	1		6.64	6.64	Brazil	National	OC	Averaging	Yes (timber) [e]
Osafo (2005)[a]	1		29.59	29.59	Ghana	Local	OC	Averaging	No
Osborne and Kiker (2005)	32	Discount rate; time horizon; carbon density & cost component	0.39	0.29	Guyana	National	OC	Averaging	Yes (non timber forest products) [e]
Potvin *et al.* (2008)	2	Cost component	3.96	3.96	Panama	National	OC, start-up, on-going & transaction cost	Averaging	No
Ravindranath *et al.* (2001)	1		0.95	0.95	India	National	Start-up and on-going cost	Modelling	No
Ruslandi *et al.* (2011)	2	Alternative land use	30.29	30.29	Indonesia	Local	OC	Averaging	No
Sathaye *et al.* (2006)	8	Carbon density & area size	170.85	165.35	Africa, SE Asia, Latin America	Regional	OC	Modelling	Yes (timber and non-timber

									forest products)
Sathaye *et al.* (2008)[b]	6	Carbon density & area size	57.77	30.82	Africa, SE Asia, Latin America	Regional	OC	Modelling	Yes (timber)
Silva-Chávez (2005)[a]	1		4.44	4.44	Bolivia	National	OC	Averaging	No
Sohngen *et al.*(2008)	20	Carbon density & area size	46.63	25.52	Africa, SE Asia, Latin America	Regional	OC	Modelling	Yes (timber)
Sohngen *et al.* (2008)[b]	6	Carbon density & area size	24.56	22.18	Africa, SE Asia, Latin America	Regional	OC	Modelling	Yes (timber)
Strassburg *et al.* (2009)	16	Alternative land use, carbon density & area size	22.55	22.90	>10 countries[d]	National	OC, start-up and on-going cost	Option ranking	No
Tomich *et al.* (2002)	10	Alternative land use	21.10	21.21	Indonesia	Local	OC	Averaging	No
Venter *et al.* (2008)	4	Alternative land use	50.14	40.76	Indonesia	Local	OC and transaction costs	Averaging	No
Wangwacharakul and Bowonwiwat (1995)	9	Discount rate	6.75	7.00	Thailand	National	OC and on-going costs	Averaging	Yes (recreation)
Yamamoto (2012)	1		11.77	11.77	Indonesia	Local	OC	Averaging	No
All studies	**227**		**26.17**	**10.27**					

[a] All in Moutinho and Schwartzman (2005).

[b] All in Kindermann *et al.* (2008).

[c] Bolivia, Brazil, Cameroon, Congo, Ghana, Indonesia, Malaysia.

[d] Brazil, Democratic Republic of Congo, Indonesia, Peru, Sudan, Congo, Mexico, Colombia, Angola, Bolivia, Venezuela, Zambia, Tanzania, Myanmar, Central African Republic, Gabon.

[e] Not applied to all estimates.

Table 2.2 Overview of variables used in the meta-regression model

Variable	Description	Unit	Mean value	St. Dev.	Min-max values
Dependent variable					
Unit cost	Cost of avoided deforestation	US$/tC	26.17	45.62	0.15-338.54
Independent variables					
1) Cost characteristics					
Opportunity costs	Only opportunity costs of alternative land use are measured in the unit cost estimate	Dummy	0.67	0.47	0-1
Additional costs	Additional cost components also included in the unit cost estimate	Dummy	0.31	0.46	0-1
Averaging	Cost estimated by using (empirically collected) data on total cost and total carbon emissions reduction	Dummy	0.69	0.46	0-1
Modelling	Cost estimated by simulating the relation between emissions reduction and carbon price	Dummy	0.21	0.41	0-1
Option ranking	Cost estimated by employing the highest empirically observed or estimated cost amongst various land use activities	Dummy	0.10	0.30	0-1
Prior logging	One-time prior logging costs included in the unit cost estimation	Dummy	0.36	0.48	0-1
Discount rate	Discount rate used to estimate NPV	%	9.11	4.91	0-20
Co-benefits	Whether co-benefits of avoided deforestations are considered in the unit cost estimate	Dummy	0.30	0.46	0-1

