Baseline Choice and Performance Implications for REDD

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Abstract

The significant contribution of deforestation to global CO_2 emissions has favored the emergence of new schemes (REDD, REDD+), which offer carbon payments in exchange for reductions in emissions from deforestation below business-as-usual scenarios. Using a general timber extraction model, we specifically assess the impact of four different crediting schemes on deforestation levels and REDD performance in a dynamic setting. We find that different performance indicators promote distinctive baselines, depending on the deforestation history of the area. Moreover, corridor bandwidth and symmetry influence REDD success. We individuate the symmetric and narrow variable corridor 2 as the overall best performer, offering top results in terms of effectiveness in reducing emissions from deforestation, guaranteeing at the same time a positive though modest increase in welfare, achieved at medium efficiency levels.

Keywords: Climate change; Deforestation; REDD projects; Baselines

1 Introduction

The importance of forest protection has been recently heightened by its central role to curb global warming. According to UN (2011), deforestation has been estimated to con-

tribute 17% of total greenhouse gas emissions (GHG). While it has globally slowed down recently[1], it remains a global issue with numerous damages to habitat and biodiversity, increased desertification, and soil erosion.

To address this problem, the thirteenth UNFCCC conference of the parties (COP 13, 2007) at Bali established a clear mandate to create solutions for emission reductions from deforestation and forest degradation (REDD and REDD+, Chatterjee (2009))[2] in the climate change mitigation framework (UNFCCC, 2007).

REDD programs, like other PES schemes, support the idea that external funds could be offered in exchange for forest preservation. They entail the possibility to forest managers from developing countries to be financially rewarded for reducing GHG emissions coming from deforestation and forest degradation, and for leading sustainable forest management practices.

Under the schemes, deforesting below a certain reference level generates carbon credits, eligible for sale on various - mainly voluntary - carbon markets (Peters-Stanley et al., 2012). International emitters[3] that are above their compliance level and short of CO_2 permits may find reducing emissions internally to be prohibitively expensive (Diaz et al., 2011) and would therefore benefit from the comparative affordability of REDD permits[4].

Despite this clear advantage, REDD schemes remain complex to implement. As pointed out by Angelsen et al. (2012), they require "*transformational change in the form of altered economic, regulatory and governance frameworks, removal of perverse incentives and reforms of forest industry and agribusiness policies.*".

[1] According to the FAO, around 13 million hectares of forests were converted to other uses or lost through natural causes each year between 2000 and 2010 as compared to around 16 million hectares per year during the 1990s.

[2] The + in REDD+ refers to conservation, sustainable management of forest and enhancement of carbon stocks through soil management or agricultural activities that would maintain carbon stock levels in existing ecosystems. (UNFCCC, 2010)

[3] These emitters could be found among the European polluting companies who, due to the EU's commitment to fight climate change, need to comply with emission reduction targets.

[4] According to the Stern report (Stern, 2008), permits from REDD+ could be as inexpensive as US \$1-2 per tCO_2 on average and while these low estimates have been subject of criticisms (Kindermann et al., 2008), experts tend to share the idea that deforestation permits will be comparatively cheap.

Their success depends on a strong coordination between multiple actors at different levels, from international institutions to local communities, ensuring that the international demand for permits remains aligned with the interests and welfare of forest stakeholders. Reaching this level of coordination is critically sensitive to the incentive structure promoted by the schemes[5].

A central aspect of the incentive structure is the establishment of reference levels, the so-called *baselines*, against which reductions in deforestation are measured. Reference levels embed the nature and magnitude of the efforts required from the local forest owners, and partially determine their activity mix (timbering, agriculture, forest protection). The performance of REDD depends on the linkage between accessible activities, their GHG reduction effectiveness and the effort required[6]:

$$\text{Emission reduction} \quad = \quad (\text{activities} \cdot \text{emissions factors}) - \text{reference emissions}$$

The present paper belongs to the stream of literature dedicated to optimal contract design of REDD schemes (Rose and Sohngen, 2011; Busch et al., 2011; Sathaye et al., 2011; Busch et al., 2009). More specifically, our analysis follows a three fold purpose. Firstly, it compares the impact of different crediting baselines on optimal harvest rates, and the inherent emissions, in a dynamic setting. Secondly, we rank baselines according to different performance indicators, while accounting for the specific deforestation history of the region. Thirdly, we explore possibilities of improving baseline performance, and highlight the importance of design features, namely corridor bandwidth and symmetry. Throughout our analysis, we focus on the implications for the first D in REDD, namely *deforestation*.

While several baseline models have been proposed in the past and new ones are in-

[5]This critical role of incentives has been formalized in the UNFCCC definition of REDD:"*policy approaches and positive incentives on issues relating to reducing emissions from deforestation and forest degradation*" (UNFCCC, 2010)

[6]Angelsen et al. (2012)

troduced on a regular basis, none of them have garnered a broad political and scientific consensus. To keep the analysis comparable with single-period studies on reference levels (Busch et al., 2011, 2009; Huettner et al., 2009), we focus on three of the most popular baseline categories: a retrospective baseline based on the fixed historical average, a model-implied prospective baseline, and a conditional-based corridor approach. Additionally, we take the chance to propose a new type of baseline, the variable corridor approach, which tries to bring together the strong points of the model-implied and the corridor baselines[7]. An overview of the main baseline methodologies can be found in either Huettner et al. (2009) or Griscom et al. (2009).

Previous research on REDD design overlooked the inter-temporality dimension in forest decisions. We attempt to fill this gap, by conducting the analysis of the respective strengths and weaknesses of baseline approaches accounting for the dynamic context of forest extraction (and land-use changes). The highly dynamic nature of forest decisions has been pinpointed first in Faustmann (1849), who proposed the inclusion of discount rates when assessing the optimal rotation age of forests. His seminal approach has then evolved to account for operating costs dependent on the harvesting rate and upper boundary on deforestation (Heaps and Neher, 1979), uncertainty and irreversibility in the opportunity cost of extraction (Morck et al., 1989; Thomson, 1992; Insley, 2002), partial knowledge of the available forest stock (Alvarez and Koskela, 2007) and volatile PES (Chladná, 2007; Clarke and Reed, 1990)[8]. Dynamic modeling is not limited to models of exogenous prices. Rose and Sohngen (2011) and Sohngen and Sedjo (2006) use a dynamic partial equilibrium model to account for temporal variations in REDD prices and access. These papers suggest that static models cannot fully capture the baseline influence on optimal extraction and may miss inter-temporal trade-offs that affect the long-term forest's prospect.

[7]Each baseline is detailed in Section 2.2 of the paper

[8]Chladná (2007) determined the optimal rotation period by considering uncertain revenue streams from timbering and carbon trading. In her model, the forester has at each moment the option to either postpone the harvest and allow forest growth, or harvest and sell the land.

To remain aligned with the optimal control methodology, we model the decisions of a single forester. This setting is both coherent with the extensive literature on protected area management and ICDP (Muller and Albers, 2004; Johannesen and Skonhoft, 2005; Robinson et al., 2010) and with the literature on optimal forest extraction (Robinson et al., 2008; Angelsen, 2007). It differs however from most of the existing literature on REDD baselines, which uses either scenario analysis (Griscom et al., 2009) or static models of partial equilibrium (Busch et al., 2011, 2009) at the national level. Aggregate national estimates are important to underline specific baseline differences and interactions between country "types", but obscure the motivational "drivers" faced by each forester or forest community.

To facilitate the comparison between the different baselines, we choose an approach similar to Busch et al. (2009), by which the forester's harvesting value is modeled as a stylized and unique composite commodity (or agricultural rental price), representing both the harvesting value of timber and a perpetual discounted flow of agricultural activities. This simplification allows us to concentrate our analysis on the dynamic decisions between protecting and harvesting, and limit the precise nature of the harvesting function, which is not central to compare the reference levels, to a proxy.

Our findings bring insights into various issues regarding the design of conservation projects. Firstly, we show that baseline choice impacts land-use behavior, with REDD having a great potential in reducing deforestation and the inherent GHG emissions. Secondly, with REDD contracts designed as voluntary projects, foresters' welfares are expected to rise above business-as-usual levels, signaling high country opt-in rates. Thirdly, in our attempt to rank baselines, we demonstrate that forward-looking baselines outperform retrospective ones. Additionally, we delve into the issue of improving baseline performance by modifying scheme attributes, and call attention to the influence of corridor width and symmetry. Fourth, our results show that the final ranking of baselines depends on the preferred performance indicator and the deforestation history in the area.

Finally, the optimal baseline choice unfolds as a balancing act between effectiveness and efficiency criteria.

The rest of the paper is organized as follows: Section 2 introduces our methodology and the main assumptions of the dynamic model. We also take the chance to describe the chosen baseline approaches. In Section 3 a numerical application is performed and key findings are highlighted. The robustness of our results is tested by varying the deforestation context and specific scheme attributes. The paper concludes with the policy implications of our results and the link with broader issues of REDD+ implementation.

2 Methodology

2.1 Model setting

The model developed here describes the behavior of a forest manager that acts on perfectly competitive timber and agricultural markets. As the *de facto* user of the forest[9], he can extract its resources according to his own preferences (disregarding the existence of ownership boundaries[10]). To limit his deforestation, the manager has been offered the possibility of taking part in a REDD+ program, that rewards him with carbon credits each time his deforestation rate is below a pre-specified threshold (or a combination of thresholds). We model the voluntary access to the REDD+ along the approach of Busch et al. (2009, 2011), where the forester can "opt in" if the REDD rental value is higher than the agricultural rental price and "opt out" otherwise.

The forester's revenues are determined by the trade-off between a composite commodity income net of costs and realized REDD+ rewards. The more the manager deforests, the higher his incomes from selling timber and using land for agricultural activities and

[9]We assume for simplicity that either the forester owns the rights of the land or act in a grey area, which encompasses institutionalized "*laissez-faire*" and illegal encroachment.

