Tropical Forest Protection, Uncertainty, and the Environmental Integrity of Carbon Mitigation Policies

Suzi Kerr, Motu Economic and Public Policy Research

P.O. Box 24390, Wellington, New Zealand

Phone: 64 4 939 4250

Fax: 64 4 939 4251

suzi.kerr@motu.org.nz

Joanna Hendy, Motu, New Zealand

Shuguang Liu, EROS Data Center

Sioux Falls, South Dakota 57198

United States

Alexander Pfaff

SIPA & Earth Institute

2910 Broadway, 104 Hogan Hall

New York, NY 10025

United States

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Abstract

Tropical forests are estimated to release approximately 1.7 PgC per year as a result of deforestation. Avoiding tropical deforestation could potentially play a significant role over the next 50 years if not longer. Many policy makers and negotiators are skeptical of our ability to reduce deforestation effectively. They fear that if credits for avoided deforestation are allowed to replace fossil fuel emission reductions for compliance with Kyoto, the environment will suffer because the credits will not reflect truly additional carbon storage. This paper considers the nature of the uncertainties involved in estimating carbon stocks and predicting deforestation. We build an empirically based, stochastic, model that combines data from field ecology, GIS data from satellite imagery, economic analysis and ecological process modeling to simulate the effects of these uncertainties on the environmental integrity of credits for avoided deforestation. We find that land use change, and hence additionality of carbon is extremely hard to predict accurately and errors in the numbers of credits given for avoiding deforestation are likely to be very large. We also find that errors in estimation of carbon storage could be large and could have significant impacts. We find that in Costa Rica, nearly 42% of all the loss of environmental integrity that would arise from poor carbon estimates arises in one life zone, Tropical Wet. This suggests that research effort might be focused in this life zone.

Keywords: climate, economics, carbon sequestration, uncertainty, policy, tropics,

1 INTRODUCTION

Tropical forests are estimated to release approximately 1.7 PgC per year as a result of deforestation. In contrast, global fossil fuel emissions are around 6.4 PgC (Schimel et al. 2001). Tropical forests have a significant impact on atmospheric CO_2 concentrations and, with appropriate policies that aim to reduce deforestation and encourage reforestation, they could be used to retain or sequester a significant amount of carbon. Niles et al (2000) and the IPCC (Brown et al., 1996) suggest that between 0.16 and 0.28 PgC respectively per year could be saved through prevention of tropical deforestation. Each of these assessments assumes that tropical deforestation could be reduced by around 15%. The IPCC Third Assessment Report (Kauppi and Sedjo, 2001), confirmed the Second Assessment Report (Brown et al., 1996) by estimating that biological mitigation as a whole (afforestation, reforestation, preventing deforestation, and forest management) could offset 12-15% of all business-as-usual fossil fuel emissions from 2000-2050. To put this in context, under the Kyoto Protocol, Annex I countries face limits on their emissions that are estimated to reduce global greenhouse gas emissions in 2010, relative to what they would have been, by around 0.29 PgC equivalent per year or 5.3 % of global emissions.[i] Thus, avoiding tropical deforestation could potentially play a significant role over the next 50 years if not longer.

Even if avoiding deforestation is actually able to deliver much smaller gains and we progressively tighten climate mitigation targets so that it is a much smaller part of aggregate reductions, these are real contributions to climate mitigation. As in most problems, the long-run solution to the climate problem is probably many small solutions rather than one grand one. In addition, if we prevent some deforestation we will reap many side benefits. We will reduce biodiversity loss and soil erosion, and help preserve indigenous culture.

The big question is whether the gains from avoiding deforestation really can be achieved. Many policy makers and negotiators are skeptical of our ability to reduce deforestation effectively. They fear that if credits for avoided deforestation are allowed to replace fossil fuel emission reductions for compliance with Kyoto, the environment will suffer because the credits will not reflect truly additional carbon storage. If the credits given exceed the true additional carbon and the credits are sold and used to meet Kyoto commitments instead of emissions reductions, a real rise in global emissions will occur relative to the Kyoto target.

Their fear stems largely from concerns about our ability to estimate carbon stocks and assess the additionality of net emission reductions from avoided deforestation activities. They fear that many avoided deforestation credits would be claimed for forest that would have been protected anyway.

This paper considers the nature of the uncertainties involved in estimating carbon stocks and predicting deforestation and simulates the effects of these uncertainties on the environmental integrity of credits for avoided deforestation. To our knowledge, this analysis has not previously been attempted.

To create policies with environmental integrity that allow these credits to be traded with emission reductions we require two things: a projection of how much forest there would have been without a policy (a forest ‘baseline’; see Pfaff (2004) in this issue for further discussion), and an estimate of the carbon stocks in the forests that are projected to be cleared. Each of these involves uncertainty.

We do not explicitly consider another form of uncertainty inherent to all biological mitigation – lack of permanence. We avoid the problem that forest protection can be temporary by calculating credits based on the actual level of forest each year. If the level of additional carbon falls (because the actual forest area falls or carbon storage per hectare changes) then some credits would have to be repaid.

We find that additionality is extremely hard to assess accurately and errors in the numbers of credits given for avoiding deforestation are likely to be very large. The major source of error in a project-based policy such as the Clean Development Mechanism is likely to be prediction of the land-use change baseline. We also find that errors in estimation of carbon storage could be large and could have significant impacts particularly in a policy that does not rely on land-use baselines, such as the Kyoto policy applied to developed countries (Article 3.3). The uncertainty in carbon storage estimates is not equally important in all life zones. The ecosystems of most importance are those that still have forest that is under threat but where deforestation might be averted. We find that in Costa Rica, nearly 42% of all the loss of environmental integrity that would arise from poor carbon estimates arises in one life zone, Tropical Wet. This suggests that research effort might be focused in this life zone.

We first present an integrated model of deforestation and carbon stocks in mature forest estimated from Costa Rican data and present deterministic results from the model. This is a simplified version of a model presented in Kerr et al (2003). We then discuss the underlying sources of uncertainty in our model with a focus on predictions of human land-use decisions; effects of policy design; carbon field measurements; process-based modeling of carbon; and scaling up of a plot-based model. We explain how we incorporate this uncertainty in our model.

We then use our integrated stochastic model to assess empirically the effects of different types of uncertainty. Uncertainty implies errors. By translating these errors into effects on environmental integrity we assess the real costs of uncertainty on the environment and hence the value of reducing it. We estimate the overall cost from uncertainty and the relative roles of different sources, land-use baselines, and carbon storage estimates in each life zones.

2 INTEGRATED MODEL DEVELOPMENT

To predict the evolution of carbon stocks as deforestation occurs, we use the simple integrated model depicted in Figure 1. Geographical information system (GIS) techniques are used to provide spatial modeling capability within the integrated model. The economic model incorporates both ecological factors (soils and ‘life zones’ (Holdridge 1967)) and economic factors (international prices, agricultural yields and production costs, the history of land use, and geographical access to markets) to determine the economic conditions on each plot of land and predict changes in land use as economic conditions change. The ecological model estimates carbon storage in mature forests.

<<Figure 1 about here>>

The economic and ecological models are coupled in two ways. First, carbon estimates from the ecological model are combined with predictions of forest cover to give us predicted carbon stock in each scenario. Second, the carbon estimates combined with carbon prices determine carbon payments per hectare for avoided deforestation. These payments affect land-use choices. In this simple model, we model the evolution of mature forest cover only; we do not consider reforestation.

For each parcel of land, a land manager chooses a land use that will maximize their expected returns from a set of potential feasible land uses, such as crops, grazing, and leaving the land in forest. Put simply, the land manager will clear the land if the return from a cleared land use is higher than the return from a standing forest. Once all land-use choices are simulated in space, we calculate the total remaining forest in each life zone type for every point in time. We then interact the remaining forest with estimates of carbon storage per hectare, calculated by the ecological model and averaged at the life zone level (given by column 1a in Table 1), to give us a prediction of carbon stock.

We can use our model to simulate the effects of policy scenarios, for example a carbon payment for forest. The carbon payment is determined by the international carbon price combined with the ecological model and varies by life zone (depending on potential carbon storage). As before, the land manager will make a land-use choice based on returns for the set of potential land uses, but in this case, the returns from forest protection are increased through our carbon payment. Fewer landowners will choose to clear because their net return from clearing is lowered. The landowners who will alter their behavior will be those whose land will yield low agricultural returns or those who have very high current carbon stocks in their forest. More forest will be left standing and more carbon will be stored relative to the baseline case. The following sections provide more details on the model components.

2.1 THE ECOLOGICAL MODEL

We estimate potential carbon storage in mature forests with the General Ensemble Biogeochemical Modeling System (GEMS) that incorporates spatially and temporally explicit information on climate, soil, and land cover (Liu et al. 2004b; Liu et al. 2004a). GEMS is a modeling system that was developed to integrate well-established ecosystem biogeochemical models with various spatial databases for the simulations of the biogeochemical cycles over large areas. The well-established model CENTURY (Parton et al. 1987; Schimel et al. 1996, Liu et al. 1999, 2000; Reiners et al 2002) was used as the underlying plot-scale biogeochemical model in this study. GEMS has been used to simulate the impacts of land use and climate change on carbon sources and sinks over large areas (Liu et al. 2004a; Liu et al. 2004b).

