Carbon Monitoring Costs and their Effect on Incentives to Sequester Carbon through Forestry[1]

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ABSTRACT

Technically, land-use change and forestry (LUCF) projects have the potential of contributing significantly to mitigation of global warming, but many such projects may not be economically attractive at current estimates of carbon prices. Payments for greenhouse-gas emission offsets can make some projects attractive and hence stimulate the development of the forestry sector. However, the costs of participating in the carbon market may be too high to make it worthwhile. Forest carbon is in a sense a new commodity that must be measured to acceptable standards for the commodity to exist. This will require credible carbon-monitoring programs be in place. Carbon monitoring is subject to both fixed and variable costs and these will affect the profitability of projects - particularly small projects, those involving geographically dispersed parcels and those with high levels of heterogeneity. Monitoring schemes need to be designed to maximize efficiency. These issues are discussed at a general level and illustrated numerically based on a model of an *Acacia mangium* plantation in South Sumatra, Indonesia. Using plausible assumptions we show that a project of this type can be economically attractive under a range of conditions and with variable monitoring costs as high as $1,500 per sampling plot, provided that the project is large enough to absorb fixed costs. Under the assumed fixed-monitoring costs and a discount rate of 15%, a 500-hectare project is shown not to be profitable from a carbon-sequestration standpoint, as a landholder would be better off not entering the carbon market and relying only on timber sales.

Keywords: Global warming, carbon monitoring, biological mitigation, economic analysis.

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1. INTRODUCTION

Concerns over global warming and the Kyoto Protocol have sparked much attention on the possibility of selling carbon-sequestration services in international markets. To be eligible to participate in carbon trading, land-use change and forestry (LUCF) projects will need to monitor carbon stocks over time in the project area, and these estimates will have to be certified by an authorised agency. If carbon monitoring is too costly, certain LUCF projects may not be attractive from an economic point of view. In other words, at high monitoring costs, the monetary incentives necessary for LUCF projects to participate in carbon markets may not exist.

Carbon monitoring costs can be classified into three types: (1) initial 'establishment' costs; (2) annual fixed costs, independent of the number of plots sampled; and (3) annual variable costs (the cost of monitoring each sampling plot). These costs will affect the profitability of projects in different ways. The situation is further complicated by the uncertainty regarding the accuracy of the carbon sequestration claimed by the project, which is based on statistical analysis of a given number of permanent sampling plots. Small projects, those involving geographically dispersed parcels and those with high levels of heterogeneity will be more expensive to monitor.

In this paper we use a simple model of an *Acacia mangium* plantation in Indonesia to illustrate the problems discussed above, and to answer two questions: (1) How do monitoring costs influence the incentives available to LUCF projects as carbon sinks? (2) How is the optimal management of LUCF projects (in terms of cycle length and sampling intensity) affected by variability, project size, discount rates and variable monitoring costs? The paper concludes with a discussion of the implications of our findings for project design.

2. CARBON POOLS AND MONITORING TECHNIQUES

The recommended approach to measuring carbon sequestration in LUCF projects is to use permanent sampling plots to monitor both the baseline and the project. Well established statistical techniques can be used to determine the sampling design and intensity required to achieve a given level of precision (MacDicken, 1997). For both small-scale and large projects, random sub samples of permanent sampling plots can be monitored each year. Larger projects may also benefit from imaging techniques and remote sensing based either on satellites or low-flying aeroplanes (Brown, 2001).

MacDicken (1997) recommends modelling as a convenient way of estimating the size of carbon pools in periods between inventories and to establish baselines. Accounting for carbon in sequestration projects involves measuring four pools (Hamburg, 2000): aboveground living biomass, belowground living biomass, soil and necromass.

Not all pools need to be measured at the same level of precision or at the same frequency during the life of the project. In the initial inventory the relevant carbon pools must be measured, but in subsequent monitoring only selected pools need to be measured, depending on the type of project (Brown, 2001). The level of precision to which each pool can be measured at reasonable cost is presented by (Hamburg, 2000).