[10]In this sense, we assume a scenario of actual encroachment that is prevalent in many tropical forests with weak property rights and limited control over use.

the lower his endowment of CO_2 permits. Alternatively, lower deforestation (below the defined baseline level) results in smaller incomes from composite commodity, but higher REDD+ revenues.

The rational manager maximizes the sum of total discounted profits, taking into account the parameters that define his investment environment: the state of the forest, the dynamics of composite commodity and carbon permit prices, the operational costs, and the pre-specified deforestation baseline. We allow for a continuous setting, in which the prices of the composite commodity and CO_2 permit follow two deterministic processes.

$$dP_t{}^F = \delta P_0{}^F dt \tag{1}$$

$$dP_t{}^R = \gamma P_0{}^R dt \tag{2}$$

Above, $P_t{}^F$ and $P_t{}^R$ stand for the instantaneous prices of composite commodity and REDD permits, and δ and γ for their corresponding growth rates. Being a composite, $P_t{}^F$ is a simplification of the actual commodity flow generated from the harvesting of one hectare of forest, which could be modeled as follow:

$$P_t{}^F = P_h(t) + \int_t^\infty A(t)e^{-\psi t}dt$$

where $P_h(t)$ represents the one-time timber harvest value and $A(t)$ are the annual flows of agricultural activities permitted by the land transformation.

In our model, the harvest of the forest is not *now-or-never*. Instead, the manager decides at each moment of time on the optimal wood volume $d(t)$ (corresponding to an optimal forest area) to be cut. In this sense, we depart from classical forestry economics, where the goal usually consists in finding out the optimal rotation age, when the entire forest is cut down at once and then replanted (Faustmann (1849), Miller and Voltaire (1983), Chladná (2007)). We focus instead on determining the optimal instant deforestation.

Contrary to the traditional dynamic setting, we enforce a very loose constraint on the

total endowed forest at inception $\left(\bar{F}(0)\right)$. However, we impose a time window $[0, T]$ during which the optimization occurs. While $\bar{F}(0)$ is not infinite, we consider its value so large that forest depletion is not likely. In this sense, we allow for a positive terminal stock at period T. We consider this modified setting to be more in line with the reality of many foresters' decision processes in tropical countries: on the one hand, forest size appears to be rarely an issue since property rights are weakly enforced and encroachment is often the norm, limiting any scarcity effect over the short-to-medium term. On the second hand, REDD schemes are currently envisioned within an explicit time frame, which compels us to consider the time constraint as the most important for the forester.

To allow for a comparable ranking of the different reference rules in terms of their overall performance, we rely on a couple of simplifying assumptions that ease calculations but have no impact on the evaluation of the reference levels. We consider a mature forest with equally-aged trees and no prospects of canopy growth. By excluding the possibility of reforestation, our model can be categorized as a problem of optimal extraction of non-renewable resources. Thinning activities are not accounted for either.

The timbering activity involves various operational costs. We follow the approach of Cherian et al. (1999) and allow for quadratic harvesting costs. This stylized representation of harvesting costs is coherent with the classical approach of Thünen (1826) where land is abundant and homogeneous and the limits on expansion are related to increased accessibility costs measured by the distance from the center (Angelsen, 1999). This assumption allows for the existence of an interior solution for the optimal deforestation rate, and guarantees increasing marginal costs, a feature confirmed empirically (Cherian et al. (1999)). No costs are incurred for zero deforestation rates.

$$C_t = a_1 d(t) + a_2 d(t)^2 \tag{3}$$

The offsetting scheme proposed by REDD has a voluntary feature: the manager is rewarded if his deforestation rate is below a certain reference level, but does not have to pay penalties in case he exceeds this limit[11]. His revenue from participating in the REDD project can be described by a simple step function:

$$RR_t = P_t{}^R(dB - d(t))^+ \tag{4}$$

A number of factors influence the revenue generated by the REDD project: the price of the CO_2 permit, and the relationship between the specified deforestation baseline (dB) and the deforestation rate (d(t)).

We consider five different scenarios: business-as-usual (no REDD project in place), historical, model-implied, and two types of corridor 2. After presenting the conditions of each setting, we provide the analytical solution for the optimal deforestation path in each case. We begin our analysis with the simple case when the forest brings only timbering benefits, in the absence of REDD initiatives.

2.2 Baseline alternatives

The Business-as-usual Scenario (Without REDD)

The *business-as-usual* scenario serves as an illustration of the deforestation trend under standard conditions, in the absence of a program targeting the reduction of emissions from deforestation. The results derived here will serve as the crediting reference for computing the REDD rewards under the model-implied and the variable corridor 2 scenarios.

When the forest is dedicated to timbering purposes only, the net revenue at time t takes

[11] This approach is similar to Busch et al. (2011) and in line with the nature of PES by which "*forest users will opt for conservation only if the net benefits are higher than those arising from forest exploitation*" (Angelsen et al., 2012)

a reduced form:

$$\pi(d(t)) = {P_t}^F d(t) - \left(a_1 d(t) + a_2 d(t)^2\right) \tag{5}$$

The optimal control problem can be described as a maximization over the deforestation rate of the total discounted net revenues resulting from timbering:

$$\max_{d(t)|t\in[0,T]} \left\{ \int_0^T e^{-rt} \pi(d(t)) dt \right\} \tag{6}$$

$$s.t. \quad \dot{F} = -d(t) \tag{7}$$

We follow the solution approach of Chiang (1992) for determining the optimal deforestation path[12]. The rate of deforestation at each moment of time is recursively linked to the initial deforestation level:

$$d(t) = d_0 e^{rt} + \frac{{P_0}^F (e^{\delta t} - e^{rt}) - a1(1 - e^{rt})}{2a_2} \tag{8}$$

The Historical Baseline

Most methodologies submitted so far propose the inclusion of the historical average deforestation rate in the computation of the crediting baseline[13], recognizing that average past deforestation, although an imperfect measure, is the best predictor at hand for short-to-medium term deforestation (Angelsen et al., 2009). We thus start the analysis of the deforestation behavior under REDD with a simple historical baseline, in which no specific adjustments are made to a fixed level calculated from past mean emissions. This baseline type is a simplification of what has been proposed by Brazil (Parker et al., 2008).

[12] For the complete derivation steps we refer to Annex 1.

[13] Out of the 6 baseline rules studied by Griscom et al. (2009), 5 rely partially or totally on historical reference levels.

The merit of a fixed baseline consists in its fair simplicity of computation and in its appeal to forest managers who need to get used to new operation rules. The baseline has received support due to its ability to reflect local deforestation trends and avoid the one-measure-for-all caveats.

The historical reference level has, however, a number of limitations. Firstly, many countries do not dispose of accurate data records (Guariguata et al., 2008). Secondly, an imperfect predictor of future deforestation has high chances of undermining the additionality principle and distorting country participation, especially if one considers the different stages each country is in according to the forest transition theory. Forest-rich states with low deforestation might decide to opt out of the REDD schemes if offered programs based on historical baselines. On the other hand, low-forest high-deforestation nations would gladly join but be rewarded on fake premises (Angelsen, 2008a).

In presence of the REDD scheme, the instantaneous income is generated by two counterbalancing activities, i.e. timbering and trading of REDD permits:

$$\pi(d(t)) = {P_t}^F d(t) - \left(a_1 d(t) + a_2 d(t)^2\right) + {P_t}^R \left(dB - d(t)\right)^+ \tag{9}$$

The timbering activity involves proportional operational costs, while REDD revenues are eligible only for deforestation rates below a fixed threshold.

The Model-implied Baseline

An alternative to the retrospective historical baseline is the prospective method of projected future deforestation trends. The *model-implied* baseline relies on a time-varying level reflecting predicted deforestation paths under the *business-as-usual* scenario. Here, the forester is rewarded for deforesting less than in the absence of the REDD program. Its design could be accommodated to include information regarding the next forest transition stage of the applying country. If the forecasting is accurate, it enforces additionality,

since only actual efforts would be rewarded. However, model-implied baselines are not exempt from criticisms, stemming primarily from its vulnerability to forecasting errors and for its reliance on model assumptions.

Reference levels are modeled using analytical, regression or simulation techniques and often explicit the influence of geographic and economic drivers (Kaimowitz and Angelsen, 1998). The ability of prospective models to combine spatial and non-spatial driver influences with forest extraction dynamics make them particularly relevant for our dynamic approach.

Under our REDD approach, the optimal control problem has the same specification as before, with the notable difference of the reference level $dB(t)$, which can fluctuate across time according to the projections of the model used:

$$\pi(d(t)) = {P_t}^F d(t) - \left(a_1 d(t) + a_2 d(t)^2\right) + {P_t}^R \left(dB(t) - d(t)\right)^+ \tag{10}$$

The Corridor 2 Baseline

The Fixed Corridor 2

The corridor approach has been jointly proposed in 2006 by the Joanneum Research Institute, the Union of Concerned Scientists, the Woods Hole Research Center, and the Instituto de Pesquisa Ambiental da Amazonia (Griscom et al., 2009). The program involves the use of a lower and an upper reference level (hence its corridor name) for comparing current emissions and establishing the volume of carbon credits generated by the REDD scheme.

Here we analyze the so-called *corridor 2* methodology, whereby deforestation rates below the lower boundary are entirely eligible for CO_2 permits, as they would under a fixed-baseline scheme. However, deforestation levels within the corridor are weighted proportionally to efforts, while still maintaining a proper level of incentives. Deforestation rates above the upper boundary, while not be eligible for carbon credits, do not

result in owed emissions (Griscom et al., 2009). The upper and lower limits of the corridor are envisioned to be constant and historically determined, over an agreed time period of five to fifteen years.

Imposing a *corridor* baseline is motivated by the need to address an important feature of deforestation, namely the inter-annual fluctuations in the levels of deforestation, caused by shifts in key market parameters, such as commodity prices, interest rates, or climate impacts (Joanneum Research Institute (2006)). It is believed that the corridor could act as a *buffer* against these factors, while still allowing countries to receive rewards for deforestation rates below the *business-as-usual* scenario.