In this study, we used GEMS to simulate carbon dynamics in Costa Rica at a spatial resolution of 1140 m length scale. We calibrated GEMS against field data collected from 32 mature forest sites in six major life zones in Costa Rica (Liu et al., 2004c). Detailed description about the field measurements can be found in Kauffman et al. (2004). The values of eight variables (i.e., carbon and nitrogen contents in aboveground biomass, litter layer, standing and down woody debris, and the top 20-cm soil layer) were used to calibrate the CENTURY model. The calibrated values of model parameters (e.g., maximum monthly potential production, maximum decomposition rates of slow and passive soil organic carbon pools, and maximum decomposition rates of dead woody debris) were averaged by life zones and then incorporated with GEMS to simulate carbon stocks under potential vegetation in Costa Rica (Liu et al., 2004c).

The life zone level mean values and their corresponding standard deviations of aboveground biomass carbon density simulated by GEMS and used in our integrated model are listed in columns 1 and 2 of Table 1. In the integrated model, we use carbon stock estimates generated by the GEMS at the life zone level to translate forest cover into total carbon stocks and then to determine the reward for land users who prevent deforestation on their land. Columns 3-11 show various other mean estimates taken from the literature, and columns 12 and 13 provide the mean and standard deviation of the literature and GEMS mean estimates combined.

2.2 THE ECONOMIC MODEL

We define the probability that a piece of land will be cleared during any period as the land-parcel's hazard rate. To predict changes in forest cover, we must explain the variability in hazard rates in terms of observable characteristics of the land parcel that are likely to affect the land managers' land-use choices.

To create our economic model, we could have tried to calculate the optimal land-use choice for every land parcel in Costa Rica, giving us economically optimal land-use choice as a function of observable land-parcel characteristics. However, people do not necessarily behave in economically optimal ways. Non-economic factors such as cultural attitudes also affect behavior. Furthermore, an analyst is unable to observe all the factors that would drive optimal choices. Consequently, to create our model we observe past land-use choices and estimate the relationships between land clearance and each land-parcel's observable characteristics, giving us a model based on actual behavior.

We estimate these relationships econometrically for each spatial unit i across the whole of Costa Rica over four time periods, (t = 1900-1962,1963-1978,1986-1996,1997-2000) using the annualized average deforestation rate during each time period as a measure of the hazard rate of deforestation. We exclude the period 1979 – 1985 because of data anomalies. We define the spatial unit of observation, our 'land parcel', as the disaggregation of each of 436 administrative districts into each of the 12 major life zones. In 1900 there were 1211 forested land parcels.

The magnitude and direction of the observable drivers of land use change are estimated using the equation[ii]:

$$\ln\left(\frac{\mathbf{h}_{it}}{\mathbf{1}-\mathbf{h}_{it}}\right) = X_{it}\beta + D_t\boldsymbol{\delta} + \boldsymbol{\varepsilon}_{it} \qquad \textbf{(1)}$$

where: h is the hazard rate; X is a matrix of observable explanatory variables; β are the estimated coefficients of observable explanatory variables; D are dummy variables for each time period; δ are their coefficients; and ε is the error. The variables we use to explain the land managers' decisions are given in Table 2, together with their means and estimated coefficients. For the regressions, we normalize returns, cleared % and distance by subtracting their global means so that the normalized hazard rate at the global mean of the variables in the first period is approximately zero and we can extract time dummy coefficients that primarily reflect national development trends and tend to zero as the effect of national development on deforestation tends to zero – this is useful for forecasting (see Appendix A). More details on the data and model development are given in Kerr et al. (2004).

<<Table 2 about here>>

Briefly, the land manager will be more likely to clear productive land that is suitable for crops with high returns. To capture this in our model we use expected returns as an explanatory variable. Current actual returns in each period are calculated from the exogenous variables international prices, yields, and production costs, for crops grown in each land parcel. We assume that expected potential returns are simply equal to current returns. Returns vary by life zone, district, and period. As we see in Table 2, returns positively and significantly increase deforestation in most samples. The returns variable has large errors because of the difficulties in generating accurate historical data. It performs better in recent periods where the data is of better quality and our implicit assumption of a market economy is more accurate.

Access to national and international markets affect the farm-gate returns that land-managers receive for different crops. This will vary temporally and spatially, with land-parcels further from cities and international ports being less accessible and hence receiving lower returns than those closer. As road networks are developed and improved, the difference in distance is likely to have less effect. Formally we model:

$$\textit{Farm-gate returns}_{it} = \textit{international returns}_{it} + (\beta_1 + \beta_2(\textit{time})) \times \textit{distance}_i \quad (2)$$

where *distance* is the straight-line distance from land parcel *i* to the closest of the three major markets in Costa Rica (Limón, San José, and Puntarenas). As we would expect, in Table 2 $\beta_1 <0$ and $\beta_2>0$. Both are significant.

Road networks will not necessarily develop uniformly across the country. The interaction of distance and time will capture only spatially uniform road development effects. Other infrastructure also will develop in a non-uniform way, for example electricity networks and agricultural distribution services. To control for this non-uniform development, we include the percentage of the forest that has been previously cleared, *%cleared*, or cumulative deforestation. In general, as people clear land, infrastructure will develop around them. This decreases the costs of production, raising returns and hence increasing the likelihood that people will clear the remaining forest. We find empirically that this has a positive and significant effect.

However, the forest on the best land (not too steep, well drained) within each observably homogeneous land parcel is likely to be cleared first. Thus, we might expect that productivity and hence potential returns on the remaining forested land will be lower and pressure to deforest will fall. This is likely to have the greatest effect as the percentage cleared becomes high so we allow for a quadratic effect of previous clearing, $\%cleared^2$. This turns out to be insignificant.

We expect that a significant amount of national development will affect the country more uniformly as private and public institutions develop (e.g. educational facilities, enforcement of laws, and capital markets). Increased returns associated with development initially result in extensification of agriculture, increasing pressure on forests. Eventually, development results in higher capital intensity and wages, and intensification of agriculture. The economy moves away from reliance on agriculture as the industrial and service sectors grow. This eases deforestation pressure. Conservation regulations are generally strengthened as countries develop. These increase forest protection. To control for national development in our regression model we introduce time-dummies for each period. We find that underlying deforestation pressure falls consistently over the period but falls most rapidly after the mid 1980s.

<<Table 1 about here>>

With this model design and these explanatory variables, we explain between 22 and 40% of each period's cross sectional in-sample variation and 37% of the overall variation. This amount of explanatory power is reasonably consistent with other economic deforestation modeling. Comparable studies that have looked at tropical land-use change include Pfaff (1999) who examines deforestation in Brazil and explains 37% of the variation, and Chomitz and Gray (1996) who study Belize and explain 39% of land-use change cross-sectionally.

3 DETERMINISTIC MODEL RESULTS

In this section, we demonstrate one simple use of the integrated model: estimation of the responsiveness of deforestation to carbon payments – the carbon supply curve. The period we consider here is the period when deforestation slows in Costa Rica, 1986 -

1997. Costa Rican real economic growth rates were on average substantially better than the rest of Central America during the period 1960-2000 (Rennhack et al., 2002). As a result, Costa Rica is one of the more developed Central American countries; other countries/regions may still be in the rapid deforestation phase, for example Guatemala, Southern Mexico, and Colombia. Studying this period could give us insight into carbon supply that we could apply elsewhere. In contrast, after 1997, Costa Rica experienced very little deforestation so would also supply very few carbon credits through avoided deforestation. Because the model is simple and based only on Costa Rican data, the simulations given below should be thought of as illustrations with an empirical basis.

When we separate the returns variable from other X variables, apply the coefficients from column I in Table 2 and include an annual carbon payment that reduces the net return from converting forest to agriculture, equation (1) becomes:

$$\ln\left(\frac{h_{(t+1)}}{1-h_{(t+1)}}\right) = 0.065 \times \left(returns_{(t+1)} - annual\ carbon\ payment \times C\ per\ ha\right) + X_{t+1}^{-r}\beta \qquad (3)$$

where X_{t+1}^{-r} are the explanatory variables other than returns.

To simulate supply we first forecast forest area in a non-policy case; this projection is based on equation (3) with no annual carbon payment. It is done iteratively. In this section we use an in-sample projection using actual data. When translated into carbon, this provides a potential ‘baseline’ against which carbon storage could be credited.

With a positive annual carbon payment, annual returns to mature forest will be equal to the annualized-equivalent carbon price times the amount of carbon that the primary forest stores. This annual payment can be thought of as interest on a payment for permanent protection, or as a simple rental payment if carbon prices are not expected to change. Actual rental payments are complex to predict as they depend on expectations about future C prices (Kerr, 2003). We can now predict forward to give us a new prediction of forest and carbon stock. The difference between the predicted carbon stock under the simulated policy case and the predictions of carbon stock with no policy will give us a measure of the effectiveness of the policy. This difference is defined as the carbon supply, the additional carbon induced by the annual carbon payment.

<<Figure 2 about here>>

In Figure 2 we show the carbon forecast in the baseline and one policy case with a $14.15 annual carbon payment. The upper curve in the figure shows how carbon stocks evolve over time if the carbon payment price is continued. The vertical projection of the difference between these two stocks shows the cumulative supply of carbon available at any point in time. The same reward elicits different amounts of additional carbon over time depending on the amount of deforestation that would have occurred. The amount of additional carbon stored in forests cumulates over the years because every year some deforestation that would have occurred is prevented. In the later years when we predict that deforestation will cease, no additional carbon is stored.