2.1 Aboveground living biomass

There are standard, well accepted methods of measuring aboveground biomass carbon in forested areas. The simplest procedure consists of measuring a sample of trees and using allometric equations to estimate biomass. Allometric equations relate tree biomass (B) to quantities (V_i) that can be measured by non-destructive means. Allometric equations have the general form (Ketterings *et al.*, 2001):

$$B = f\left(V_1, V_2, \ldots, V_n\right) \tag{1}$$

The independent variables (V_i) may include diameter at breast height, height and wood density. Experience with generic equations has shown that diameter explains more than 95% of the variation in tree biomass (Brown, 2001). Brown (Brown, 1997) has published allometric equations for tropical environments, and presents wood density values for a large number of species. The assumption that 50% biomass (on a dry weight basis) is carbon is well accepted (Brown, 2001; Hamburg, 2000), so it is straightforward to convert measured biomass to carbon units.

Allometric methods have been shown to be robust among species and genera, and can predict biomass of closed-canopy forest to within ±10% (Hamburg, 2000). In some cases it may be necessary to use destructive techniques to estimate allometric equations for a project (the techniques used to undertake these measurements are explained by Brown, 1997), but often, parameter values available in the literature can provide acceptable levels of precision. Hence the main expense would be costs associated with field measurement of trees and the analysis of data.

2.2 Belowground living biomass

Belowground living biomass consists mostly of roots. This is an important pool that can represent up to 40% of total biomass (Cairns *et al.*, 1997). It can be very expensive to sample directly and requires destructive techniques (Brown, 2001). This pool can be estimated with some accuracy, but at lower precision than aboveground biomass.

The simplest approach to estimating belowground biomass is to apply a constant root/shoot ratio (R/S ratio). Although the R/S ratio varies with site characteristics and stand age, a range of R/S ratios can be obtained from the scientific literature (Hamburg, 2000). To avoid measuring roots, a conservative approach recommended by MacDicken (1997) is to estimate root biomass at no less than 10% or 15% of aboveground biomass. Hamburg (2000) recommends a default R/S ratio for regrowing forests of 0.15 in temperate ecosystems and 0.1 in tropical ecosystems. Although ratios as high as 0.4 have been measured in temperate forests, the author recommends erring on the side of caution, to avoid the possibility of crediting non-existent carbon.

2.3 Soil carbon

Soil carbon can also be expensive to measure directly, particularly because of the strong influence that soil characteristics have on carbon dynamics, so modelling may have an important role here. Hamburg (2000) argues that by using a few generalized principles it should be feasible to measure soil carbon to an acceptable level of accuracy for biological mitigation projects. Hamburg recommends that the soil carbon be measured to at least 1 m depth, and that measurements of soil carbon and bulk density be taken from the same sample. MacDicken (1997) suggests measurement only of changes in the rooting zone, where most soil carbon changes due to human activity are likely to take place.

Fortunately, for projects that are known to have non-decreasing effects on soil carbon, it may not be necessary to measure soil carbon after the baseline is established. Rates of soil oxidation (a process that releases CO_2) under different land uses are available in the literature (Brown, 2001). As a general rule, reforestation projects in agricultural or degraded land would tend to increase soil carbon. If the marginal cost of measuring this carbon pool is greater than the marginal benefit of the carbon credits obtained, the project developer would be better off not measuring this pool.

The Alternatives to Slash-and-Burn (ASB) group have argued that most of the sequestration potential in the humid tropics is aboveground rather than in the soil. In tree-based systems planted to replace degraded pastures, they found that the time-averaged carbon stock increased by 50 Mg ha^{-1} in 20 years, whereas the carbon stock in soil increased by 5-15 Mg ha^{-1} (Palm *et al.*, 1999; Tomich *et al.*, 1998).

Modelling can complement monitoring techniques (Brown, 2001). This can be particularly useful to forecast slow changes in soil carbon pools. An example of this technique, using a complex model, is presented by (Wise and Cacho, 2002).