Under the REDD scheme, the shape of the profit function will be strongly influenced by the new design of the reward program:

$$\pi(d(t)) = {P_t}^F d(t) - (a_1 d(t) + a_2 d(t)^2) + {P_t}^R \left(1 - \frac{(d(t) - dB^L)^+}{dB^U - dB^L}\right) \left(dB^U - d(t)\right)^+ \quad (11)$$

In equation (11) the third term represents the incomes generated by the REDD project, which is determined by two indicator functions. The first indicator function behaves such that:

$$1 - \frac{(d(t) - dB^L)^+}{dB^U - dB^L} = \begin{cases} 1 - \frac{d(t) - dB^L}{dB^U - dB^L} & \text{, if d(t)} > dB^L \\ 1 & \text{, if d(t)} \leq dB^L \end{cases}$$

This formulation is necessary for the corridor weighting mechanism: in case the deforestation rate lies within the corridor, rewards will be proportional to the distance between the deforestation rate and the lower boundary. Deforestation rates smaller than the lower boundary are rewarded full credits.

The second term of the REDD income, $(dB^U - d(t))^+$, makes sure that rewards are received only in case deforestation remains below the upper boundary of the corridor.

The Variable Corridor 2

Similar to the difference between the static fixed historical baseline and its dynamic model-implied counterpart, we improved on the proposed corridor baseline by implementing it dynamically. The variable corridor 2 replaces the constant lower and upper corridor bounds with time-varying levels, established below and above the deforestation rate of the dynamic business-as-usual scenario (in absence of REDD).

With this new baseline rule, we bring together the strong points of both the model-implied and the fixed corridor baseline schemes. Firstly, linking corridor boundaries to the baseline-as-usual deforestation trend is expected to offer not only a dynamic but also a forward-looking perspective on deforestation paths, more likely to insure additionality. Secondly, the corridor reward system should dampen the negative effects coming from estimation errors and protect against inter-annual fluctuations in deforestation levels.

In terms of profits, the scheme is similar to the one of the fixed corridor 2 baseline, the only difference being the dynamic boundary levels:

$$\pi(d(t)) = {P_t}^F d(t) - (a_1 d(t) + a_2 d(t)^2) + {P_t}^R \left(1 - \frac{(d(t) - dB^L(t))^+}{dB^U(t) - dB^L(t)}\right) \left(dB^U(t) - d(t)\right)^+ \tag{12}$$

To summarize, the different REDD rewards ($RR(t)$) offered to the land user under

the different baseline methodologies are the following:

$$RR(t) = \begin{cases} {P_t}^R \left(dB - d(t)\right)^+ & \text{, if Historical} \\ \\ {P_t}^R \left(dB(t) - d(t)\right)^+ & \text{, if Model-implied} \\ \\ {P_t}^R \left(1 - \frac{(d(t) - dB^L)^+}{dB^U - dB^L}\right) \left(dB^U - d(t)\right)^+ & \text{, if fixed Corridor 2} \\ \\ {P_t}^R \left(1 - \frac{(d(t) - dB^L(t))^+}{dB^U(t) - dB^L(t)}\right) \left(dB^U(t) - d(t)\right)^+ & \text{, if variable Corridor 2} \end{cases} \tag{13}$$

2.3 A numerical application

Considering the relative complexity and non-linearity of the profit functions (especially for the Corridor 2 schemes), we resort to a numerical approach to compare the forester's decisions under the different baseline rules. The details of our solution method as well as the calibration details are provided in Annex 2 and 3.

For the numerical solution, we calibrate the model to match observed data. Considering the representativeness of the region for future REDD projects, we take the view of a forest manager operating in Peru. The country is highly representative for the REDD candidate regions both in terms of specificities and market volume[14]. Peru is rich in forest resources with a generally low deforestation rate (Angelsen et al. (2009), Griscom et al. (2009)). With 70 million hectares of tropical forest covering nearly 60% of its territory, it has the fourth largest area of tropical forest in the world[15]. Of this, more than 80 percent classifies as primary forest. The annual deforestation rate for 1990 - 2005 ranged between 0.35-0.5%, remaining at low levels relative to its neighboring countries (FAO, 2005). However, more recent estimates show that during 2000 - 2010 deforestation rates

[14] According to Diaz et al. (2011), the Peruvian and Brazilian Amazon dominate the forest carbon market, with Latin America accountable for not less than 60% of the 2010 total primary market volume.

[15] After Brazil, the Democratic Republic of Congo and Indonesia.

experienced an increasing trend, which is predicted to persist in the near future mainly due to cropland expansion in the Andes (Wassenaar et al., 2007).

Deforestation and forest degradation in Peru are multi-causal, being the result of subsistence agriculture[16] and varied development activities, such as illegal logging, commercial agriculture (cocoa and soybean cultivation), gold mining, gas and oil operations, and road constructions (Buttler, 2012).

3 Results and discussion

3.1 Performance indicators

A successful REDD program should target the reduction of CO_2 emissions at low costs and contribute to the sustainable development of the host country (Angelsen, 2008a). We evaluate the performance of the REDD program under different baseline schemes with the help of three indicators constructed in the spirit of the *3E Criteria* proposed by Stern (2008). The performance measures we consider are: effectiveness, efficiency, and forester's welfare, with and without the presence of REDD programs in the region. Their computation is detailed in Table I.

Table I: Performance Criteria of Baseline Schemes

Indicator	Definition	Formula
1. Effectiveness (E_1)	Avoided deforestation (%)	$E_1 = \frac{{S_T}^{BaU} - {S_T}^{i}}{{S_T}^{BaU}}$ $S_T = \int_0^T d(t)dt$
2. Forester's welfare (E_2)	Change in profits (%)	$E_2 = \frac{{\Pi_T}^{i} - {\Pi_T}^{BaU}}{{\Pi_T}^{BaU}}$ $\Pi_T = \int_0^T e^{-rt}\pi(d(t))dt$
3. Efficiency (E_3)	Average cost per ha (Eur/ha)	$E_3 = \frac{\int_0^T RR(t)^i dt}{\int_0^T d_{BaU}(t)dt - \int_0^T d(t)dt}$

Notations: $i \in MI, H, C2$; MI = model-implied; H = historical; C2 = corridor 2; BaU = business-as-usual, d(t) = deforested area; $\pi(t)$ = total land use profit at time t; RR(t) = REDD revenue.

[16] Attributed to Andean farmers migrating from the highlands to the Amazon.

The effectiveness indicator (E_1) is an overall measure of avoided deforestation, and the inherent abstained emissions. It quantifies differences in deforested area between the business-as-usual (no REDD) and the different baseline scenarios for REDD, being therefore a measure of additionality. As Angelsen (2008a) points out, it assumes the verifiability of realized emissions through reliable monitoring and the accurate estimation of deforestation paths in the absence of REDD programs.

REDD initiatives target additional benefits besides the carbon reduction goals, such as positive externalities on local communities. For measuring the financial co-benefits of REDD we introduce a simple indicator (E_2) quantifying the changes in forester's income with and without REDD.

Finally, the efficiency indicator (E_3) is relevant for the financial performance of REDD, providing an estimate of the average cost of forest preservation (assuming an exogenous price) per hectare of avoided deforestation.

While consensus has been reached on the desirability of achieving high effectiveness levels and small costs of avoided deforestation, the discussion on the advantages of high increases in forester's income due to participation in REDD is still on-going. With bountiful financial transfers the country opt-in rates are expected to be very high, jeopardizing climate negotiations. This is the argument McKibbin and Wilcoxen (2002) make when promoting programs that minimize transfers across national borders, laying thus the emphasis on climate treaties as vehicles that focus primarily on mitigation and not poverty alleviation. As Angelsen (2008b) points out, since poverty is indeed an important issue in the candidate REDD countries, positive expected net benefits are needed in order to insure country participation in climate programs. Reward levels should however be case-specific, being biased towards the more needy, while avoiding large transfers to middle-income countries that are progressively responsible for greenhouse gas accumulations in the atmosphere.

3.2 A first comparison

We start the analysis of the different baseline schemes by first assuming a historical deforestation rate of 200 hectares per year. This corresponds to the average level of the yearly deforested area in the business-as-usual case for the period under consideration, and can be thought of as a scenario in which deforestation trends remain similar over consecutive time intervals. We compare the performance of the historical (H), model-implied (MI), and corridor 2 baselines. For simplicity, the *fixed* and *variable* corridors are labeled $C2(f)$ and $C2(v)$ hereafter.

The $C2(f)$ type assumes that the upper and lower bounds of the corridor are fixed at 10% below and above the historical baseline respectively. While maintaining the corridor bandwidth assumption, the $C2(v)$ sets the bounds in relation to the business-as-usual deforestation path and is therefore time-varying[17]. Even if the difference in design seems small, the change in performance will prove to be considerable. The assumptions regarding the corridor width and its symmetry around the reference level are relaxed later on (Section 3.3).

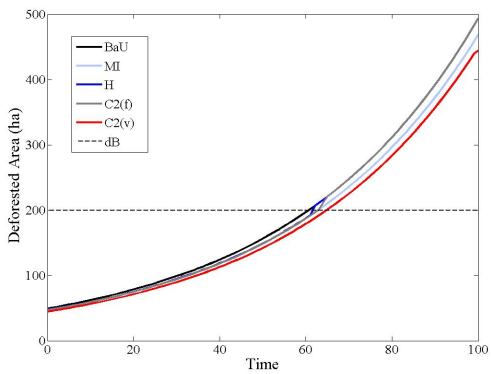

Figure 1: Deforestation Paths

Indicator	Effectiveness E_1 (%)	Welfare E_2 (%)	Efficiency E_3 (Eur/ha)
MI	4.77	12.84	4,680.18
H	1.54	2.26	73,096.66
$C2(f)$	1.76	2.76	78,043.75
$C2(v)$	9.08	0.92	9,318.13

Notations: $i \in MI, H, C2$; MI = model-implied; H = historical; C2 = corridor 2; BaU = business-as-usual.