$14.15 is chosen because in our model it reduces the deforestation rate by 15%, which is around the level both Brown et al (1996) and Niles et al (2000) assume when estimating the potential contribution of avoided deforestation to climate change mitigation. This payment is very high relative to current estimates of likely international carbon prices. With a 10% discount rate, this could translate to around US$145 per tonne of permanent reduction.

If we vary the policy across a range of prices, we can map out a supply or cost curve. (See Appendix C for details on the derivation). In Figure 3, we show a cumulative supply curve 11 years after the introduction of a carbon rental price (1986-1997). At low payments, the curve is reasonably straight, but as the payment increases, it begins to curve upward. A $1 annual payment per tonne of C, seems more likely than $14.15. Our model is also probably more accurate when dealing with simulations that involve small policy perturbations. A $1 annual payment leads to a reduction in deforestation of 1.2%. The cumulative stock after 11 years for a $1 rental price, is 261 million tonnes and the baseline stock is 260.5 million tonnes, suggesting a cumulative supply of 0.5 million tonnes in Costa Rica. Thus at what might be considered reasonable prices, our results suggest that the potential for avoided deforestation to contribute to climate change mitigation may not be as great as some anticipate.

The supply or cost curve can also be used to estimate the cost of storing a given level of additional carbon. The horizontal distance is the cumulative amount of storage offered at each price up to that year. The integral under the curve up to the chosen level is the cost of continuing to protect that level in the given year. The first units are cheap to store but they get increasingly expensive as forest on more valuable agricultural land is protected.

<<Figure 3 about here>>

4 UNCERTAINTY: STOCHASTIC MODEL DEVELOPMENT

4.1 SOURCES OF UNCERTAINTY IN A CARBON CREDIT SYSTEM

In a policy situation, the land use baseline will be an out-of-sample forecast and the carbon numbers will be estimates. We can quantify some of the uncertainty in these and extend the deterministic simulations above to produce predictive distributions of deforestation and carbon supply.

$$\text{Credits Created} = (\text{Actual forest area} - \text{Predicted baseline forest area}) \times \text{Estimated C per hectare} \quad 4)$$

As we discussed earlier, carbon sequestration will be rewarded based on the amount of actual forest retained, net of predicted baseline, times the estimated carbon storage per hectare (Equation (4)). Uncertainty in each of these terms will result in uncertainty in environmental outcomes from the policy.

Here we focus on the second two terms: land-use baseline and carbon per hectare. Environmental losses occur when the number of credits created exceeds the actual amount of additional carbon that is stored as a result of the policy. Environmental loss occurs if the baseline forest is underestimated, or the amount of carbon that is actually stored per hectare is overestimated; each results in a relative rise in emissions.

$$\textit{Environmental Loss} = \textit{Credits Created} - \textit{True Additional Carbon} \quad (5)$$

4.1.1 Predicting deforestation out of sample

We apply the economic model with statistically estimated coefficients to predict out-of-sample deforestation rates and thus forest stock using an iterative process (see equation (6)). To predict deforestation, we need to predict values for the right-hand-side variables (listed in Table 2) at *t+1* for every land parcel in Costa Rica. We predict a development path by fitting a curve to the time dummies' coefficients. It does not seem reasonable to suppose that the development process simply stops. The prediction process is described in the Appendix. We can then move forward along this curve to get *development* predictions over time, i.e. $\hat{\delta}_{(t+1)}$. $\%cleared_{t+1}$ is evaluated at the beginning of the prediction period. It is known for the first period of prediction, based on current forest, but after that is updated based on the prediction of deforestation in the previous period. 'Returns' is a function of price, yield, and cost of production of a crop. An accepted forecast for price is a product's current price. We cannot predict crop-specific technology change, thus cannot predict changes in production costs or yields. Consequently, we assume in our deterministic modeling that returns stay constant.

We can now evaluate the equation, for each land parcel, based on the predicted values of the explanatory variables:

$$\ln\left(\frac{h_{t+1}}{1-h_{t+1}}\right) = 0.065 \times returns + \left(-0.020 + 0.029 \times (t+1)\right) \times dist + 1.9 \times \%cleared_{t+1} + 0.16 \times \%cleared_{t+1}{}^{2} + \hat{\delta}_{t+1} \tag{6}$$

We solve for the hazard rate, $h_{,t+1,}$ giving us the predicted deforestation rate for the time period *t+1*. We then repeat this process for period *t+2*.

4.1.2 Errors in land use baselines

Errors associated with the prediction of a land-use baseline are unobservable; we are predicting an event that will never occur if there is a policy. Uncertainty in baseline projections will arise from uncertainties in the estimation of the model parameters, prediction of the driving variables of the model, and model specification errors. The underlying sources of error in land-use baselines are the complexity of human behavior and the large range of unobservable and unpredictable factors that affect that behavior.

Deforestation pressure depends heavily on national level economic, political and even natural conditions. War, recession, hurricanes or pests in key crops can have major impacts on the profitability of land clearing. On a more mundane level, the rate of economic development depends on a wide range of domestic policies and development in key economic and legal institutions. Corruption and political instability can reduce the returns to investment significantly. Foreign aid, such as for road building, can provide impetus for development. These conditions can change dramatically over time and are almost impossible to predict. They affect the common component of deforestation that affects all parcels and do not average out across the country.

Changes in key international commodity prices, such as coffee or beef can be critical. These tend to be unpredictable – otherwise people would profit from them in financial markets. They will affect some areas more than others and create uncertainty in our 'returns' variable. Pfaff (2004) illustrates the effect on our baseline predictions of one such "shock", showing the impact on the predicted baseline if the banana market collapsed. Even if average returns were known, actual plot level returns and responses to them would be highly variable. Our empirical model primarily captures land user responses to measures of average returns to different land uses in large aggregated areas and to birds-eye distances to markets. Actual agricultural returns on newly cleared land will vary enormously depending on the specific characteristics of the plot, the technology available at different points in time, and the farmer's access to capital to invest in the plot. The transport costs of getting different products to market will vary depending on road access and the crop type. Birds-eye distance is a weak proxy for this. Even with the same transport costs, different farmers may have differential access to the more valuable export markets because of marketing systems. Even if we could estimate the actual farm-gate returns accurately, different farmers will respond differently because of their age, past experience, education, the security of their land tenure, their attitudes to conservation and many other factors. Some of these sources of heterogeneity will wash out over large areas but others will not.

4.1.3 Errors in estimates of carbon storage

The carbon density in forest in a system that offers rewards for carbon storage will need to be estimated by field measurements or by model simulations parameterized and validated with local field measurements. Thus uncertainty will arise in estimating carbon density through sampling design, measurement, and model simulations.

Uncertainty is inherent in field measurements and laboratory analysis. Random and/or systematic errors can be introduced in the measurements of tree diameter at breast height (DBH), tree height, carbon content in plant tissue, and wood density (Brown 1997; Phillips et al. 2000). Errors in the application of allometric equations, which are frequently used to estimate carbon density from tree measurements (e.g., DBH, height and wood density), can contribute to the overall uncertainty as well (Keller et al. 2001; Brown 1997; Phillips et al. 2000). Another source of error in regional carbon estimates comes from the selection of field sites (Smith 2002; Macdicken 1997; Phillips et al. 2000). Nevertheless, this error can be minimized with an adequate deployment of sampling plots (Macdicken 1997).

Carbon stock estimates generated by models inevitably contain errors. Major sources of error include an imperfect representation of the reality by the model or the weakness of model structure, as well as errors contained in model parameters and input data. Calibration and validation of ecosystem models have suggested that certain model parameters vary in space and time. It is often difficult to predict the spatial and temporal variations of parameters. Poor predictions are likely to introduce errors in carbon estimates. Input data, such as land cover, soil, and climate variables, also contains various degrees of error, which can potentially propagate to the carbon estimates through the modeling system. To minimize the error in model simulations, it is crucial to have the model calibrated and verified first.

4.1.4 Errors introduced by policy design

The most accurate carbon measurement would require fieldwork on every plot by qualified, objective ecologists. This may work well when projects are few and small but will probably be inordinately expensive relative to the value of the credits when projects are large. Even with this level of effort, errors and bias will still arise. Accurate measurement also risks non-transparency and potential corruption because results cannot be easily replicated. Allowing project organizers to do measurement invites bias. All these factors suggest that a wide-scale, effective program needs to simplify carbon measurement and reward. For example, we model a system where only one level of carbon storage per hectare of mature forest is assumed for each life zone. The tradeoff is that this introduces errors in carbon measurement. We do not assert that one level per life zone is optimal. Further research needs to compare the costs of the environmental losses we identify and the costs of more accurate measurement.

In addition, with the reward formulated as in equation (3), we reward only carbon stored in a forest. We are making an implicit assumption that all land uses, soil types, and vegetation other than those in forests store zero carbon. This introduces a bias in the integrity of environmental outcomes; we may be rewarding more carbon storage than actually occurs. In fact, however, it appears that very little carbon is stored in pasture – the main use of recently deforested land in Costa Rica. The carbon that does remain tends to be in remnant trees that are gradually harvested (personal communication with Judith Jobse and Boone Kauffman). Allocating baseline carbon to all the potential land uses on a plot could reduce the error in carbon credited. However, it would require more understanding of the carbon processes in different land uses.