2.4 Necromass

The necromass pool includes the carbon contained in dead trees, leaves, branches and other vegetation. Annual leaf litter inputs do not need to be accounted as part of the necromass pool, since this input is balanced by decomposition losses within the soil and the net effect is included in the measurement of the soil pool (Hamburg, 2000).

The amount of necromass varies considerably with forest type and disturbance history, and estimating this component accurately can be very time consuming and subject to high uncertainty. Fortunately this component can be ignored (Hamburg, 2000) if we are confident that it will not decrease as a result of the project. In contrast, (Brown, 2001) states that dead wood, both lying and standing, is an important carbon pool in forests and should be measured. According to her, methods for this component have been tested and require no more effort than measuring living biomass.

3. METHODS

3.1 Economic model

This section presents a general economic model of a forest cycle starting with bare ground and including carbon sequestration payments. The model is based on the "ideal" carbon payment method described by Cacho *et al.,* (2002). Under this method, carbon payments are made at the end of the year for the amount of CO_2 sequestered during that year, and any CO_2 released by the project causes a liability. This method is compatible with the temporary CER concept proposed by Colombia (Blanco and Fornier, 2000) and the rental carbon scheme proposed by (Sedjo *et al.*, 2001).

The long-term profit obtained from a forestry cycle of T years duration is:

$$NPV_T = v_T \cdot p_v \cdot \delta^{-T} + \sum_{t=0}^{T} \left[\Delta C_t \cdot p_C - m_t \right] \cdot \delta^{-t} - E - C_T \cdot p_C \cdot \delta^{-T} \quad (1)$$

where NPV_T is the net present value (\$ ha^{-1}) of profits obtained by the landholder when harvesting in year T ; v_T is the volume of wood harvested (m^3); p_v is the price of timber net of harvesting costs (\$ m^{-3}); ΔC_t is the reliable minimum estimate (RME) of carbon sequestered during year t (Mg ha^{-1}yr^{-1}); p_C is the price of carbon (\$ Mg^{-1}), m_t are annual monitoring costs; E is the cost of establishing the plantation (\$ ha^{-1}) and δ is the discount factor (1+r) for the discount rate r. C_t is the "stock" of credited carbon in a given year, i.e. the total amount of carbon credited from the start of the project up to year t.

The first term on the right-hand side of equation (1) is the present value of profits obtained from timber sales, the second term is the present value of the stream of benefits obtained from carbon sequestration payments, and the last term is the cost of redeeming carbon-credit payments upon harvest.

The establishment cost (E) is the cost incurred in preparing the land, planting and maintaining the trees, and establishing monitoring capability; this may include any fees paid to register the project for C payments, tools and equipment purchased, as well as the cost of training project personnel (or landholders) to measure carbon stocks.

The optimal rotation can be obtained by finding the cycle length (T) that maximizes the value of equation (1). However, a single-cycle model ignores the opportunity cost of the land in the future, after the trees are harvested. This is well studied in the forestry economics literature including most textbooks of resource economics.

Both, the volume of timber available for harvest (v_T), and the amount of carbon at any time (C_t) depends on the type of trees, their growth rate, and the way in which the forest is managed. The path of these variables through time can be simulated by existing forest growth and soil carbon models, or can be approximated by single-equation nonlinear models. In this paper we follow both approaches, as explained in the following section.

3.2 Representative production system

The economic performance of a plantation, as described in equation (1), is driven by the growth rate of the forest and the type of forest, which will determine carbon sequestration rates (ΔC_t) and volume (v_t) at any time during a forestry cycle. The rate of carbon sequestration in any given year is calculated by the difference in the stock of carbon between the end of the current year and the end of the previous year:

$$\Delta C_t = C_t - C_{t-1} \quad (2)$$

And the total stock of carbon is the sum of carbon contained in the four pools discussed in Section 2: aboveground biomass (b_t), soil (CS_t), underground biomass