2) Carbon storage characteristics					
Area size	Total area conserved	Mha	24.26	39.60	25 ha-258
Carbon density	Carbon density of area	tC/ha	134	116	17-884
Below ground	Below-ground carbon also included in carbon accounting*	Dummy	0.66	0.48	0-1
Soil carbon	Soil carbon also included in carbon accounting*	Dummy	0.35	0.48	0-1
Time horizon	Time horizon considered in calculating the NPV of the unit cost	Years	31.59	11.52	10-50
3) Alternative land uses considered in opportunity cost calculation and beneficiaries					
Logging	Commercial logging	Dummy	0.37	0.49	0-1
Plantation	Rubber and palm oil plantations	Dummy	0.50	0.50	0-1
Cropping	Crop farming	Dummy	0.59	0.49	0-1
Animal farming	Animal farming	Dummy	0.36	0.48	0-1
Private	Private agents as beneficiaries of non-forest land uses	Dummy	0.78	0.42	0-1
State	State as beneficiary of non-forest land uses	Dummy	0.26	0.44	0-1
4) Other location characteristics					
SE Asia	Study location is in South-East Asia	Dummy	0.38	0.49	0-1
Africa	Study location is in Africa	Dummy	0.22	0.41	0-1
Latin America	Study location is in Latin America	Dummy	0.40	0.49	0-1
Local	Study scope is local, i.e. village level	Dummy	0.28	0.45	0-1
Regional	Study scope is regional, i.e. (sub)continent	Dummy	0.46	0.43	0-1
National	Study scope is national, i.e. country level	Dummy	0.28	0.50	0-1
Deforestation	Deforestation rate in study country	%/year	1.09	0.98	0.02 – 6.00
Agriculture share	Share of agriculture in GDP	%	17.81	9.58	4-54

* In addition to above-ground carbon, which was reported in all studies.

Note: variables also used in van Kooten *et al.* (2004, 2009) are highlighted in bold.

At study level, the unit cost of avoided deforestation ranges from US$ 0.4/tC to US$ 171/tC, with a mean of US$ 26.2/tC (Table 2.1). Despite the considerably lower overall median cost value of US$ 10.3/tC, the range of median values (US$ 0.3/tC – US$ 165/tC) is very similar to the range of mean values. At individual observation level, the range is twice as large and estimates vary between US$ 0.15/tC and US$ 339/tC (Table 2.2). The meta-regression analysis was carried out based on the unit costs at observation level. Given that the analysis focuses exclusively on forest conservation in developing countries, we only targeted case studies carried out in Central and South America (hereafter: Latin America), Asia and Africa. Most country studies were conducted in Indonesia (7), followed by Brazil (4), Panama (2) and Tanzania (2). The highest unit cost (US$ 339/tC) was observed in Indonesia. On average, there is a significant difference between the unit costs estimated for different locations, with the highest cost values observed in case studies conducted in South-East Asia (US$ 35/tC)[5]. The average unit costs in studies carried out in Africa are fairly similar to those in Latin America (around US$ 20/tC).

The scope of the studies varies from local to national and regional scale, where local refers to village or community level and regional in this case to (sub-) continents. Most studies focus on the national level (46%), followed by the local (28%) and regional level (26%). A significant difference can be detected between the unit costs in local, national and regional scale studies. Studies that focus on the regional scale produce the highest average cost estimate (US$56/tC) and also a relatively higher standard deviation, followed by local (US$ 30/tC) and then national studies (US$ 7.5/tC)[4]. Two studies (Grieg-Gran, 2009; Strassburg *et al.*, 2009) focus on a number of specific countries in Africa, South America and Asia.

Concerning the methods used to derive the unit cost, three main methodologies were employed in the selected studies: averaging (156/227 obs.), modelling (49/227 obs.), and option ranking (22/227 obs.). In this study, we find significant differences between unit costs calculated by these different methods with modelling generating the highest estimate (US$ 64/tC), followed by option ranking (US$ 24/tC) and then averaging (US$ 15/tC). The averaging technique depends on the total costs and the total carbon emission reduction accruing from avoided deforestation and are typically calculated manually based on the collected information on costs and carbon sequestration capacity in the underlying forest

[5] The Mann-Whitney test is used throughout the paper to examine the significance of observed differences.