Table II: REDD improvements over BaU

Figure 1 illustrates the optimal deforestation path chosen under each crediting baseline

[17]The lower and upper bounds for the fixed corridor are set as $dB^U = (1+x)dB$ and $dB^L = (1-x)dB$, while for the variable corridor they are computed as $dB^U = (1+x)d_{BaU}(t)$ and $dB^L = (1-x)d_{BaU}(t)$.

scheme. The pattern of deforestation follows the increased value of the forest resulting from the upward-trending price dynamics.

By comparison, the area of deforested land in the different baseline scenarios remains each year lower or equal to the business-as-usual case. This is an important result, showing that REDD programs provide significant incentives to decrease deforestation in all baseline cases. Moreover, this feature entails positive permanence indications: reductions in deforestation at a certain moment of time will not be counterbalanced by raising deforestation trends at later periods above the business-as-usual scenario. REDD incentives appear sustainable - as opposed to temporary - conservation efforts.

The baseline scenarios differ in their performance (Table II). Interestingly, each indicator reveals a new ranking of the baselines. The variable corridor 2 ($C2(v)$), with its dynamic reward system, achieves the best results in terms of avoided deforestation (E_1). It is followed at quite some distance by the model-implied baseline (MI). The fixed corridor 2 ($C2(f)$) and the historical baseline (H) lag far behind in terms of effectiveness.

The outcome on any REDD scheme on forester's welfare ($E2$) is essential on both a moral ground (it could be hard to argue in favor of programs that impoverish local communities) and for cooperation reasons, since REDD projects that provide positive net benefits are expected to have high country opt-in rates. Due to their voluntary participation and limited liabilities design, all baseline schemes guarantee an increase in profits from the business-as-usual scenario. The MI baseline is the most attractive for the forester, providing an increase in total revenues by around 13% over the entire optimization horizon. Both types of corridor 2 together with the historical baseline allow for only modest changes in welfare. It is however not clear whether substantial REDD transfers can be considered an unquestionably desirable feature of the program. One should therefore be careful when declaring the superiority of the model-implied baseline based on welfare considerations.

Finally, a successful REDD scheme should provide a cost-efficient solution to the emis-

sions reduction problem, otherwise buying countries might be discouraged from financially supporting the programs. The model-implied baseline is the top performer based on the cost-efficiency criterion ($E3$), followed by the $C2(v)$ and the distant historical baseline and $C2(f)$, with almost twenty times higher costs than the model-implied baseline rule.

Overall, the poor results of the historical baseline across the different criteria can be explained by its static threshold, kept constant during the time span of the project while deforestation slopes upward. The scheme is weak in matching the dynamic nature of the deforestation path and fails to provide the forester with continuous incentives to preserve.

The findings presented here offer contrasting support for either the variable corridor or the model-implied baseline. A robust ranking of the different schemes requires however the careful consideration of both the deforestation context (the historical reference level dB) and the attributes of each family of baselines. This is the task we tackle in the next section, first by testing the sensitivity of the baseline models to different reference levels and then by addressing two key aspects of the corridor methodology, the corridor bandwidth and its symmetry.

3.3 The influence of deforestation context and scheme attributes

Deforestation history

We focus first on testing the sensitivity of baseline performance to different past deforestation contexts. This translates into adjusting the constant boundary against which rewards are accrued for the historical and fixed corridor 2 schemes below and above the assumed level of 200 ha per year[18]. Results are displayed in Figure 2.

[18]The level of 200 ha/year was based on the projected average of the business-as-usual deforestation path and the assumption that averages over consecutive time periods remain constant. Considering different fixed crediting levels corresponds to either allowing for different past deforestation averages or keeping the assumption regarding the historical average and adjusting the fixed crediting threshold below and above this level. The first case allows us to assess the performance of each baseline scheme

The performance and ranking of the baseline schemes is not constant across the different performance measures. Changing the assumptions regarding the fixed threshold leads to different choices regarding the most appropriate baseline scheme. The fixed corridor 2 and the historical baselines gain ground as the crediting level is increased above the average past deforestation, both in terms of effectiveness and welfare. The result is not surprising, since higher crediting baselines are more generous in terms of REDD revenues. However, these advantages come at a high cost: from an efficiency point of view performance deteriorates considerably.

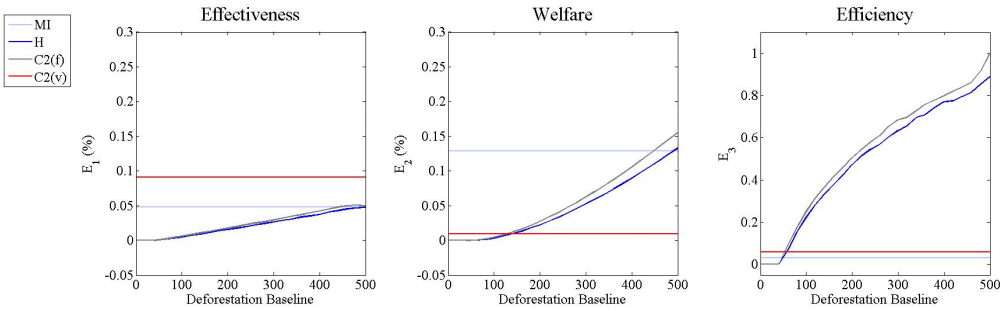

Figure 2: Performance Indicators of Different Baseline Scenarios

Note: The figure illustrates performance results of the model-implied, historical, and fixed and variable corridor 2 baselines based on three indicators (Table I). The efficiency indicator is normalized such that the highest cost takes value 1. The past deforestation average is allowed to range between 1 and 500 ha/year. Corridor width is maintained at 10%.

Let us now identify the cause for the improvements in performance of the historical and fixed corridor 2. We have seen in Figure 1 that optimal deforestation paths curb upwards in time. Anchoring REDD rewards to a higher crediting threshold determines a later switch to a no REDD regime, and a longer substitution between forestry and REDD revenues. The constant reward level reflects in this case the higher end of future deforestation trends. To sum up, if steep slopes are expected, regulators should adjust the fixed threshold well above the deforestation average. This kind of adjustment requires however to have reliable forecasts at hand.

for countries that are at different stages in their forest transition curve.

Corridor Bandwidth and Symmetry

The complexity of selecting the most appropriate reference level for REDD consists not only in identifying the best-performing baseline type, but also in defining the optimal attributes for the selected scheme. The corridor bandwidth is one of the factors policy makers need to analyze and choose optimally.

We relax the previous assumption regarding the fixed corridor width and allow it to vary widely ($x \in [0.1, 1]$), corresponding to different reward magnitudes granted for reducing deforestation in the case of the fixed and variable corridor 2 baselines.

Let us first discuss the changes in performance for the fixed corridor 2[19]. Varying the corridor width brings new insights into the ranking of crediting baselines. Firstly, for past deforestation levels above 150 ha/year, wide corridors where the upper and lower bounds are set far away from the historical average ($x \geq 0.8$) lead to large increases in effectiveness for the fixed corridor 2, above those attained by the model-implied scheme. Secondly, such wide corridors also ensure the highest increases in forester's welfare, for crediting levels above 300 ha/year. Moreover, the positive impact on welfare is marginally increasing. Thirdly, broadening the corridor width lowers the efficiency performance, and here the model-implied baseline remains the sole dominant choice.

Another baseline attribute that should undergo careful scrutiny is the corridor symmetry around the historical deforestation average. We hereby allow for both an upward- and downward-biased corridor[20].

Our previous findings regarding the effects of widening the corridor bandwidth hold across the different assumptions of corridor symmetry.

After loosening the symmetry assumption, a threefold conclusion emerges. Firstly, the upward-biased corridor dominates in terms of effectiveness, regardless of the corridor

[19] For a detailed overview of the results, we refer the reader to Annex 4.

[20] Corridor bounds in the upward-biased case are computed as $db^L = db(1-x)$ and $db^U = db(1+2x)$, while in the downward-biased case they are equal to $db^L = db(1-x)$ and $db^U = db(1+x/2)$, where $x \in [0.1, 1]$

width. Also, welfare increases are best supported by upward-biased broad corridor baselines. Efficiency reasons argue strongly for a downward-biased corridor. Secondly, as corridor width increases, differences in performance across distinct symmetry scenarios widen considerably. Lastly, results depend on past deforestation levels, such that lower corridor bandwidths perform better in terms of effectiveness and efficiency for smaller past averages, but worse for higher cases.

The performance responses of the fixed corridor 2 to widening corridor size and loosening the restrictions on symmetry were positive. We are now motivated to check whether the variable corridor 2 would benefit as well from such changes. The results are detailed in Annex 5.

Contrary to the findings obtained in the case of the fixed corridor, wider bandwidths are less effective in reducing deforestation for the symmetric and the downward-biased cases. Symmetric wide corridors lead instead to ample welfare transfers and poor efficiency levels. Effectiveness and welfare performance is even weaker under the downward-biased corridor assumption; however, large improvements in efficiency are realized ($x \leq 0.9$). Effectiveness improvements are noticed for the upward-biased corridor type. This case also achieves higher welfare transfers, but sluggish efficiency results.

Let us now conclude our investigation regarding the design of the variable corridor 2 by going back to the discussion started earlier regarding the support for or against large improvements in financial welfare due to REDD programs. Parties in favor of large financial transfers to REDD countries should rely on a symmetric corridor 2 of narrow to medium intensity ($x \in [0.1, 0.5]$). Those that put more weight on efficiency and effectiveness criteria than on welfare, should advocate for a downward-biased corridor, with a lower bound of 20% below and an upper bound of 10% above the business-as-usual scenario ($x = 0.1$). This would entail considerable deforestation reduction (at least as high as the model-implied baseline), at high efficiency levels and modest but positive

changes in welfare.

3.4 Optimal Design and Welfare Transfers

This section aims at offering a brief overview of baseline dominance, after taking into account the possible improvements in design discussed above.