4.2 QUANTIFICATION OF UNCERTAINTY

We quantify the effects of uncertainty on environmental losses using two approaches: first we introduce variation into the model by varying the estimated and predicted variables and parameter values within confidence limits in Monte Carlo simulations; and second we compare our predictions with out-of-sample measurements.

We use both approaches within our economic model. We must always use a Monte Carlo to assess uncertainty in supply and hence need to model uncertainty in economic returns. For each sample, we vary the returns for each crop each year using a random walk that varies by crop to create returns paths that vary by land parcel. We assume that the returns error distribution is normal with standard deviation equal to the standard deviation of the changes in crop-price over time. We do not vary yield or production costs because we have no good way to predict either the trend change or the uncertainty in that change.

The use of a random walk means that shocks will propagate through time in each sample. Uncertainty is also inherent in the estimated return coefficient in our economic model. When the model was estimated using regression analysis, the error distribution for each coefficient was also generated. We repeatedly randomly draw the return coefficient based on its regression-estimated mean and variance-covariance matrix, assuming normally distributed errors.

When we use a Monte Carlo to study uncertainty in land-use baseline forecasts we vary the returns variable and coefficient as above and also vary all other coefficients. For the time dummy coefficients, we stochastically vary the two estimated parameters in our national development function, using their variance-covariance matrix, and solve for the third parameter so that the required constraint is met.

Each perturbation of the model parameters will alter the land-managers' clearance decisions, and thus lead to a different deforestation rate. In this way, we generate predictive distributions of forest levels. This modeling generates the confidence intervals around our supply simulations and land use baseline forecasts.

We also quantify uncertainty in the baseline predictions using the second approach, by comparing predictions with out-of-sample measurements. These are the numbers presented in the results. We can do this because while in a real policy a baseline projection will be unobservable, there was no policy in our omitted period. Forecast errors were assessed during different periods, by omitting the appropriate period, and in certain land parcels, by omitting those parcels during model estimation. Our forecast forest error is the difference between actual and predicted forest. This comparison leads to errors that fall within one standard deviation of the errors that were predicted when we used only the Monte Carlo approach, which suggests that our specification of economic model uncertainty is not too bad.

To quantify carbon uncertainty we use only the Monte Carlo approach. True carbon is unobservable. We consider two sources of error in carbon density estimations: errors in mean estimates of life zone carbon density, ε_m, and errors because of heterogeneity in carbon density within life zones, ε_v. We define actual carbon stored in a hectare of mature forest as:

$$c = \tilde{c} + \varepsilon_m + \varepsilon_v \qquad (7)$$

where $\tilde{c}$ is estimated carbon storage. By taking the mean of the above equation, we define carbon bias:

$$\bar{\varepsilon}_m = \bar{\tilde{c}} - \bar{c} \qquad (8)$$

where $\bar{\varepsilon}_m$ is the mean error, $\bar{\tilde{c}}$ is the mean of the carbon estimates and $\bar{c}$ is the mean of actual carbon.

We use the carbon estimates generated by GEMS (see Table 1) as the levels of carbon for the reward system, $\tilde{c}$ and assume that actual carbon varies relative to this. To simulate carbon uncertainty we must estimate each of the components in equation (7). The variability within life zones was simulated by randomly drawing ε_v from distributions empirically estimated from the GEMS results (the variance of these data is shown in the second column in Table 1, see Liu 2002, Liu et al. 2002 for more detail). To include variability from the distribution of mean estimates, we also need to know how ε_m is distributed. Because *c* is unobservable, we cannot quantify the bias, $\bar{\varepsilon}_m$ (equation (8)). In this study, we arbitrarily set the bias to be negative so actual carbon is systematically lower than our estimates. We randomly draw ε_m from a lognormal distribution with $\bar{\varepsilon}_m$ set to be -10% of $\tilde{c}$ and standard deviation derived from variation in literature estimations of carbon values (see last column in Table 1). The combined standard deviations from both sources are listed in the first column in Table 5. They range from 35 – 54% and on average are much larger than the Houghton et al (1996) illustrative estimate of a 16.5% one-standard-deviation range for uncertainty in emissions factors for land use activities.[iii]

5 ENVIRONMENTAL COSTS OF UNCERTAINTY

In this section, we use our stochastic model to look at the effects of uncertainty on the environmental implications of policies that aim to prevent carbon loss through deforestation. In other words, we quantify the environmental costs of uncertainty. Following (6) we define environmental loss *(EL)* as:

$$EL = \underbrace{\left[F(r\tilde{c}) - \tilde{F}(0)\right]}_{\text{carbon credits created}} \times \tilde{c} - \underbrace{\left[F(r\tilde{c}) - F(0)\right]}_{\text{total additional carbon}} \times c \tag{9}$$

where r is the carbon payment (US\$ per tonne of C per year), $F(0)$ is actual baseline forest in hectares, $\tilde{F}(0)$ is predicted baseline forest, and $F(r\tilde{c})$ is the forest stock generated with annual carbon payments based on the estimated carbon.

Environmental losses can be decomposed further into three terms that represent the sources of that uncertainty: 'wrong supply times carbon error', 'baseline error' and error interaction'. By rearranging equation (9) we can see:

$$EL = \underbrace{\left[F(r\tilde{c}) - F(0)\right] \times \left[\tilde{c} - c\right]}_{\text{'wrong' supply times carbon error}} + \underbrace{\left[F(0) - \tilde{F}(0)\right] \times c}_{\text{baseline error}} + \underbrace{\left[F(0) - \tilde{F}(0)\right] \times}_{\text{error interactic}} \tag{10}$$

The first term in equation (10), '*wrong' supply times carbon error*, is environmental loss arising from incorrect carbon estimates that lead to over- or under-payment of credits for additional forest. The more additional forest is created, and the larger the carbon error is, the larger is the environmental loss. Carbon error also influences the land-use decision in the economic model when a carbon rental payment is introduced; higher carbon estimates lead to higher carbon payments and more protection. A positive initial error in carbon estimates is compounded by a positive land use response that means the error affects more land. Even if carbon estimates are unbiased, environmental losses occur on average. A positive bias in carbon estimates will exacerbate the inappropriate land use response.

For example, suppose two ten-hectare plots are identical in all ways. In particular, the farmer on each plans to clear 2 hectares (or equivalently have the same probability of deforestation in the baseline). Their land contains 100 tonnes C per hectare. When the policy is introduced, because of errors in C estimation, the farmer on one plot is offered a carbon payment for more carbon that his land really contains, 110 tonnes per hectare, while the farm on the other plot is offered less, 90 tonnes per hectare. If they both responded identically to the carbon payment and reduced their clearing to one hectare, each would receive an incorrect carbon payment but the C credits given would be correct on average; additional carbon protected would be equal to the carbon credits created. Suppose however, that, the first farmer with the high payment decides not to clear any land while the other, with the lower payment, decides to ignore the potential payment and continue to clear two hectares. The additional forest will still be two hectares but the carbon payment will be higher than it should. Even an unbiased C payment can lead to environmental losses.

The second term in equation (10), *baseline error*, is the environmental loss that arises solely from land-use baseline errors. This is the combined effect of uncertainty in all the economic and ecological variables that influence a land managers' clearing decision when no carbon payment is in place. This term is not affected by carbon measurement errors as no carbon price is paid in the baseline case.

The third term, *error interaction*, is the interaction of the two errors. If both land use and carbon errors were unbiased, the second term should be small when aggregated to the national level, as we would not expect the baseline error and the carbon error to be correlated. However, our errors will very likely have a significant bias so this term will not be zero. With the introduction of the uniform carbon bias into our model, the contribution of the *error interaction* term to *EL* will simply be 10% of the baseline error.

5.1 SIMULATING ENVIRONMENTAL LOSSES

In this section, we consider three scenarios and use out-of-sample observed forest cover and our integrated stochastic model in Costa Rica to estimate environmental losses. First, we consider the potential environmental losses in the year 2000, and their decomposition, assuming a policy had been implemented in Costa Rica in 1997. This scenario will approximately represent behavior during the developed phase of Costa Rica and give us some insight into the impacts of implementing a policy now.

Second, we investigate our cross-sectional predictive power. If we have accurate measures of the land-use paths on some land parcels over a period, how well can we estimate the behavior of other parcels? With this experiment, we can gain some understanding of the usefulness of using control plots as predictors for the baseline deforestation that would have occurred in other plots where the credit system has been adopted. If control plots work well, a system that uses them might involve much smaller environmental losses. We simulate this by first estimating the model using a 90% random sample of all the land parcels, stratified across life zones, for all periods. We then predict out-of-sample on the other 10% of land parcels in 1997-2000.[iv]

Third, we estimate the *EL* for the period 1986-1997, creating a hypothetical "other country" using out-of-sample data from Costa Rica and compare it to the predictions from our model. For both the first and third scenarios, we produce our baseline simulations from an economic model estimated excluding the time period in which we simulate (columns II and III in Table 2) so they are true predictions.

5.2 RESULTS

Following equation (9), *EL* is broken down into carbon credits created and total additional carbon. We present our estimates of environmental loss in Table 3 as a percentage of the 'baseline carbon loss'. Baseline C loss between periods 0 and T is defined as $(F_0(0)- F_T(0))c$. Between 1986 and 1997, 19% of forest was lost and between 1997 and 2000 around 0.5% of forest was lost. We choose to use this for scaling because it is unaffected by the simulations. Another obvious comparison would be with the level of true additional carbon. However this changes with the carbon rental price and with the carbon error. All the results presented here are based on a carbon rental price of (1997)US$1 and are averaged over 10,000 samples.