studies. Simulation models, on the other hand, construct marginal cost curves to reflect the amount of money paid for an incremental reduction of carbon emission. There are currently three main global simulation models that have been used, known as GTM, DIMA and GCOMAP (Wertz-Kanounnikoff, 2008). Generally, marginal costs yield higher estimates than average costs (van Kooten *et al.*, 2009)[6]. Last but not least, a few studies such as Börner and Wunder (2008), Butler *et al.* (2009), and Strassburg *et al.* (2009) calculated the unit costs for different land use options based on empirical data and then adopted the one with the highest value as the "marginal" cost estimate (for the whole study area). Data collected from the field therefore play a vital part, not only in averaging, but also in ranking alternative options.

In terms of cost components, a distinction was made between unit costs based on opportunity costs (OC) only and unit costs based on additional cost components such as start-up, on-going and transaction costs (Table 2.1). The number of observations was too low to be able to explicitly distinguish between the latter three cost components separately, and for this reason a single dummy variable was created (Table 2.2) with the aim of examining how additional cost components affect the observed variation in cost estimates. Giving sole consideration to opportunity costs was anticipated to underestimate the true economic cost (World Bank, 2011). In total, about 30% of all observations relate to studies in which other cost components besides opportunity costs are also included. Not controlling for any other influencing factors, the mean unit costs based solely on opportunity costs (US$ 31/tC) are, surprisingly, almost twice as high as the mean unit costs based on opportunity costs and other cost components (US$ 16/tC). However, the difference proves to be statistically insignificant at the 10% level. The unit costs without co-benefits (US$ 27/tC) are, as expected, slightly higher than those with co-benefits (US$ 24/tC), but this difference too is not statistically significant. All in all, 30% of the observations take account of other joint benefits of forest conservation besides maintaining carbon stocks. Of these, 15 observations from two studies (5% of all observations) incorporated both additional cost items and co-benefits.

[6] Note that van Kooten *et al.* (2004, 2009) used a dummy variable distinguishing between marginal and average unit cost as an explanatory variable in their meta-analyses. We find, however, that the distinction is related to different methodological approaches used to estimate the unit costs, and therefore use method dummies in our analysis instead.

Given that opportunity costs depend directly on available alternative land uses, different types of non-forest land use were identified as additional explanatory variables in the meta analysis. Non-forest land uses were grouped into four categories: (i) commercial logging, (ii) rubber and palm oil plantations, (iii) cropping and (iv) animal farming. As expected, significant differences are found when comparing unit costs based on the opportunity costs associated with these four categories, with rubber and palm oil plantations having the highest mean unit cost (US$ 34/tC), followed by cropping (US$ 31/tC), animal farming ($US 25/tC) and logging ($US 21/tC).

Alternative non-forest land uses were also examined in terms of their beneficiaries. To this end we distinguish between the type of benefits generated by private and state agents[7]. If the beneficiaries are private agents, they generate income from the land by selling the products and produce derived from forest land conversion, e.g. crops, cattle, timber and plantation products, while the benefits generated by the state or government agents consist mainly of the revenues from issuing forest use rights, taxation, employment, and infrastructure development (Kremen *et al.*, 2000; Diaz and Schwartzman, 2005; Osborne and Kiker, 2005; Irawan *et al.*, 2011). Comparing the mean unit costs between these two groups of beneficiaries, the unit opportunity costs are found to be significantly higher for private stakeholders (US$ 132/tC) than for state stakeholders (US$ 53/tC).

Turning to the carbon storage characteristics, the average area of protected forest was very high, namely almost 25 million hectares (varying between 25 ha and 258 Mha), owing to the fact that some of the studies covered entire continents. These forested areas are reported to store, on average, 134 tC per hectare (ranging from 17 to 884 tC/ha). The fact that the studies differ in the extent to which carbon sink sources are accounted for was factored in. Besides above-ground carbon storage, some studies also account for carbon storage in below-ground biomass (e.g. root systems) and soils. Compared to previous reviews (Sedjo *et al.*, 1995; Richards and Stokes, 2004; van Kooten *et al.*, 2004, 2009), we did not include carbon stored in long-lived products, since this type of carbon sink is not included in any of the more recent cost studies in the present meta-analysis. The expectation is that if below-ground carbon storage is also taken into account, i.e. additional to above-