Our analysis has individualized four baseline alternatives with strong performance results: the model-implied (MI), the upward-biased broad corridor 2 ($C2(f, x1, ubias)$), the symmetric narrow variable corridor 2 ($C2(v, x01, sym)$), and finally the downward-biased narrow variable corridor 2 ($C2(v, x01, dbias)$). We also consider the historical (H) baseline for comparison purposes.

Table III: Baseline Dominance over Different Historical Deforestation Averages

Historical Deforestation (ha/year)	Effectiveness	Welfare	Efficiency
1	C2(v,x01,sym)	MI	H
100	C2(v,x01,sym)	MI	MI
200	C2(v,x01,sym)	MI	MI
300	C2(v,x01,sym)	C2(f,x1,ubias)	MI
400	C2(f,x1,ubias)	C2(f,x1,ubias)	MI
500	C2(f,x1,ubias)	C2(f,x1,ubias)	MI

The table captures the dominant baseline type in terms of different indicators (effectiveness, welfare, efficiency) for different assumptions regarding the historical deforestation average (dB $\in [1, 500]$ ha/year).
Notations: MI = model-implied, H = historical, C2(v,x01,sym) = symmetric variable corridor 2 with corridor width equal to 10% below and above the reference, C2(v,x01,dbias) = downward-biased variable corridor 2 with corridor width equal to 10%, C2(f,x1,ubias) = fixed upward-biased corridor 2 with corridor width equal to 100%.

Each performance indicator points to a different superior baseline type (Table III). In terms of effectiveness, the symmetric variable corridor 2 is the best choice for low to medium historical deforestation rates; for high deforestation levels ($db > 300$ ha), the upward-biased fixed corridor 2 proves to be the most successful in avoiding emissions from deforestation. Promoters of large financial transfers towards REDD participators should advocate for either a model-implied baseline or for an upward-biased fixed corri-

dor 2 with boundaries computed for large deforestation averages. The efficiency indicator points in favor of the model-implied baseline, with the downward-biased corridor 2 as second runner[21].

Table III offers a clear image of the dominant baseline schemes when considering each indicator separately. However, decision makers are frequently interested in rankings based on the overall performance of the alternative REDD reward schemes. With this aim, we build several scores that weight the performance of each baseline in a different manner. We distinguish between indicators that favor large financial transfers to the REDD countries (High Transfer), and those that promote more conservative welfare changes (Low Transfer). Also, we are interested in observing changes in rankings when allowing each indicator to have a stronger weight in the overall performance evaluation. To bring the different indicators at the same magnitude, we replace their values by their actual rank, given each historical deforestation level. The different weighting schemes for constructing the overall indicator as well as the results are presented in Annex 7.

Two important conclusions emerge: first, baseline dominance is not influenced by the region's deforestation history when large financial transfers are promoted, as baseline choice is constant across all deforestation averages. However, threshold levels play an important role when preference is placed on low transfers. Second, taking a pro-transfer position regarding increases in financial welfare individuates the model-implied baseline as the best performer, unless the effectiveness criterion is primarily weighted and crediting levels are set above 300 ha/year; supporting moderate transfers brings the symmetric variable corridor 2 to the forefront across most weighting alternatives, with the downward-biased variable corridor 2 as a good alternative for the case when the welfare is biased negatively. The historical and the fixed corridor 2 baselines dominate in very few positions.

[21] For the full description of the results please refer to Annex 6.

4 Conclusions and Further Discussions

REDD programs are designed to avoid business-as-usual emission levels from cutting down existing forests that are exposed to the risk of land-use change. A key issue of REDD is the establishment of reference levels, the so-called *baselines*, against which reductions in deforestation are measured.

The aim of the present paper is to assess the performance of different crediting baselines for the REDD projects. In the process, we are also able to determine optimal land use changes when REDD activities are available. We analyze differences in behavior in the case of the most frequently proposed baselines: historical, model-implied, and fixed corridor 2. We also take the chance to propose a new type of baseline, namely the variable corridor 2, whose bounds form a corridor around the business-as-usual deforestation path.

Past studies have focused primarily on differences in distribution of benefits and total costs arising under different baseline types. While we give considerate attention to these issues, one of the main findings we were able to identify is that baseline choice has a significant impact on land-use behavior. Land users choose different deforestation paths when incentivized by distinctive crediting reference levels. We believe this point is key for REDD programs that aim at counteracting climate change.

For evaluating the success of the different baselines in achieving REDD goals, we build three performance indicators that describe the effectiveness, welfare increases, and efficiency levels for the analyzed baseline types. We find that each indicator individuates a different baseline as the best performer, similar to the results of Huettner et al. (2009). In our analysis, the model-implied and the corridor 2 baselines emerge as the strongest candidates.

Our study is also exploring further ways of improving baseline performance, by adjusting two key design features, namely corridor width and symmetry. We find that the fixed

corridor 2 benefits from being more generous on the upside, i.e. when the upper bound is set far away from the fixed historical deforestation level. On the other hand, the variable corridor 2 is performing best when its bounds are set very close and symmetric to the business-as usual scenario.

A preference for a strong effectiveness indicator leads to choosing the variable corridor 2, with narrow and symmetric bounds. The model-implied and the upward-biased corridor 2 provide the highest increase in forester's welfare above the business-as-usual scenario. Efficiency reasons advocate for the model-implied baseline, with the downward-biased variable corridor as runner-up.

The baseline types with highest performance, namely the model-implied and the variable corridor 2, allow for dynamic REDD rewards when reducing emissions below the business-as-usual scenario. We thus confirm the findings of Griscom et al. (2009) that the best-performing crediting schemes need to anchor payments to forward-looking baselines. One should note that our results are based not only on credited versus actual emissions as in the study mentioned above, but on considerations of effectiveness, efficiency and welfare.

Similar to actual REDD proposals, our model assumes no liability for deforestation rates above the crediting baseline. As proved by our results, this feature actually ensures that if forest managers opt-in, their total profits will be superior to the baseline-as-usual level, for all baseline approaches. We can conclude that all baseline types analyzed promote country participation.

We have also seen that high crediting baselines lead to increases in effectiveness, which might initially appear counterintuitive. This was the case of the historical baseline for large deforestation averages, as well as for the upward biased fixed and variable corridor 2 types. In order to understand this result, we need to go back to the forest manager and his optimization function, which is defined as a trade-off between composite forestry and agricultural rent and REDD revenues. As baseline levels are increased his total

REDD rewards are larger, i.e. standing forests become more valuable and the owner has stronger incentives to keep the forest intact and cash in REDD revenues, with negative effects on efficiency. Establishing levels for the crediting baselines turns out to be a balancing act between efficiency and effectiveness considerations.

Due to the delicate trade-off that appears between the different performance measures, it is difficult to individuate an overall winner scenario. To this adds the discussion on welfare transfers between participating countries. Trying however to disentangle the complexity in order to draw a final conclusion, we advocate for the symmetric and narrow variable corridor 2, which has the capacity to offer top results in terms of effectiveness in reducing emissions from deforestation, guaranteeing at the same time a positive though modest increase in welfare, achieved at medium efficiency levels. This approach has the advantage of being forward-looking, and in this sense of rewarding as much as possible only *de facto* emission reductions. Also, due to the corridor design, it reduces estimation errors that occur inevitably when trying to predict the business-as-usual scenario against which rewards are accrued. We consider this to be a strong point ahead of the model-implied baseline.

This paper assumes a market-based mechanism for the funding of REDD rewards. In comparison to voluntary funds, international carbon markets can mobilize much larger amounts of money and favor cost-efficient emission reductions (Angelsen, 2008b). However, the weak carbon markets we face nowadays, characterized by low liquidity and permit overallocation, will most probably have difficulties in handling additional amounts of permits coming from the forestry sector. Therefore, when trying to decide on the most appropriate baseline type, one might postpone the implementation of the most effective one in order to avoid collapses in CO_2 prices until the stabilization of the carbon market. In this sense, REDD programs could be designed to allow for a less effective baseline, as the model-implied, in its initial phases and then switch to the variable corridor 2. We believe the variable corridor 2 should be the long-term goal in the climate negotiations.

Our one-player study is limited through its assumption that all accrued credits will be cashed in, such that the supply of permits will always be satisfied by a counterparty demand. We have therefore neglected liquidity issues on the carbon markets or potential drops in permit prices occurring in case a huge amount of forest credits are released at the same time. While we acknowledge that accounting for this feature might have a significant impact on baseline performance, it will however not influence baseline ranking and we would remain true to our conclusions.

A more robust understanding of the optimal decision process would require an improved description of the different players having a say in REDD implementation. As Griscom et al. (2009) point out, the selection of reference levels will be based not only on technical considerations (like effectiveness), but also on political negotiations among participating countries. REDD projects implemented at the national level will motivate countries to take a strategic position at the negotiation table and try to influence the decision regarding the crediting levels in their favor. Seen in this way, the adjusted deforestation decision will result in emission reductions of other magnitudes than the ones presented in this study, and might as well reveal a different ranking of baseline approaches. Future research built on a dynamic decision model placed in a setting of multiple players with contrasting interests could be relevant for this issue.