<<Table 3 about here>>

In each scenario, a $1 carbon payment would save about 1.2% of the carbon that would have been lost without a policy. In Costa Rica, this equates to about 360,000 tonnes/year for the period 1986-1997 and only about 9,500 tonnes/year of carbon for the period 1997-2000.

However in each scenario the number of credits is much larger than the additional carbon. In the first experiment, 1997-2000, the number of credits created is nearly 40 times larger than the true additional carbon. This results in large environmental losses: 39.9% of the baseline carbon loss. For the 10% sample for the 1997-2000 period, the overall environmental loss was much smaller, though it was still four times as large as the total additional carbon gained. For the development period, 1986-1997, the number of credits created is negative. The error is still large, 32%, but is an environmental gain. The negative credits arise because the baseline prediction, $\widetilde{F}(0)$, is significantly higher than the actual forest baseline.

What is driving these large errors? Understanding this may help us develop research strategies to reduce them and design policies to minimize their effects.

5.2.1 Decomposition of Total Error

Table 4 shows the decomposition of environmental losses by source for our three different experiments. This allows us to explore the importance of different sources of uncertainty. In all three cases, the *baseline error* swamps the other two errors. In the national simulations, the *baseline error* alone is about 30-40 times larger in absolute value than the additional carbon supplied with a $1 rental price. In the first two scenarios, the *baseline error* contributes to environmental loss. In the third scenario, the *baseline error* contributes to environmental gains.

The baseline error and magnitude of environmental loss is much smaller in the case of the 10% sample. By identifying the national development trend from other areas, the baseline errors are confined to spatial extrapolation. In the case of the 10% sample, if we repeatedly drew samples, on average there would be no baseline error. There would still be supply errors and because of the carbon bias, the error interaction would still be positive on average. This suggests that the use of control plots in this case might have been a relatively good indicator for baseline behavior.

This inference probably depends on two factors. First, a small percentage of the country (10% of forest parcels) was exposed to the carbon reward. The policy-induced changes in these areas probably would not have large effects on development that would spill over to other areas. Thus other areas might be reasonably assumed to be at their true baseline – i.e. the control plots are a true control. If a large part of the country were involved in projects, the remaining area would no longer be a valid control. Second, the sample chosen was random so comparable to the non-sampled area. Real projects that cover part of the country are unlikely to be randomly located. Controls might need to be strategically chosen to closely match projects.

In contrast the effects of errors in carbon measurement seem relatively minor. Through the '*wrong' supply times carbon error* term, the carbon error accounts for only about 1% of the environmental loss in the national scenarios (A & C). It accounts for a larger percentage in the 10% sample because the baseline error is smaller in that case, but error is a similar magnitude as a percentage of baseline carbon loss in all three cases. Because we set the carbon bias to be consistently +10% of mean carbon, the error interaction term is always 10% of the baseline error. Carbon bias exacerbates the land use baseline errors.

5.2.2 Sensitivity of environmental losses to specification of errors

and scenarios

In the previous section, we found that the errors in estimating the baseline land use dominated any errors in carbon measurement. Here we explore whether this is a robust result or a result of specific model assumptions. We also consider what this means for the importance of reducing the errors in carbon storage estimates which is where ecologists have a real potential contribution.

Are land-use baseline errors likely to be this large? In the two national scenarios we over- or under-estimate baseline forest loss by between 30 and 40%. Predicting forward from 1997 for three years we predicted 0.68% cumulative deforestation where it was only 0.5%. Using our modeled uncertainty, these draws fall within one standard deviation of our predicted land-use baseline. This suggests that our specification of land-use uncertainty may be a reasonable representation. It also suggests that land-use baseline errors could be much larger still even when predicted on a broad spatial scale with relatively good data. The uncertainty in our model is likely to be close to a lower bound on uncertainty in real projects.

It is possible that the errors in baselines are much larger in particular years than over a long period. Over 50 years it might be reasonable to predict that a country will reach an agricultural equilibrium where all good land is developed but poor quality land is untouched, regenerating or replanted. This long-run equilibrium might be easier to predict than the timing of change. Thus overly generous baselines in some years might be offset by less generous ones in others leading to lower cumulative errors in a long-term policy.

Carbon errors might be much greater than our model suggests. The land-use baselines are compared with true out-of-sample data. In contrast, the specification of uncertainty in carbon measurement is largely based on educated guesses. Comparing literature estimates, the range is very large in some cases. For example, in tropical wet forest Helmer and Brown (1998) predict 259 tonnes per ha while Brown and Lugo (1982) predict 139 tonnes. Bias could be as large as 250%.

The land-use baseline errors interact with the carbon errors. If the bias in carbon measurement were +100%, the interaction would magnify the baseline error and double the overall error; i.e. from 37% of potential carbon loss in the first scenario (baseline error only) to 72%. Thus, carbon measurement is particularly important where there are land-use baseline errors.

Carbon errors also have effects that are independent of baseline errors. Suppose the policy was defined in such a way that the baseline was not important. For example, in developed countries, the Kyoto 'baseline' for land use change is set fairly arbitrarily. The rules in Articles 3.3 and 3.4 implicitly define a 'baseline' relative to which gains can be identified and rewarded. The errors in baselines for developing countries might be no larger than the errors in these Kyoto 'baselines'. If developing countries moved toward negotiated baselines at a regional or national level, there would be a one-off impact on environmental integrity. This could be offset by setting stricter targets elsewhere, either in the same country or in other countries. After that, the baseline is no longer an issue. Carbon measurement is always an issue.

In Table 4 we showed that with a carbon payment of $1 and carbon bias of 10%

carbon measurement error led to losses of 0.3% of baseline carbon loss. This translates to a roughly 25% environmental loss on each credit created. This is roughly split between the direct effect of the bias on every unit of carbon protected and the effect of variance in carbon estimates combined with the land use response to the varying carbon payments. If in contrast, the carbon payment was $10 and the bias was 100%, the carbon measurement error would be much more significant. A percentage increase in carbon error will have the same effect on supply as the same percentage increase in international price because they operate through the same process – i.e. by increasing carbon rewards. The 100% bias would raise the effective payment to $20. Additional carbon at $20 would be roughly 24% of baseline carbon (assuming linearity in supply) and the direct environmental loss resulting from the bias would also be around 24% with at least a 100% environmental loss on each credit.

In contrast, land-use baseline errors are 'lump sum'; they occur independent of the magnitude of carbon rental price and the estimates of carbon. Overall, baseline errors are likely to dominate if carbon prices are low. At low carbon prices, carbon errors would matter only because of their interaction with land-use baseline errors. If prices are high and carbon bias and variance are large, however, carbon errors could lead to significant environmental losses.

As well as the effects on the environmental integrity of the program, the behavioral effect of carbon errors means that they have implications for the efficiency of the policy. In areas where we over-estimate carbon per hectare, more forest will be protected than is efficient. In other areas, under-estimation will lead to carbon-rich forest being inefficiently deforested. Even if the same area of forest is protected overall, if the carbon rewards are wrong, the 'wrong' forest will be protected. This poor targeting of rewards raises the overall cost of achieving the environmental goal. Incorrect baselines have no effect on efficiency.

In summary, carbon errors may be larger than they appear. They are most significant for environmental loss when they interact with large land-use baseline errors and when carbon prices are high. Carbon errors cause inefficiency and raise the cost of mitigation. They will continue to be important even if developing countries move toward having national targets as developed countries do. Ecologists can reduce the level of carbon error.

5.2.3 Contribution of Uncertainty in Different Life zones

Here we consider how and why the effects of carbon errors vary across ecosystems (life zones). This could help target future ecological research to reduce this source of uncertainty and environmental losses more effectively. It can also suggest how accurately carbon rewards should be defined in each life zone.

The first column in Table 5 shows the modeled coefficient of variation in carbon in each life zone. This combines heterogeneity within life zones with variance in the estimates provided by field studies from the literature. This uncertainty can be reduced either by better estimates of the mean for the life zone, or through more carefully targeted carbon rewards that take heterogeneity within the life zone into account.

The life zones with the greatest overall uncertainty in carbon measurement are premontane moist forest and montane rain forest. Looking back to Table 1 we can see that the variance in the montane rain life zone is heavily driven by uncertainty in field studies. Montane wet also has high uncertainty in field studies. The high level of uncertainty might make this seem important to study. In contrast, premontane moist forest is in areas with highly heterogeneous conditions so might require a more differentiated policy.

Not all errors in estimates of carbon storage are equally important however. If there is no forest in a life zone, no forest can be protected so it does not matter if we do not know how much carbon could have been protected. As a first cut, studying the prevalent forest types makes sense. In Costa Rica, this suggests emphasis on tropical wet forest, premontane wet forest and tropical moist forest, (Table 5 Column 2). Although montane rain forest is a life zone with considerable ecological uncertainty, there is little forest left so, for rewarding avoided deforestation in order to reduce carbon release, it is relatively unimportant.

In addition, however, some life zones may have forests that cover large areas but these forests may not be at risk. Some life zones are unprofitable for agriculture. As long as the forest is not clear cut for forestry or inefficiently cleared by desperate peasants it may never be cleared. Measuring carbon accurately in these areas may also be less important.