[7] The distinction between "state" and "private" beneficiary is based on the type of income generated from alternative land uses and does not necessarily capture formal or informal landownership. Private beneficiaries may therefore include farmers generating income on state land. Insufficient information was available about landownership, both formal and informal, and this could therefore not be included as an additional explanatory factor in the regression analysis.

ground storage, this will significantly affect the unit cost estimate. Given the same cost estimate, a higher carbon storage capacity based also on below-ground carbon storage should, theoretically speaking, result in a lower unit cost per tonne of carbon. In the present study, however, accounting for below-ground and/or soil carbon resulted in a significantly higher mean unit cost estimate (US$ 29/tC compared with US$ 15/tC for aboveground carbon only), due to the fact that these studies also report substantially higher estimates for opportunity costs.

Finally, deforestation rates and the share of agriculture in GDP were also included in the analysis to represent pressures on forest conservation. In general, high opportunity costs tend to be associated with high deforestation pressures (World Bank, 2011). Similarly, a high share of agriculture in GDP is also considered an important indicator of the opportunity costs of non-forest land use. These variables capture more general location or region specific state variables, which are expected to provide insight into general trends in the economic costs of avoided deforestation comparable to more general economic trends and their effects on for instance the housing market and house prices. Hence, we try to also filter out those more general trends in our analysis that may have an influence on the economic costs. Data about the share of agriculture in GDP was obtained from the World Bank's open access database (www.data.worldbank.org) and showed a relatively high average dependency rate of almost 18%. Data on deforestation rates at both the national and regional level were obtained from FAO (2005). For studies focusing on local-level forest conservation projects and not reporting deforestation rates the national deforestation rate was applied. This was only the case for 19 observations from 4 of the 32 studies, so we assume that this procedure did not significantly affect the final outcomes. The mean deforestation rate was just over 1% per year, ranging from 0 to 6% across countries.

2.4 ESTIMATED META-REGRESSION MODEL

The estimated meta-regression models are presented in Table 2.3. Four different models, with and without random effects to account for variation within and between studies, are presented in order to examine the estimated models' robustness and the stability of the coefficients. The first two models, i.e. OLS and GLS, were also employed in van Kooten *et al.* (2004, 2009), while the two Tobit models are introduced as new models in this study. The Shapiro–Wilk statistic was used to test the normal distribution of the dependent variable. Based on the test result, the null hypothesis of a normal distribution was rejected at the 1% level. Given the censored nature of the distribution, a Tobit model was considered more appropriate than the OLS or GLS model. In addition, a Hausman test was also carried out to examine the impact of random effects on model results, justifying the inclusion of random parameters to account for correlated estimates between and within studies. Given this result, we employed both the fixed and random effects Tobit model with a preference for the latter model.

Table 2.3 Estimated meta-regression models

Explanatory variable	**OLS fixed effects** Coefficient estimate	Std. err.	**GLS random effects** Coefficient estimate	Std. err.	**Tobit fixed effects**[a] Coefficient estimate	Std. err.	**Tobit random effects**[a] Coefficient estimate	Std. err.
Intercept	42.880**	20.861	53.254*	29.068	42.880**	19.824	54.070**	25.489
1) Cost characteristics								
Additional costs	19.049**	8.738	16.592	14.352	11.735**	5.414	9.857	7.780
Averaging	-55.748***	9.176	-34.191**	17.273	-37.637***	6.670	-24.851**	10.100
Option ranking	-73.777***	14.079	-47.034*	28.637	-26.841***	3.038	-22.871***	7.211
Prior logging	41.577***	7.647	29.088***	8.539	26.518***	5.098	18.982***	5.639
Discount rate	-4.826***	1.910	-1.247	2.297	-2.810***	1.062	-1.026	1.281
Discount rate sq.	0.235***	0.094	-0.001	0.113	0.137***	0.052	0.021	0.065
Co-benefits	-8.883	6.784	-4.497	8.612	-5.026	3.548	-3.449	4.508
2) Carbon storage characteristics								
Area size	0.356***	0.073	0.366***	0.073	0.207***	0.041	0.208***	0.045
Carbon density	-0.106*	0.060	-0.162***	0.058	-0.062*	0.034	-0.087***	0.034
Carbon density sq.	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
Below-ground carbon	-11.152*	6.107	-1.541	7.634	-6.678*	3.581	-2.377	4.325
Soil carbon	-11.213	7.274	0.920	9.109	-6.358*	3.82	-0.664	4.971
Time horizon	-0.912***	0.330	-0.725	0.601	-0.531***	0.184	-0.547*	0.295
3) Alternative land uses and beneficiaries								
Logging	27.798***	6.707	27.516***	7.694	17.110***	4.181	16.823***	4.871
Plantation	-2.135	6.084	0.955	6.788	-1.243	3.366	0.574	3.709
Animal farming	-18.919**	8.729	-20.355**	9.729	-10.552**	4.452	-11.049**	5.030
Private beneficiary	17.561*	9.166	14.435	9.512	9.452**	4.336	8.736*	4.674