Appendix

Annex 1: Determination of optimal deforestation rate under the business-as-usual scenario

When no REDD program is in place, the net revenue of the forest manager at time t takes a simplified form:

$$\pi(d(t)) = {P_t}^F d(t) - (a_1 d(t) + a_2 d(t)^2) \tag{14}$$

The optimal control problem can de described as follows:

$$\max_{d(t)} \int_0^T e^{-rt} \pi(d(t)) dt \tag{15}$$

$$s.t. \dot{F} = -d(t) \tag{16}$$

$$F(0) = F_0 \tag{17}$$

We build the current-value Hamiltonian as:

$$H^c = \pi(d(t)) - \mu d(t) \tag{18}$$

The equations of motion follow immediately:

$$\frac{\partial H^c}{\partial d(t)} : \pi'(d(t)) - \mu = 0 \tag{19}$$

$$-\frac{\partial H^c}{\partial F} + r\mu = \dot{\mu} \tag{20}$$

$$\dot{F} = -d(t) \tag{21}$$

Given that the partial derivative of the Hamiltonian with respect to the forest stock is zero, we obtain that:

$$\dot{\mu} = r\mu \Rightarrow d\mu = \mu r dt \tag{22}$$

Solving this simple partial differential equation leads us to the following identity:

$$\mu(t) = \mu(0)e^{(rt)} \tag{23}$$

Letting $\mu(0) = k$, for an arbitrary k, it follows that we can find a solution for each $\mu(t)$:

$$\mu(t) = ke^{(rt)} \tag{24}$$

By replacing the last result into Equation 16, we can solve for d(t):

$$d(t) = \frac{{P_0}^F - a1 - ke^{(rt)}}{2a_2} \tag{25}$$

Replacing for d(t) into the third equation of motion and integrating both sides of the equality leads us to the following identity, where c is the constant of integration:

$$F(t) = c - \frac{1}{2a_2}\left[{P_0}^F \frac{e^{\delta t} - 1}{\delta} - a_1 t - \frac{k}{2a_2}\frac{e^{rt} - 1}{r}\right] \tag{26}$$

What we have obtained is an equation in two unknowns, k and c. The system can be easily solved by imposing the boundary conditions. Replacing for the first boundary condition, gives us the solution to c:

$$c = F(0) \tag{27}$$

Further on,

$$k = \left[{P_0}^F \frac{e^{\delta t} - 1}{\delta} - a_1 T - a_2 F_0 \right] \frac{r}{e^{rT} - 1} \tag{28}$$

From here, the solution to the optimal deforestation rate is easily determined:

$$d(t) = \frac{{P_0}^F e^{\delta t} - a_1}{2a_2} - \frac{e^{rt} r}{e^{rT} - 1} \left[{P_0}^F \frac{e^{\delta t} - 1}{\delta} - a_1 T - a_2 F_0 \right] \frac{1}{2a_2} \tag{29}$$

Annex 2: Solution Method for the deforestation path under REDD

The simultaneous presence of REDD rewards for lower-than-baseline and absence of penalties for higher-than-baseline deforestation levels brings discontinuities to the profit function. The resulting non-smoothness in the objective function impedes the application of standard optimization methods. To overcome this difficulty, we develop a solution approach based on regime switches. This method allows for a break in the continuity of the deforestation path, which would otherwise be forced under the standard Hamiltonian procedure. A smooth deforestation path would not be able to guarantee optimality in the context of a non-smooth objective function. Here, we allow the manager to decide at each moment of time whether to deforest below or above the reference level, i.e. he makes his choice between a *REDD regime* (later referred to as Regime 1) and a *No REDD regime* akin to business-as-usual (Regime 2).

One observation is key for solving the optimization problem: in the absence of stochasticities, the decision regarding deforestation levels at each moment of time can be taken from the beginning for all future periods. Otherwise said, the entire optimal deforestation path can be computed based on the initial relationship between parameters and will not be altered during the lifetime of the project. While it could be possible in theory that the forester switches between regimes multiple times, in practice, the dynamic requirement at equilibrium ensures smooth evolution for the deforestation path within each regime and limited shifts between regimes over the entire horizon. We begin by explaining the solution approach for the historical and the model-implied cases. Since it requires an additional modification, we present the solution to the corridor 2 scenario at the end of this section.

In the case of the historical and the model-implied baselines, the forester chooses moderately sized deforestation rates and stays in *Regime 1* as long as the benefits received from emission reductions (REDD credits) remain higher than the benefits of harvesting and selling larger quantities of timber. Once profits from lavish harvesting out-pace REDD

benefits, a switch to *Regime 2* takes place. Depending on the values of the parameters, the regime switch can occur either from the beginning, somewhere during the lifetime of the maximization period, or never at all.

Formally, the optimization procedure can be described as follow:

$$\max_{d(t)|t\in[0,T]} \left\{ \int_0^{t^{Switch}} e^{-rt}\pi^{R1}(d(t))dt + \int_{t^{Switch}}^{T} e^{-rt}\pi^{R2}(d(t))dt \right\} \tag{30}$$

with

$$t^{Switch} = \inf\{t \geq 0 | d(t) \geq dB\} \tag{31}$$

We adapt the solution method of Chiang (1992), by allowing for the regime switches. We build the current-value Hamiltonian as:

$$H^c = \begin{cases} H^{R_1} = \pi^{R_1}(d(t)) - \mu_1(t)d(t) & \text{, if } t \in [0, t^{Switch}) \\ H^{R_2} = \pi^{R_2}(d(t)) - \mu_2(t)d(t) & \text{, if } t \in [t^{Switch}, T] \end{cases} \tag{32}$$

It is important to underline that if Regime 1 occurs in our parametrization, it will precede Regime 2, due to the different profit dynamics of the two activities. On the one hand, the manager can gain by increasing his production of timber, as long as his revenues do not exceed operating costs. In time, his marginal profits raise due to the increasing price of timber. On the other hand, even if revenues from REDD increase due to raising permit prices, these profits are limited, since the deforestation rate is bounded from above by the reference level and from below by zero (we do not allow for reforestation). Therefore, even if initially absolute marginal benefits from REDD could be higher than marginal benefits from timbering, this advantage decreases in time. As a consequence, for low permit prices, remaining in Regime 1 might become suboptimal at a certain moment of time (t^{Switch}) and the manager will decide to move on to Regime 2. Figure 3 captures the evolution of discounted profits in time and for different deforestation rates. The gray area represents profits occurring when the forest takes part in the REDD project, while

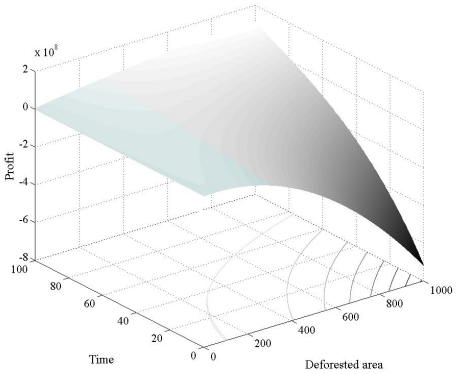

Figure 3: Discounted Profits

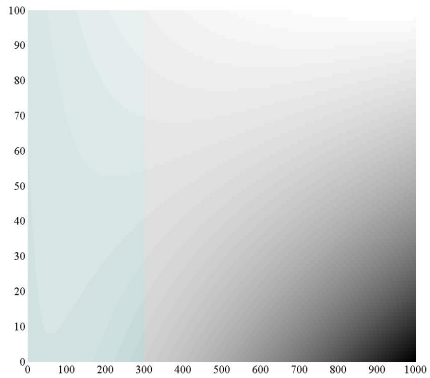

Figure 4: Discounted Profits: View from top

the blue area symbolizes profits realized under the No-REDD scenario. Within each color palette, lighter colors stand for higher profit values. The two surfaces of REDD and No-REDD scenarios are dominant in terms of higher profits in different parts of the graph. As long as the deforestation rate is below the fixed baseline, the optimal regime to choose is the REDD one, as can be observed in Figure 4. This holds for initial time periods. As time passes, the overall optimum is to be found in the No-REDD regime. The two figures support the hypothesis that if a regime switch does occur at some moment of time, this switch is expected to take place one time only, as the color alternation takes place only once. Moreover, Figure 3 shows that the REDD regime should precede the No-REDD one, since for later periods of time profits are increasing in deforestation rates and the manager will be better off opting for the No-REDD regime. The solution for the optimal deforestation path is given by:

$$d(t) = \begin{cases} d_{0,1}e^{rt} + \frac{{P_0}^F(e^{\delta t}-e^{rt})-a1(1-e^{rt})-{P_0}^R(e^{\gamma t}-e^{rt})}{2a_2}) & \text{, if } t \in [0, t^{Switch}) \\ \\ d_{0,2}e^{rt} + \frac{{P_0}^F(e^{\delta t}-e^{rt})-a1(1-e^{rt})}{2a_2} & \text{, if } t \in [t^{Switch}, T] \end{cases} \tag{33}$$

Considering the lack of continuity at t^{Switch}, we solve the forester's maximization using a numerical search algorithm that combines all possible combinations of Regime 1 and Regime 2 paths at different switching points[22]. We select the combined path that yields the highest profits.

In the case of the corridor 2 scenario, we deal with a profit function which is non-smooth at two points, i.e. at the boundaries of the corridor (dB^U and dB^L), and therefore the manager can switch between three different regimes. Depending on the relationship between initial parameter values, he will choose an optimal deforested area that satisfies:

$$d(t) = \begin{cases} d_{0,1}e^{rt} + \frac{{P_0}^F\left(e^{\delta t}-e^{rt}\right)-a1\left(1-e^{rt}\right)-{P_0}^R\left(e^{\gamma t}-e^{rt}\right)}{2a_2}) & \text{, if } t \in [0, t^{S_1}) \\ d_{0,2}e^{rt}\frac{a_2-\frac{{P_0}^R}{dB^U-dB^L}}{a_2-\frac{{P_0}^R e^{\gamma t}}{dB^U-dB^L}} + \frac{{P_0}^F\left(e^{\delta t}-e^{rt}\right)-a_1(1-e^{rt})-{P_0}^R\left(e^{\gamma t}-e^{rt}\right)\left(1+\frac{dB^U+dB^L}{dB^U-dB^L}\right)}{2\left(a_2-\frac{{P_0}^R e^{\gamma t}}{dB^U-dB^L}\right)} & \text{, if } t \in [t^{S_1}, t^{S_2}) \\ d_{0,3}e^{rt} + \frac{{P_0}^F\left(e^{\delta t}-e^{rt}\right)-a1\left(1-e^{rt}\right)}{2a_2} & \text{, if } t \in [t^{S_2}, T] \end{cases} \tag{34}$$

In our setting, the order of the switching times, i.e. $0 \leq t^{S_1} \leq t^{S_2} \leq T$, is due to the combination of two characteristics of our model. Firstly, the benefits of taking part in the REDD program decrease over time: for later periods of time, net timber revenues outpace REDD revenues due to higher timber prices and higher deforestation rates. Secondly, REDD gains get marginally smaller as the deforestation level gets closer to the upper corridor boundary until it eventually fades away for rates above the corridor. Therefore, the motivation to stay in REDD decreases over time, but at different paces within each interval.