Column 3 of Table 5 indicates the environmental losses per hectare of forest in each life zone relative to the average loss.[v] This measure combines the risk that land will be cleared, the level of carbon storage and the uncertainty in carbon measurement. These results are derived from our model. For this analysis, we set baseline errors equal to zero. That is we set $F(0) = \widetilde{F}(0)$ in equation (10). As before, the bias is assumed to be constant at 10% of the mean, the annual carbon payment is $1 and results are averaged over 10,000 samples.

Tropical moist forest has high carbon uncertainty and constitutes a reasonable fraction of remaining forest. However it faces a low risk of clearing and therefore low environmental losses when there are carbon errors. In contrast, although tropical wet forest has quite low carbon uncertainty, this forest is at high risk because it is in areas that are suitable for agriculture so these errors lead to high environmental losses.

<<Table 5 about here>>

Combining all these effects in the final column, we find that tropical wet forest, which has both the largest amount of forest and the greatest environmental loss per hectare, contributes most to the total environmental losses. It contributes nearly half of all losses in our model.

6 CONCLUSION

We tentatively conclude that, if other countries are like Costa Rica, it might be costly for avoided deforestation to contribute as much to climate mitigation as some IPCC estimates suggest. We more confidently assert that land use baselines are extremely difficult to estimate and that the errors they create could have significant environmental impacts if the scale of avoided deforestation projects is large. We do not necessarily believe that this means we should not include avoided deforestation in Kyoto or a similar agreement, just that relying on project mechanisms that require baseline estimates might not be a good idea. Estimating baselines for any economic activity is extremely hard and possibly baselines should be set once and for all for large geographic areas, regions or countries, through negotiation as they are for developed countries. Analysis such as ours that attempts to predict deforestation can be useful inputs to these negotiations.

Although ecological uncertainty appears to be on a smaller scale than land use uncertainty, we find that it could be very significant if carbon prices are high or if the true carbon bias is higher than we assume. Also, while baseline uncertainty disappears in an agreement with fixed targets, ecological uncertainty that arises from difficulties in estimating mean carbon levels cannot be avoided through policy design.

Appropriate targeting of future ecological research aimed at reducing uncertainty should take into account the relative areas of different types of forest, the level of threat those forests face (or the potential for reforestation if this is the interest) and the existing level of ecological uncertainty. We find that in the case of Costa Rica, this suggests further effort in the Tropical Wet life zone. Of course, the likely progress in the research should also be taken into account in setting priorities. It may be easier to reduce uncertainty in relatively understudied ecosystems.

We believe that three areas provide the most potential for reducing the error in carbon stock estimation over large areas. First, allometric equations used to calculate carbon stock from tree characteristics should be verified for a specific area, improved if necessary, and applied to only similar environmental and stand conditions. Correct application of these equations requires a reasonable stratification of the area of interest using one or multiple environmental features (Macdicken 1997; Kauffman et al. 2002). To ensure that a general allometric equation is not biased for a specific stratum, verification of the equation might be needed in a given area by sampling and weighing some trees, especially large ones (Brown et al. 2000), growing in the full range of conditions within the stratum. The second area that might reduce the error in carbon stock estimates significantly is the installation of field plots. Various options exist for sampling design (Macdicken 1997; Smith 2002; Brown et al. 2000). The locations of field plots should be predetermined before going to the field according to land cover maps to avoid subjectivity. Deploying plots along certain features such as roads should be avoided to minimize the introduction of potential errors.

Finally, models, after calibration and validation, should be used to simulate carbon dynamics in space and time, especially when the study area is highly heterogeneous and the cost of establishing many permanent plots for measuring and monitoring carbon changes is prohibitive. Validated models are very useful to explore carbon sequestration potentials under various physical, social, economic, and policy scenarios. Well-established plot-scale models have been extensively used for scaling-up carbon dynamics from sites to regions by incorporating detailed spatially-explicit information on climate, soil and land cover and land use change (Liu et al. 2003c). However, the applicability of ecosystem models to support the establishment of carbon sequestration projects has not been rigorously evaluated so far. Given that many carbon sequestration projects have been set up almost solely relying on field measurements of carbon change on permanent plots, an add-on evaluation of some models on characterizing carbon dynamics would be useful. If successful, the overhead cost for setting up carbon sequestration projects could be reduced and more management options could be explored using modeling approaches before implementation (Kerr et al. 2003).

Research cannot reduce within-life-zone variability but it does help us understand the spatial variability of carbon stocks. If the variability is very large in life zones that create a lot of environmental losses, it might be worth targeting carbon rewards more accurately by having different rewards within life zones. For example, if life zones can be further stratified by topography, and this stratification reduces within-stratum uncertainty, carbon rewards could vary by life zone and topography.

Our analysis has looked at one small country, only at avoided deforestation and only at the environmental losses from one potential policy. We have also considered only aboveground biomass and one characterization of the landscape. We believe future research could productively extend this research either using our model or similar ones to explore the robustness of the results, the effects of uncertainty on reforestation, the impacts of changing policy design – for example, increasing the accuracy of rewards but also increasing the costs of measuring carbon – and incorporating belowground biomass and different characterizations of landscape. This potential research stream would help the global community take optimal advantage of the biological mitigation opportunities in tropical forests without creating unacceptable global environmental risks.

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Figure 1 The Integrated Model

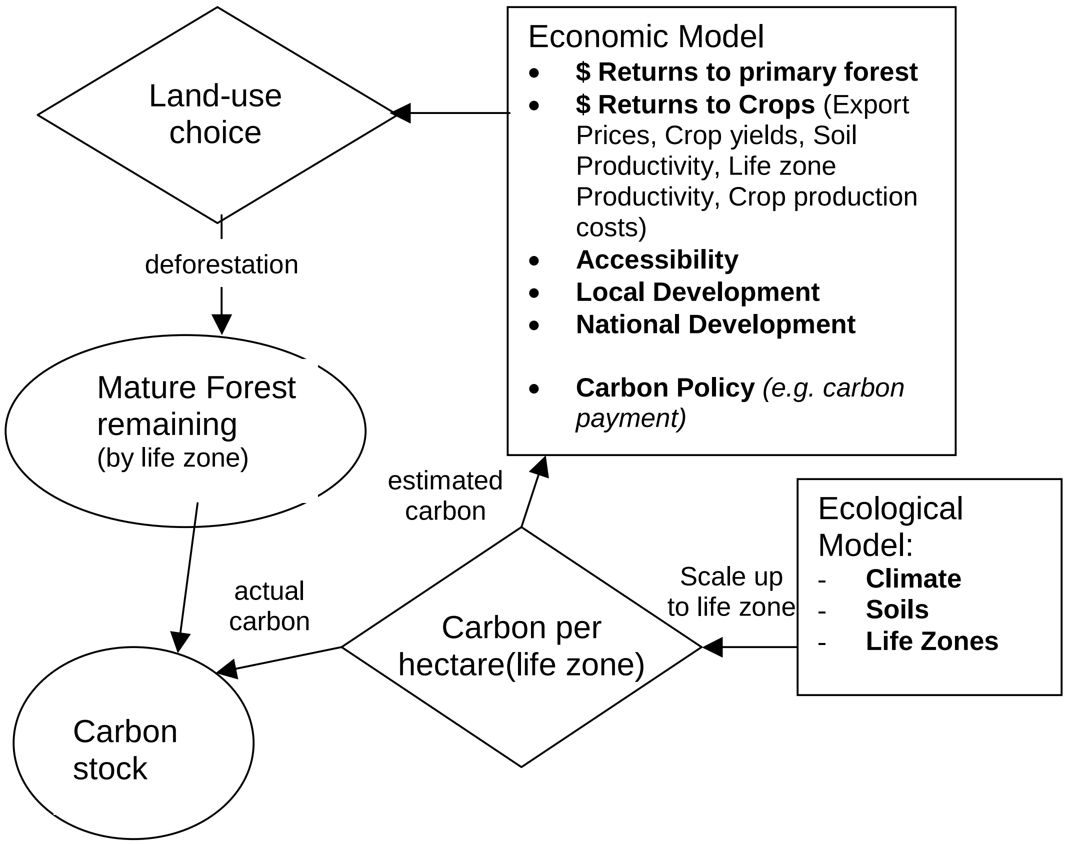

Figure 2 Forecast carbon stocks with and without a carbon price: This is an in-sample prediction that assumes no change in returns and sets the time dummy for the forecast period at its actual level.