4) Other location characteristics								
National scale	-8.414	8.492	-22.372	15.357	-4.875	4.658	-10.715	7.466
Deforestation rate	1.567	3.490	-4.620	4.702	0.912	1.931	-1.891	2.536
Agriculture % in GDP	0.555	0.382	0.627*	0.353	0.323	0.212	0.356*	0.201
Continent is Africa	-32.656***	8.036	-34.047***	7.931	-16.366***	3.329	-16.916***	3.783
Model summary statistics								
F-test statistic	11.01***							
Wald χ^2 (21)			93.05***				108.25***	
R-squared	0.5301		0.4180					
Within variation			0.3054					
Between variation			0.3543					
Sigma_μ			31.510				22.474	
Sigma_ε			28.383				27.676	
Rho (fraction of variance due to μ_i)			0.5521				0.3974	
Shapiro-Wilk Nomality test statistic			9.916***					
Hausman test χ^2 (20)			49.70***					
N	**277**		**277**		**277**		**277**	

*, **, *** statistically significant at 10%, 5% and 1% respectively.

[a] All estimated coefficients except the constant terms are calculated as marginal effects for the expected value of the dependent variable, conditional on being uncensored $E(y|y>0)$.

The presented models were found after a careful (backward and forward elimination) search process in Stata version 11 based on a priori theoretical expectations regarding influencing factors (see Section "Methodology") and the limited empirical evidence concerning relevant factors. Possible correlation between explanatory factors was tested (and not found to play a significant role), as were linear and non-linear (e.g. quadratic or logarithmic) relationships between the dependent and independent variables[8]. To account for the possible effects of including explanatory variables that are also components of the dependent variable, we excluded those and re-ran the regression. Results show no major changes either in the significance levels or the sign of the estimated coefficients (negative or positive) of other explanatory variables[9].

Sixty percent of the variables (13 out of the 21) included in the meta-regression models in Table 2.3 are dummies. Table 2.3 presents the marginal effects of the two estimated Tobit models. The estimated models are highly significant, as shown by the outcome of the F-test for the OLS model and the Wald chi-square test for the random effects GLS and Tobit model. The explanatory power could only be measured through the adjusted R-squared for the OLS and GLS regression models (the Tobit models were estimated using maximum likelihood regression techniques), which shows that the overall explanatory power is fairly high (42–53%). From both the random effects GLS model and the Tobit model it appears that a relatively high fraction of the error variance (40–55%) is furthermore attributable to between-study variation.

Explanatory factors that that were found to be robust, i.e. with a consistently significant effect on the estimated unit cost of avoided deforestation in all four meta-regression models, include the following eight variables: the use of averaging or option ranking (compared to econometric modelling, which is the baseline category in the estimated regression models), if the benefits foregone included revenues from prior logging

[8] Tests were conducted to examine various transformations, but these all produced the same results as presented in Table 2.3.

[9] As can be seen from Eq. (2.1), these variables are the discount rate and its squared term, carbon density and its squared term, and time horizon. Excluding these variables only the variable 'animal farming' changed from being significant in all models to being significant in the GLS and the Tobit random effects model at the 15% level, while the variable 'national scale' changed from being significant in the GLS and the Tobit random effects model at the 15% level to significant in the OLS, fixed and random effects Tobit model at the 10% level or better. We therefore believe the results presented here are robust.

instead of slash and burn (which is the baseline category in the estimated regression models), area size, carbon density, if the second best alternative land use was (timber) logging or animal farming instead of cropping (the baseline) and if the study was conducted in Africa instead of Latin America or South-East Asia (the baseline)[10].