Formulating the forester's optimization requires in this case to account for three regimes:

$$\max_{d(t)|t\in[0,T]} \left\{ \int_0^{t^{S_1}} e^{-rt}\pi^{R1}(d(t))dt + \int_{t^{S_1}}^{t_{S_2}} e^{-rt}\pi^{R2}(d(t))dt + \int_{t^{S_2}}^{T} e^{-rt}\pi^{R3}(d(t))dt \right\} \tag{35}$$

[22] We allow for all possible switching points in the range $[0, T]$

To determine the optimal moments for switching regimes and the overall profit maximization for the forester, we first define optimal paths within each regime for all possible combinations of switching times. We then use a numerical search algorithm that selects the combination of the three paths yielding the highest profits. From this, we infer the optimal switching times t^{S_1} and t^{S_2}.

Annex 3: Calibration parameters for the numerical models

Table IV: Calibration Parameters

Parameter	Explanation	Value	Source
P_0^F	Composite commodity price	500 Eur/m^3	ITTO (2010)
δ	Composite commodity growth rate	2.3% p.a.	ITTO (2010)
C	Eur/m^3 to Eur/ha	158 m^3/ha	IPCC (2003)
P_0^R	REDD permit price	5 Eur/tCO_2	Forest Trend (2011)
γ	Carbon growth rate	2.5% p.a.	Forest Trend (2011)
Ω	ha to tC emitted	179 tC/ha	OSIRIS (v3.4)
ψ	tC to tCO_2	3.67 tCO_2/tC	Assante (2011)
r	Discount rate	2% p.a.	Engel et al. (2012)
a_1	Cost parameter	3.3198 Eur/ha	Angelsen (1996), Verissimo et al. (1992)
a_2	Cost parameter	798.0811Eur/ha^2	Angelsen (1996), Verissimo et al. (1992)
dB	Historical baseline	$[1, 500]$ ha	-
dB^U	Upper boundary	$dB(1+x)$ ha	-
dB^L	Lower boundary	$dB(1-x)$ ha	-
x	Corridor width	$[0.1, 1]$	-
T	Time horizon	100 years	-

For consistency of computational base, we convert the price of the composite commodity (timber and agriculture) from $\$/m^3$ into $\$/ha$, relying on the IPCC Good Practice Guide LULUCF (Penman et al., 2003). The price of the commodity and its long term mean (δ) are computed for the Peruvian market from the Annual Review and Assessment of the World Timber Situation (ITTO, 2010). We use the State of the Forest Carbon Markets 2011 (Diaz et al., 2011) for the identification of the REDD permit price and its growth rate. The conversion of the deforested area into tons of carbon emitted is achieved with the help of another converter (Ω), whose value for Peru can be found in the OSIRIS model for the above and below ground biomass carbon and for soil carbon (Busch et al., 2009). Another converter, ψ, transforms the quantity of tons of carbon emitted into tons of CO_2 emitted (Assante, 2011). The discount rate used for comparing profits over time is of 2%, a standard value also employed by Engel et al. (2012). For the calibration of

the production cost, we adapt the cost function of Angelsen (1996), calibrating it to data from Verissimo et al. (1992) for the Amazonian forest. We allow the historical baseline level to vary in a large interval (between 1 ha and 500 ha per annum), in order to cover a broad spectrum of scenarios[23].

[23]The mean of the deforestation rate obtain in the business-as-usual scenario (absence of REDD) was close to 200 *ha/period*.

Annex 4: The fixed corridor 2: corridor bandwidth and symmetry

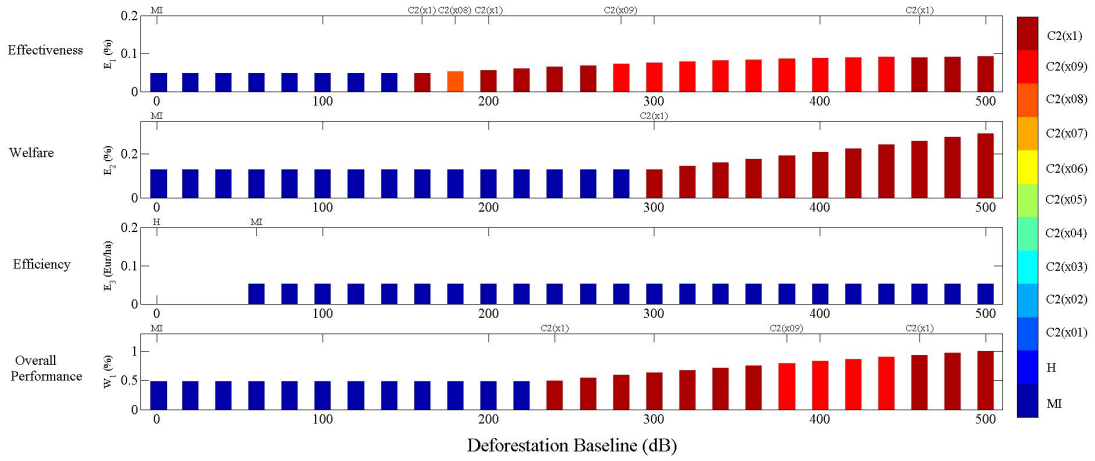

Figure 5: Dominant Baseline Scenarios across Different Historical Deforestation Rates

Note: We compare performance results of the model-implied, historical and fixed corridor 2 baselines. The figure emphasizes the results of the dominant baseline at each deforestation average. The first three panels refer to individual indicators, while the last one captures overall performance, based on equally weighting the individual indicators. Various widths are considered for the fixed corridor 2: the bounds are set between 10% and 100% above and below the historical baseline ($x \in [0.1, 1]$). The moment a baseline starts dominating is marked on the upper x-axis.

Figure 5 captures the performance dominance when opting among the model-implied, historical, and fixed corridor 2 baselines at different corridor widths. The variable corridor 2 is not considered momentarily. We evaluate the performance based on the three individual indicators (Table I) and an overall score computed by weighting the indicators equally. Figure 6 below displays effectiveness, welfare, and efficiency results for different widths of the fixed corridor 2 baseline.

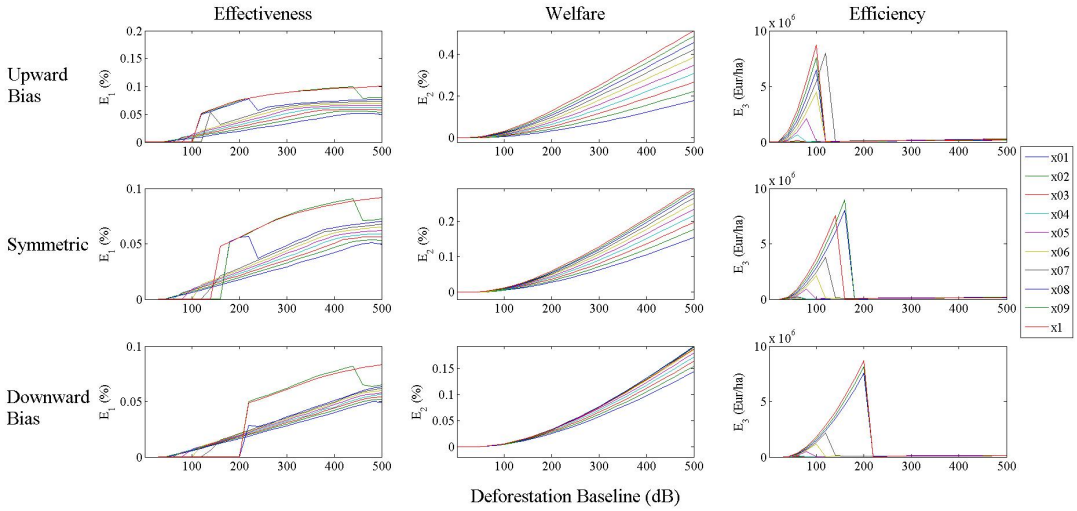

Figure 6: Baseline Performance across Different Historical Deforestation Rates

Note: The figure captures performance results of the fixed corridor 2 when both the corridor width and its symmetry assumptions are relaxed. We allow the corridor to be either symmetric, upward or downward-biased. The corridor bounds are set between 10% and 100% above and below the historical baseline ($x \in [0.1, 1]$).

Let us also specifically investigate differences in performance when playing around with the symmetry assumption regarding the corridor width. We present in Figure 7 only the extreme cases, when the corridor width is either very low ($x = 0.1$) or very large ($x = 1$).

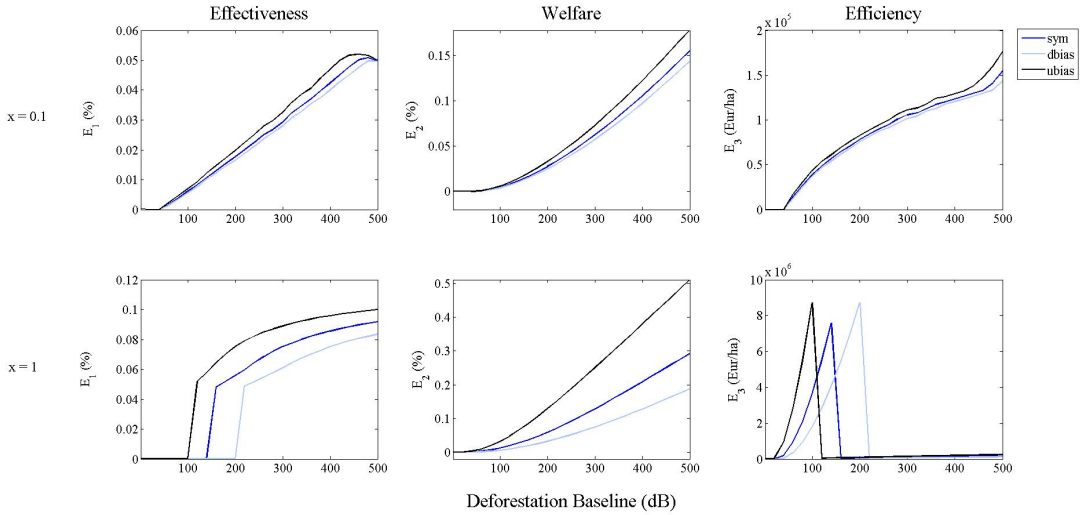

Figure 7: Performance of the Fixed Corridor 2

Note: The figure captures performance results of the fixed corridor 2 when both the corridor width and its symmetry assumptions are relaxed. We allow the corridor to be either symmetric, upward or downward-biased. Here we study two extreme cases of corridor width of either 10% or 100% above and below the historical baseline ($x \in [0.1, 1]$).