(CU_t) and necromass (CN_t). Assuming that 50% of aboveground biomass (dry weight) is organic carbon, we have:

$$C_t = 0.5 \cdot b_t + CS_t + CU_t + CN_t \tag{3}$$

Accumulation of aboveground biomass is well described by the Chapman-Richards function (Venn *et al.*, 2000):

$$b_t = \theta[1 - \exp(-\varphi \cdot t)]^{\mu} \tag{4}$$

where θ, φ and μ are parameters specific to a given species, site and management. θ is the maximum woody biomass (Mg DM ha^{-1}) in the mature forest and φ and μ determine the slope and shape of the function. These parameters were adjusted to represent an *Acacia mangium* plantation in south Sumatra, Indonesia (Table 1). In estimating parameters values we assumed that biomass in year 9 is 190 Mg ha^{-1} (Hardiyanto *et al.*, 2000) and constrained the maximum volume of a mature plantation (θ) to be 400 Mg DM ha^{-1}.

The relationship between volume and biomass was based on two simple assumptions: 70% of the woody biomass is merchantable wood, and the density of *A. mangium* wood is 0.56 Mg m^{-3}. So volume at any time was calculated from biomass as:

$$v_t = \frac{0.7 \cdot b_t}{0.56} \tag{5}$$

This value was inserted in equation (1) to estimate the profit from selling timber.

Fluctuations in soil-carbon stocks as a result of land-use changes are sensitive to factors such as previous land-use (which determines initial soil-carbon stock), soil type and soil fertility, management variables (soil-tillage, fertilizing, thinning and harvesting) and species selection (Polglase *et al.*, 2000). The sign and magnitude of these fluctuations are often not known because of the high costs and long time periods required to accurately measure soil carbon changes within and across sites, and over an entire project lifespan. Also, changes in soil carbon can be difficult to detect because of the generally high background levels and natural variability of the soils within which they occur (Blair *et al.*, 1995). Therefore, simulation of soil-carbon changes under tree plantations using biophysical modelling can be a valuable tool. The biophysical process model CenW (Kirschbaum, 1999) was calibrated for an *A. mangium* plantation in Indonesia to estimate soil carbon accumulation.

CenW simulates the effects of changes in environmental factors such as CO_2 concentration, temperature and rainfall on biophysical processes in tree plantations such as biomass accumulation (photosynthesis), water use, soil carbon storage and nutrient cycling in soil organic matter. It does this by simulating fluxes of carbon, nutrients and water between and within the soil, the plant components and the atmosphere on a daily time step. The *A. mangium* plantation simulated for this study resembles that reported by Hardiyanto *et al.* (2000, p. 45). However, the initial soil nitrogen and soil carbon values used in calibrating CenW were lower than the 6.6 Mg N ha^{-1} and 76.7 Mg C ha^{-1} given by Hardiyanto *et al.* (2000, p. 45), this was done to obtain more conservative estimates of land productivity, reflecting grasslands available for reforestation.

The model described so far assumes that carbon stocks are known with certainty, which is equivalent to assuming that the coefficient of variation is 0. However, given the variability between trees and between areas of a plantation, carbon stocks can only be measured within a certain confidence level. The higher the confidence required, the higher the costs of monitoring, this is discussed in the next section.

3.3 Monitoring costs

The annual monitoring costs (m_t) depend largely on the number and diversity of trees in the project, as well as on the diversity of the environment; because the precision achieved by a given sampling strategy is affected by these factors. For the purpose of this paper carbon credits are measured in terms of the Reliable Minimum Estimate (RME) as defined by MacDicken (1997):

$$RME_t = \bar{b}_t - \mathrm{t}_{0.05,\mathrm{df}} \cdot \frac{s_t}{\sqrt{n}} \tag{6}$$

where $\bar{b}_t$ is the estimate of the mean aboveground biomass in the plantation (Mg ha^{-1}), $\mathrm{t}_{0.05,\mathrm{df}}$ is the one-tailed t-statistic for α=0.05 with degrees of freedom (df) equal to n-1; n is the number of sample plots used to estimate standing biomass and s_t is the standard deviation.