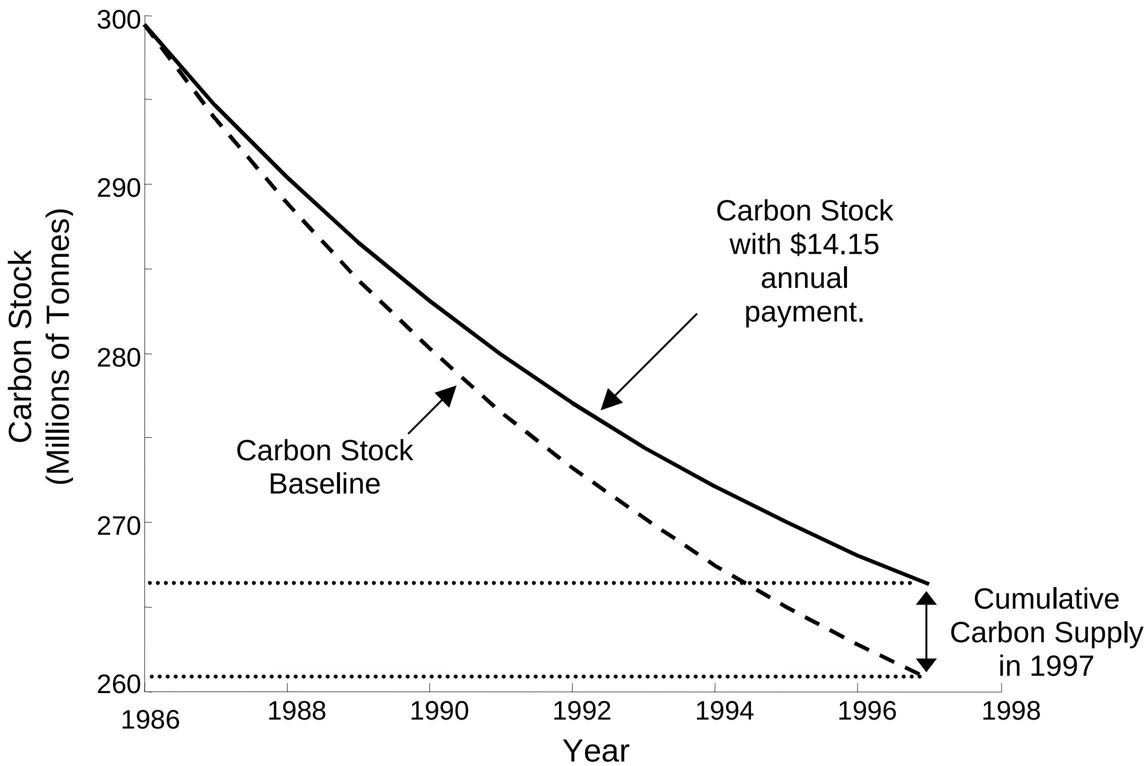

Figure 3 The supply curve for additional carbon for period 1986-1997

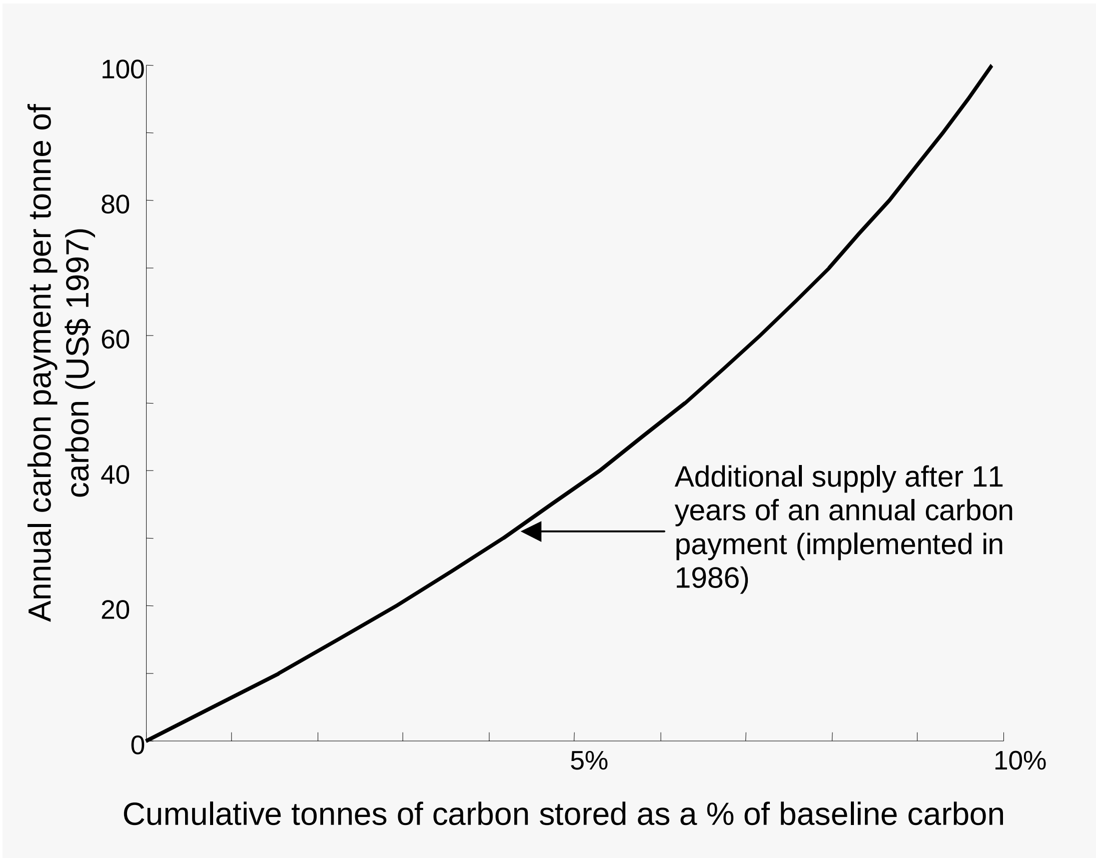

Table 1. Carbon density in aboveground biomass (tC ha^{-1}) by life zone as estimated by the GEMS model and field measurements.

Life zone	GEMS		Data From Literature									Overall literature	
	Mean	Std dev as % of mean	Brown (1997)	Brown and Lugo (1982)	Helmer and Brown (1998)	Brown et al (1989)	Delaney et al (1997)	Fehse et al (2002)	Tosi** (1997)	MINAE (1997)	DeAngelis et al (1981)	Mean	Std Dev as % of mean
Premontane moist	135	47			104				122	70	42	95	40
Lower montane moist	250	38			159		173		85	289		191	42
Tropical Moist	112	21	147	139	259	187	179	166	169	117	97	157	30
Premontane wet	149	28			153				133	111	66	122	29
Lower montane wet	222	40			210				86	174	183	175	31
Montane wet	258	42					157	134	47	154		150	50

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Tropical Wet	204	35	82	129	182			264	178	138	100	160	37
Tropical Dry	63	17	39	110	51*	55	70		78	34	57	63	38
Premontane rain	187	47	87		159				91	94	92	118	37
Lower montane rain	208	34			162				56		124	138	47
Montane rain	228	37			154				32	139	88	128	57

* This is the average of the range provided by Helmer and Brown (1998) of 7–94 tonnes of C/ha.

** Derived from Tosi (1997) by Shuguang Liu.

Table 2 Observable variables and regression results

Effect	Explanatory Variable	Non-normalized mean	Estimated Coefficient All I	1986-1997 excl. II	1997-2000 excl. III
Land Parcel Productivity and International Prices	Agricultural returns per hectare (US1997$1000/ha)	0.6	0.065* (0.023)	-0.15* (0.05)	0.052* (0.027)
Accessibility	Minimum distance to market (100km)	0.7	-2.0* (0.1)	-2.4* (0.1)	-2.2* (0.1)
	Minimum distance to market × time	4.8	0.029* (0.002)	0.039* (0.002)	0.033* (0.002)
Local Development	Percentage cleared	0.2	1.9* (0.1)	1.9* (0.2)	2.0* (0.2)
Limited Quality Land	Percentage cleared ^2	0.04	0.16 (0.29)	0.5 (1.4)	-0.03* (0.3)
National Development	Time Dummy (1900-1963)	–	*Omitted*		
	Time Dummy (1963 – 1979)	–	-0.44* (0.08)	-0.7* (0.1)	-0.58* (0.09)
	Time Dummy (1986-1997)	–	-2.4* (0.1)	*Dropped*	-2.6* (0.1)

Time Dummy (1997-2000)	_	-3.5*	-3.7*	
		(0.1)	(0.2)	*Dropped*
Constant	_	-2.7*	-2.6*	-2.6*
		(0.1)	(0.08)	(0.07)
R-squared		37%	36%	37%
N		3966	3056	3033

*** Significant with 99% Confidence**

Table 3 Environmental losses, carbon credits created, and total additional carbon as % of baseline C loss.

Scenarios	**A** **1997-2000**[vi]	**B** **Cross-section 1997-2000, one 10% Sample**[vii]	**C** **1986-1997**[viii]
Environmental Losses (EL)	39.9	5.01	-31.68
Broken down using Equation (9)			
Carbon Credits Created	41.1	6.23	-30.48
Total Additional Carbon	1.2	1.22	1.20

Table 4 EL Decomposition (using Equation (10))

Scenarios	A 1997-2000[ix]	B 1997-2000, one 10% Sample[x]	C 1986-1997[xi]

	Mean % of EL	Mean % of baseline loss	Mean % of EL	Mean % of baseline loss	Mean % of EL	Mean % of baseline loss
'Wrong' Supply						
×Carbon Error	0.8	0.3	5.7	0.3	0.9	0.30
Baseline Error	91.9	36.7	87.8	4.4	-93.1	-29.5
Error interaction	7.3	2.9	6.4	0.3	-7.8	-2.5
	100	*36.7*	100%	5.01	-100%	-31.68

Table 5 Effects of errors on environmental losses by life zone (1997-2000)

Life zone	Carbon Standard Deviation as % of mean carbon*	% 1997 CR Forest	$\frac{\text{EL per ha of forest in lifezone}}{\text{average EL per ha}}$	EL from life zone as % of total EL
Premontane moist forest	51%	5.8%	1.3	7.5%
Lower montane moist forest	42%	0.2%	2.7	0.6%
Tropical Moist	46%	17.1%	0.5	8.4%
Premontane wet forest	35%	19.1%	0.8	14.9%
Lower montane wet forest	37%	2.8%	1.0	2.9%
Montane wet forest	46%	0.04%	1.8	0.1%

Tropical Wet	36%	31.0%	1.3	41.8%
Tropical Dry	46%	2.6%	0.2	0.5%
Premontane rain forest	33%	10.4%	0.7	7.6%
Lower montane rain forest	47%	8.3%	1.3	10.4%
Montane rain forest	54%	2.6%	2.0	5.3%
		100.0%		100.0%

*This was estimated with both within-GEMS and between-literature-mean-estimates standard deviations being perturbed.