Annex 5: The variable corridor 2: corridor bandwidth and symmetry

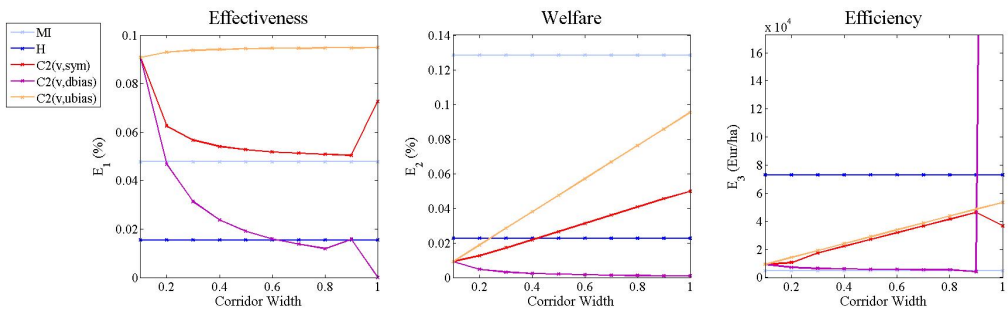

Figure 8: Performance of the Variable Corridor 2 at Different Corridor Widths

Note: The figure captures performance results of the variable corridor 2 compared to the model-implied and the historical baselines. We allow the corridor to be either symmetric, upward or downward-biased. The corridor bounds are set between 10% and 100% above and below the business-and-usual deforestation scenario. For the downward-biased case, the corridor bounds are computed as $dbU = 1.1d_{BaU}(t)$, $dbL = (1 - x)d_{BaU}(t)$, while for the upward-biased case $dbU = (1 + x)d_{BaU}(t)$, $dbL = 0.9d_{BaU}(t)$, with $x \in [0.1, 1]$.

Figure 8 displays changes in the performance of the variable corridor 2 baseline as we allow for different corridor widths ($x \in [0.1, 1]$) and both symmetric, and upward and downward-biased corridor bounds around the business-as-usual deforestation scenario. We compare these results with those of the model-implied and the historical baseline[24]. Since effectiveness was highest for the narrow corridors, we detail the analysis here and allow the corridor width to vary in the range $[0.01, 0.2]$. Figure 9 presents the results for the three performance criteria and checks sensitivities to small variations in corridor width for the symmetric case.

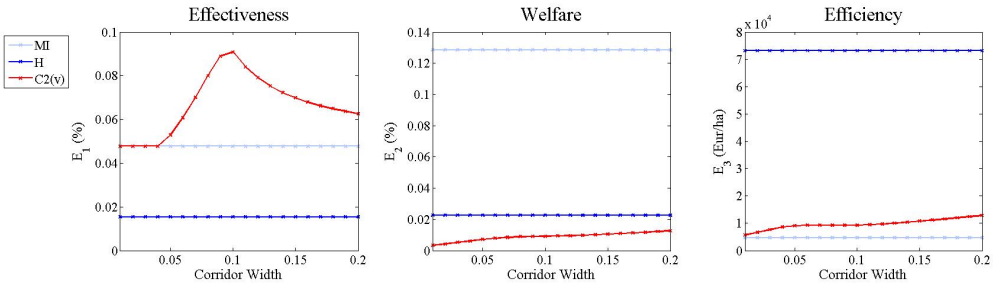

Figure 9: Performance Indicators for The Narrow Variable Corridor 2

Note: The figure captures performance results of the symmetric variable corridor 2 compared to the model-implied and the historical baselines. The corridor bounds are set between 1% and 20% above and below the business-and-usual deforestation scenario.

The results form a clear image. Effectiveness performance is non-linear and peaks at a corridor width of 10% ($x = 0.1$), while welfare is an increasing function in corridor size. Broader corridors diminish the efficiency of the REDD programs.

Annex 6: Overall performance indicators

Figure 10 displays the values obtained for the three performance indicators. Below each indicator, we place an emphasis on baseline dominance across the broad range of historical deforestation rates.

[24]Considering an average deforestation rate of 200 ha per year.

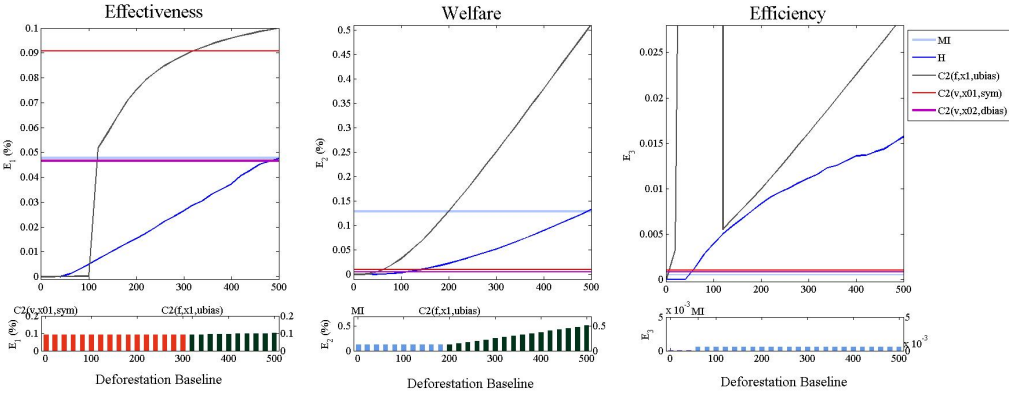

Figure 10: Performance Indicators and Dominant Baselines

Note: The figure displays performance results for five baseline types (historical, model-implied, upward-biased fixed corridor 2, symmetric variable corridor 2, and downward-biased corridor 2). While the upper panel illustrates results for all baselines, the lower one focuses only on the dominant baseline at each past deforestation average (the moment a baseline starts dominating is marked on the upper x-axis).

Table V: Weighting Alternatives for the Overall Performance Indicator

	High Transfer	Low Transfer
1. Equal Weights	$W_1 = \frac{R_{E_1}+R_{E_2}-R_{E_3}}{3}$	$W_5 = \frac{R_{E_1}-R_{E_2}-R_{E_3}}{3}$
2. Effectiveness Bias	$W_2 = \frac{2R_{E_1}+R_{E_2}-R_{E_3}}{4}$	$W_6 = \frac{2R_{E_1}-R_{E_2}-R_{E_3}}{4}$
3. Welfare Bias	$W_3 = \frac{R_{E_1}+2R_{E_2}-R_{E_3}}{4}$	$W_7 = \frac{R_{E_1}-2R_{E_2}-R_{E_3}}{4}$
4. Efficiency Bias	$W_4 = \frac{R_{E_1}+R_{E_2}-2R_{E_3}}{4}$	$W_8 = \frac{R_{E_1}-R_{E_2}-2R_{E_3}}{4}$

Note: Here $\{R_{E_j}\}_{1\leq j\leq 3}$ refers to the ranking obtained when ordering baselines according to each performance criterion and not the value of the indicator itself. The rank takes values from 1 to 5, where 5 corresponds to the highest indicator value. The efficiency indicator refers to average cost of avoiding one hectare of deforestation and is taken into account with the minus sign, to reflect preference for lower costs. Preference for high transfers (E_2) is captured by the plus sign, while preference for low transfers by the minus sign.

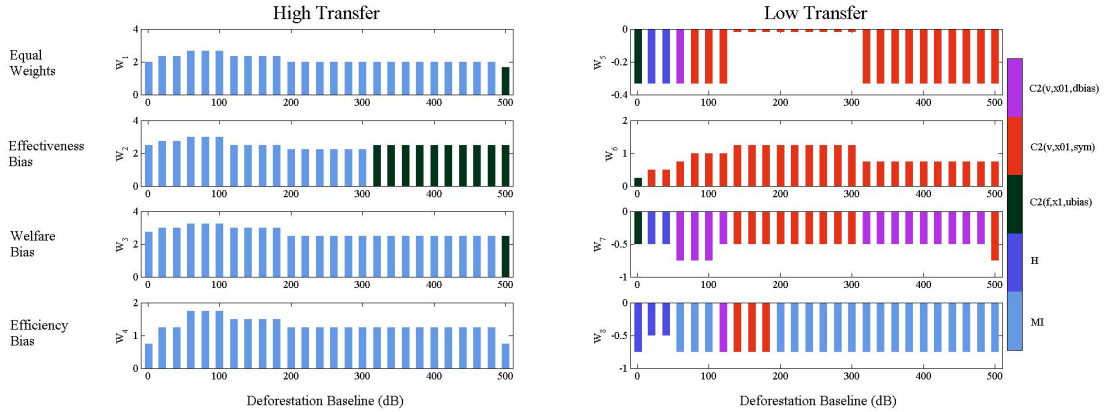

Figure 11: Overall Scores of Baseline Dominance

Note: The overall scores of baseline dominance $\{W_j\}_{1 \leq j \leq 8}$ are computed as detailed in Table V, reflecting the average ranking obtained by each baseline type. Only scores of the dominating baseline are displayed for each average past deforestation level.

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