The mean biomass was estimated with equation (4) and the effect of variability on monitoring costs was evaluated by testing different coefficients of variation (cv); substituting the relationship: $s_t = cv \cdot \bar{b}_t$ into equation (6).

Annual monitoring costs have a fixed (α_m) and a variable (β_m) component. The variable component varies in direct proportion with the number of plots sampled (n), while the fixed component is independent of n. So monitoring costs are estimated as:

$$m_t = \frac{\alpha_m + \beta_m \cdot n}{A} \tag{7}$$

where A is the area of the project (ha). The value of α_m includes the cost of transporting the crew into the project area, β_m includes the cost of keeping the monitoring-crew on the ground (salaries and per-diems), as well as consumables, transportation between plots and data entry and analysis costs.

As mentioned earlier, establishment costs (E) include once-off costs of monitoring, such as purchasing tools, setting up a database, training of project field workers, purchase of remote sensing, design of sampling forms etc. (MacDicken, 1997).

3.4 Base-case assumptions

The assumptions used in the base runs of the model are presented in Table 1. Note that the establishment costs were divided into two components: a per-hectare cost of \$600 to prepare the land and plant and fertilise the trees, and a fixed cost of enabling the project for C trading of $10,000. The latter cost would include any fees payable to register the project for C trading, plus the cost of estimating the baseline and designing the sampling strategy.

Table 1. Parameter values and assumptions.

Parameter/ Variable	Value	Description
θ	400	maximum aboveground biomass (Mg ha^{-1})
φ	0.109	growth parameter
μ	3.333	growth parameter
C_0	42.22	initial soil carbon level (Mg C ha^{-1})
N_0	4.48	initial soil nitrogen level (Mg N ha^{-1})
cv	0.4, 0.8	coefficient of variation
p_C	20	price of carbon ($ Mg^{-1})
p_v	30	price of wood ($ m^{-3})
r	5, 15	discount rate (%)
A	1,000	area of project (ha)
α_m	5,000	annual fixed costs of monitoring ($)
β_m	500	variable cost of monitoring ($ per plot)
E	$FC + FM / A$	establishment cost ($ ha^{-1})
FM	10,000	cost of enabling C-monitoring and trading ($)
FC	600	establishment cost ($/ha)

In the economic evaluation below, only aboveground biomass will be considered; so the last three terms of equation (3) will be set to zero. The implications of this simplifying assumption are discussed later and do not affect the general conclusions of the paper.

4. RESULTS

4.1 Base simulations

The time-trajectory of the simulated changes in total soil carbon (to a depth of 100cm), under an *A. mangium* plantation over a 40-year rotation, is presented in Figure 1.

The initial soil-carbon value of 42.2 Mg C ha^{-1} seen in Figure 1 falls within the expected range of 10 to 105 Mg C ha^{-1} for soils under a range of land uses in Sumatra, Indonesian (Roshetko *et al.*, 2002; van Noordwijk *et al.*, 2001). Assuming the previous land use was *Imperata* grassland, which typically has a soil-carbon level of between 30 Mg C ha^{-1} (Woomer *et al.,* 2000, p. 107) and 60 Mg C ha^{-1} (van Noordwijk *et al.*, 2001), this initial soil carbon value is plausible.