Controlling for a wide variety of other influencing factors in the meta-regression model, unit costs calculated using averaging as the estimation method are, as expected, ceteris paribus US$ 24.85 lower than model based unit costs in the random effects Tobit model presented in the second last column of Table 2.3. Meanwhile, the use of option ranking results in a decline of US$ 22.87 in the unit cost. Regarding carbon accounting, based on the OLS model estimated with a reduced data set, van Kooten *et al.* (2009) identified a linear relationship between carbon density and unit cost, with the latter declining by US$ 0.34 as a result of a one tonne increase in carbon density. In this study we also find a significant negative effect for carbon density in the random effects Tobit model, indicating that the unit cost will drop by US$ 0.09 if carbon density increases by one tonne. A quadratic relationship between carbon density and the unit cost could, however, not be detected in the estimated regression models.

Compared with commonly practiced slash and burn, prior logging generates US$ 18.98 more per tonne of carbon. While animal farming produces US$ 11.05 less compared with cropping, land used for (timber) logging yields ceteris paribus a US$ 16.82 higher unit cost in the random Tobit model. An increase in forest area by one million hectare results ceteris paribus in an increase in the unit cost of US$ 0.21. Studies conducted in Africa furthermore produce ceteris paribus significantly lower unit cost estimates of US$ 16.92 compared with studies carried out in Latin America or South-East Asia, possibly due to the generally lower degree of economic development in Africa compared with the other two continents (and hence generally lower economic returns on alternative land uses).

Contrary to expectations, the inclusion of the squared term for carbon density, whether unit cost estimates included co-benefits or whether the value was extracted from a national study instead of a local or regional one did not have a significant effect in any of the estimated meta-regression models. This latter finding corresponds with the result reported

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[10] Due to a high correlation between the two variables "Latin America" and "South-East Asia" and other variables, both of them were used as the baseline in our models. For the same reason also, the "regional" and "local" variable were both used as the baseline category to avoid multicolinearity.

in van Kooten *et al.* (2009), who were also unable to detect a significant influence of the (regional) scope or scale of the study in their metaregression models. In addition, compared with cropping, rubber or oil-palm tree plantations also never show a significant effect irrespective of model specification, while the same holds for the new variable 'deforestation rate' included in the present meta-analysis.

There are a number of explanatory factors that only have a statistically significant effect on the unit costs in the fixed effects OLS and Tobit models, such as the inclusion of additional cost items, below-ground carbon accounting, and the rate used to discount the costs of avoided deforestation and its squared term. At the 5% significance level, additional cost components had a positive impact on the unit cost, increasing the unit cost ceteris paribus by US$ 11.74, while taking into account carbon stored below-ground in addition to above-ground leads to a US$ 6.68 lower unit cost. As expected, the discount rate has a significant negative effect on the unit costs, whilst the magnitude of the effect depends on the time horizon as well. A 1% increase in the discount rate results ceteris paribus in a US$2.81 decrease in the unit cost based on the fixed effects Tobit model. However, the significant positive squared effect in the fixed effects models implies there is a turning point, in this case at 10%[11]. After this point, the effect of the discount rate becomes positive. A possible reason underlying this result is that the effect of the discount rate on the NPV depends strongly on the point in time when the cost occurs. If costs occur early on in the projects, then the discount rate will have little effect on the NPV. van Kooten *et al.* (2009) observed both positive and negative coefficients for the discount rate in their models, but none of them was statistically significant.

Finally, the variable 'share of agriculture in GDP' has a small, but statistically significant positive effect on the unit costs in the random effects models at the 10% level. Ceteris paribus, a 1% increase in the share of agriculture in GDP results in an increase in the unit costs of avoided deforestation of US$ 0.36. While soil carbon is only significantly correlated with the dependent variable in the fixed Tobit model at the 10% level, time horizon and private beneficiaries both have significant effects in all models except for the GLS model. Inclusion of soil carbon ceteris paribus reduces the cost per tonne of carbon by

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[11] van Kooten *et al.* (2009) studied the effects of discount rates used separately for carbon yields and costs (and neither had a significant impact on the forest carbon offset costs considered in their study). Discounting of carbon yields was more commonly employed in afforestation projects in the older studies screened in their meta-analysis, but is not commonplace in the studies reviewed here.