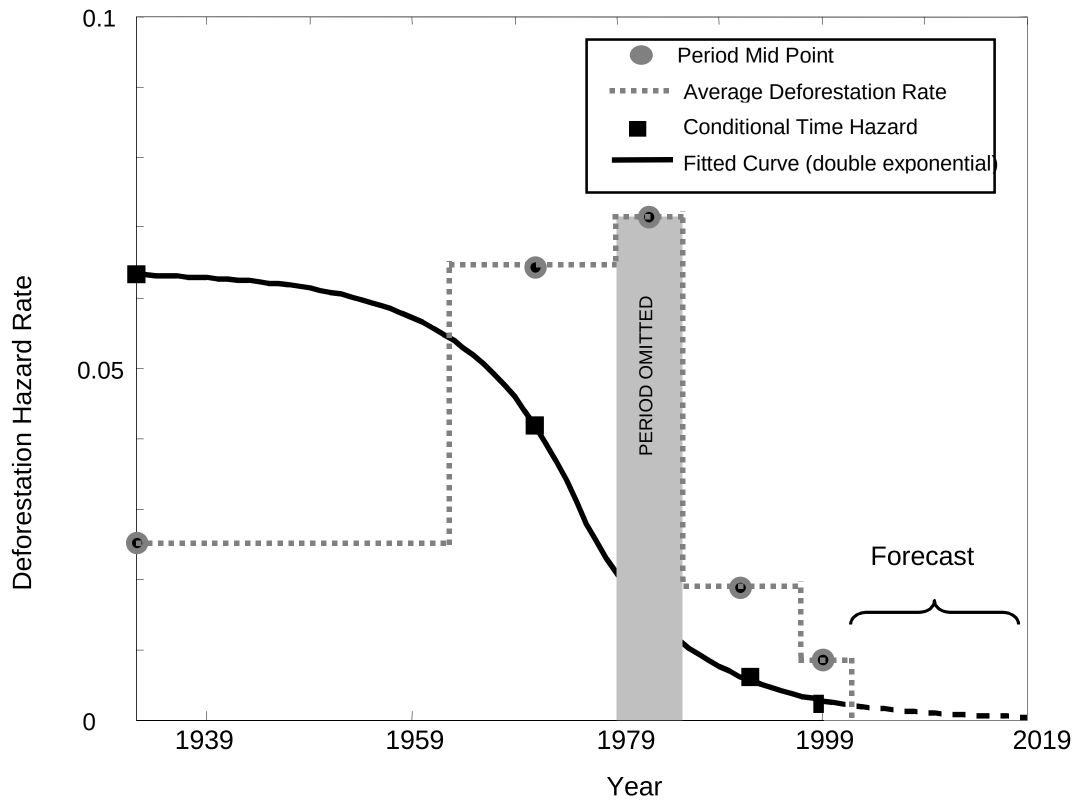
A. FITTING THE DEVELOPMENT CURVE

We first take the mean coefficients of our four time-dummies, δ_t, and transform them into their hazard form:

$$h_t = \frac{e^{\delta_t}}{e^{\delta_t} + 1}. \tag{11}$$

These are the hazard of deforestation for each time-period on a land parcel when all spatial variation has been controlled for; we show these and the actual deforestation rate in the Figure below.[xii] To fit a curve to these points, we must first decide on an appropriate functional form. The four data points in the figure area consistent with the shape of a stretched reverse-S, with two periods of relatively stable deforestation rates connected by a short sharp change period. This shift could be thought of as country moving from an undeveloped phase into a developed phase. Because of this shape, and the need to have degrees of freedom greater than zero, we choose a double exponential function to fit the points.[xiii] We fit the function to the vector, h_t, (shown by the black line in Figure) and then transform $\hat{h}_t$ back to $\hat{\delta}_t$.[xiv]

Figure A.1 Deforestation rate and development curve



The fitted curve has a coefficient of determination, or R^2, of 0.999. However, how well the curve fits *national development* is highly uncertain. There is no explicit theoretical basis for choosing this curve; we are only applying our theoretical expectations about the first and second derivatives of deforestation over time in Costa Rica to choose a functional form for extrapolation.

B. ESTIMATING SUPPLY

To give us the best estimate of supply during the relevant period, we simulate forest supply $F(r\tilde{c})$ relative to actual baseline forest $F(0)$. We predict supply using an in-sample regression, constraining the development function to equal the time dummy that covers the period in which we are evaluating the *EL*. We then calculate our policy supply as usual. This method eliminates error in our supply due to incorrect baseline estimates, leaving only the error in estimating land-use choice with a reward.

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[i] 2010 - MIT EPPA model v3 Reference Case compared to Bonn Agreement forever case. Results provided by Mustafa Babiker. If the US achieves its Kyoto target as well, reductions would be 7.6%.

[ii] We estimate this equation using a grouped logit regression pooled over time. We include in our regression all land parcels that have forest on them at any point in time, including those that have been reforested as they will still be subject to deforestation hazard in the next periods. We do not include national parks in our regression, however, as they will not be subject to the same kinds of deforestation pressure.

[iii] This number is based on an interpretation of the uncertainty information presented in IPCC (1992).

[iv] This choice of predicting land use for 10% of the land parcels is completely arbitrary.

[v] All the life zones have a positive EL, due to our uniform positive 10% bias.

[vi] This is the simulated EL in year 2000 after 3 years of a $1 carbon reward. To estimate the supply that would have occurred with a reward during the 1999 period, we simulate deforestation in-sample based on a regression model estimated using data from all periods (1932, 1971, 1992, and 1999; we omit 1982 because of spurious returns data from that period). Our development curve is constrained to equal the 1999 dummy - an approximation of development in that period.

Our baseline predictions for this period are based on out-of-sample simulations, with our regression equation estimated off the 1933, 1972 and 1993 periods and with our development curved constrained to equal the 1992 time dummy coefficient - a prediction of development in that period. We produce predictive distributions by randomly varying the regression coefficient for farmgate returns and coefficients of the development curve. We compare our baseline predictions with "actual" baselines (in-sample baseline estimations, which approximately equal actual measurements).

We estimated our regression model using a dataset that at each point in time includes any parcel of land that was forested. However, we only include land parcels that were in forest in the beginning of the simulation period for comparing our simulations out-of-sample, as our model only predicts deforestation not reforestation.

[vii] This is the EL for 2000 for a 10% sample of district-life zones. We calculate it as described in endnote vi, except we predict out-of-sample for only 10% of the life zones (the regression equation is estimated using the other 90%).

[viii] This is the EL in 1997 after 11 years of a $1 carbon reward. We calculate it as described in endnote vi except we predict out-of-sample for the 1992 period, the in-sample development curve constrained to equal the 1992 time dummy coefficient, and the out-of-sample development curve constrained to equal the 1972 time dummy coefficient.

[ix] This is the EL for 2000, based on a simulation run forward from 1997. See endnote vi for details.

[x] This is the EL for 2000 for a 10% sample of district-life zones. See endnote vii for details.

[xi] This is the EL for 1997, based on a simulation run forward from 1986. See endnote viii for details.

[xii] The deforestation rates are annualized rates, plotted at the midpoints of the periods 1899-1963, 1964-1979, 1986-1997, and 1998-2000 (1932, 1971, 1992, 1999). We omit 1979-1984 because of spurious returns data from that period.

[xiii] The function fitted is a double-exponential survival function. The double exponential hazard is given by:

$$\hat{h}_t = \begin{cases} \dfrac{p_3}{p_2}\left[1-\dfrac{1}{2}\exp\left(\dfrac{t-p_1}{p_2}\right)\right] & for \left(\dfrac{t-p_1}{p_2}\right) < 0 \\ \dfrac{p_3}{p_2}\left[\dfrac{1}{2}\exp\left(\dfrac{p_1-t}{p_2}\right)\right] & for \left(\dfrac{t-p_1}{p_2}\right) \geq 0 \end{cases}$$

where t is *time,* and p_1, p_2, and p_3 are the function parameters (p_1 is the displacement of the development period, p_2 the spread of the development period, and p_3 the scale). We fit p_1 and p_2 using a quasi constraining p_3 so that $\hat{h}_t$ is equal to the transformed mean coefficient, h_t, at the initial forecast period. That is:

$$p_3 = \frac{1}{\hat{h}_t}\begin{cases} \dfrac{p_2 h_t}{\left[1-\dfrac{1}{2}\exp\left(\dfrac{t-p_1}{p_2}\right)\right]} & for \left(\dfrac{t-p_1}{p_2}\right) < 0 \\ \dfrac{p_2 h_t}{\left[\dfrac{1}{2}\exp\left(\dfrac{p_1-t}{p_2}\right)\right]} & for \left(\dfrac{t-p_1}{p_2}\right) \geq 0 \end{cases}$$

[xiv] The function to transform hazards into their log form is: $\hat{\delta}_t = \log\left[\dfrac{1}{1-\hat{h}_t}\right]$.