US$ 6.36, which is comparable to the case of below-ground carbon. One extra year in the time horizon of the cost estimate results ceteris paribus in a US$ 0.55 decrease in unit costs, and if the opportunity costs accrue to a private agent rather than the state, this results ceteris paribus (based on the Tobit random effects model) in an increase of US$ 8.74 in the unit cost per tonne of carbon, indicating that non-forest land use benefits generated by private agents are higher than the state.

2.5 CONCLUSIONS AND DISCUSSION

In this study, a meta-regression analysis was used to examine and test the relationship between the unit cost of avoided deforestation in developing countries and its main underlying driving factors. Given the fact that deforestation has significantly accelerated in developing countries in recent decades, the results of this study are deemed to be of special relevance for forest conservation projects implemented in these specific regions. Our results may serve as a reference point for cases where cost estimates are not available yet. Compared with previous meta-analyses, the present analysis zoomed in on the economic costs of avoided deforestation in developing countries in Africa, Asia and Latin America. This resulted in the creation of a new database and new additional variables that are believed to significantly govern the cost per tonne of carbon in forest conservation projects. These new variables relate to factors 'internal' to the studies themselves, such as inclusion of additional cost components like transaction costs, co-benefits of forest conservation, alternative land uses and beneficiaries of non-forested land uses, and to 'external' factors taken from sources outside the studies such as deforestation rates in the study area and the share of agriculture in GDP, as indicators of land use pressures.

Data related to the cost and carbon accounting methodology employed in each primary study, alternative non-forested land uses and their beneficiaries, and other location- or region- specific factors were collected from 32 studies, providing a total of 227 observations. The unit costs of avoided deforestation were regressed against these explanatory variables using several different regression models, yielding significantly correlated estimates between and within studies. At the same time this permitted testing of the robustness and stability of the factors that have a significant impact on the unit cost. Sensitivity analysis was also carried out to test the possible effect of oversampling across primary studies, the extrapolation and upscaling of data from original studies, and the use of independent variables, which jointly make up the response variable (discount rate, carbon density, and time horizon). Results from these tests further confirm the robustness of our estimated models.

This study confirms that in developing countries, the magnitude of the unit costs depends significantly on a mixture of both study design and context factors, with 5 out of the 11 design related and 4 out of the 8 context related variables showing a significant impact on the unit cost. Amongst those are the method used to calculate costs (averaging and option ranking approaches based on empirically collected data yield ceteris paribus lower cost estimates than econometric models), the rate used to discount costs over time (a higher discount rate results in lower unit costs) and carbon density (the higher the carbon density, the lower the unit costs). Compared with findings in van Kooten *et al.* (2009), the amount of carbon stored per hectare of land was also here found to play a significant role in driving the cost per unit of carbon emission reduction, despite the fact that the carbon accounting procedures used in the different studies face substantial uncertainties and require considerable investments in both technology and capacity building, especially in the developing world. In addition, we find that the inclusion of additional cost components, prior logging, area size, alternative land uses (logging rather than cropping), beneficiaries of non-forest land uses (private rather than state) and land use pressure measured via the share of agriculture in GDP all have a significant positive effect on the unit costs of avoided deforestation.

Our results suggest, furthermore, that forest conservation projects appear to be cheaper if implemented in Africa rather than Latin America or South-East Asia. It should be borne in mind, however, that most of the studies examined here possibly neglected other relevant factors, including the transaction costs related to weak institutions and limited governance capacity in the regions concerned. Taking into account transaction costs will certainly raise the costs of avoided deforestation, thereby challenging the cost-effectiveness of conservation projects in developing countries. Our effort invested in identifying and categorizing different cost features in the database has shown that incorporating more cost components into the calculation influences the magnitude of the unit cost estimate. Contrary to expectations, none of the two newly introduced variables “co-benefits” and “deforestation rate” appears to have a significant effect on the unit costs of avoided deforestation. Future research should focus more explicitly on these additional cost components, non-market co-benefits of forest conservation, and deforestation rates.

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