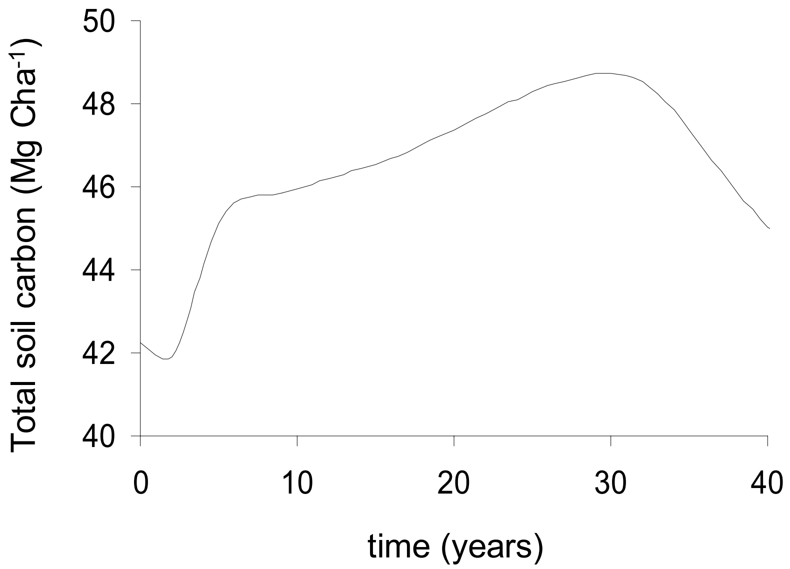

Figure 1. Trajectory of total soil carbon to one meter depth in a simulated *A. mangium* plantation in South Sumatra.

The simulated trajectory of carbon in aboveground biomass is presented in Figure 2. The known mean C stock (actual) is compared with the amount that would be eligible under the reliable minimum estimate (RME) for given coefficients of variation (*cv* = 0.4 or 0.8) and number of plots sampled (*n* = 10 or 40). The greater the number of plots sampled, the closer the RME is to the actual mean, and hence the more CERs can be sold. As the *cv* increases, a larger number of plots is required to achieve a given level of precision (compare Figures 2A and 2B).

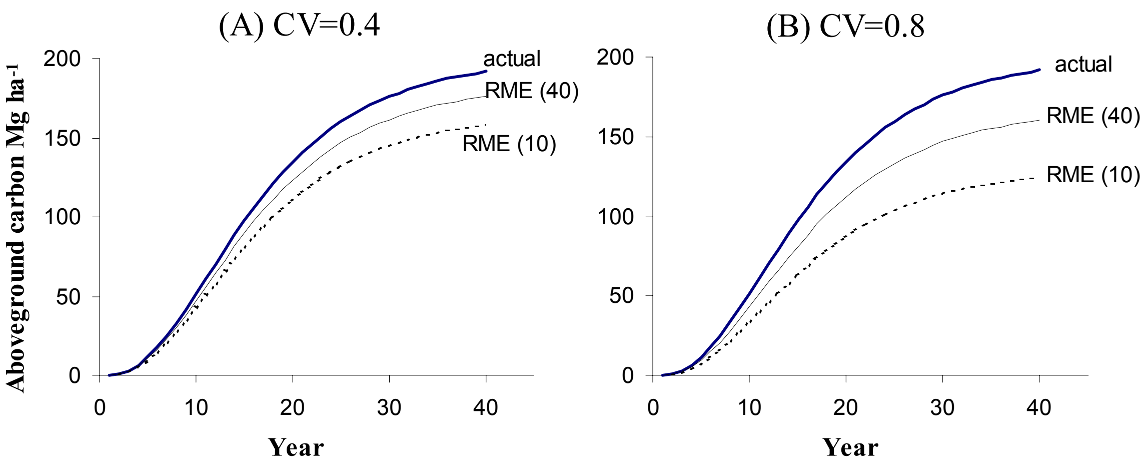

Figure 2. Predicted aboveground-biomass carbon in simulated *A. mangium* plantation in South Sumatra. Two coefficients of variation (CV = 0.4 or 0.8) and two sampling intensities (10 or 40 plots). RME(*n*) is the reliable minimum estimate when *n* plots are sampled. The actual carbon stock is the same for both charts.

The simulations described above (Fig 2) were repeated for values of *n* ranging between 2 and 30 and for two values of *cv*; the amount of eligible CERs for each sampling strategy was then calculated as the time-averaged RME of C sequestered over the 40 years simulated (Fig 3). There is a sharp increase in the number of CERs obtained as the number of plots increases between 2 and about 10. Beyond this point, additional gains in CERs with further increases in the number of sampling plots becomes quite small and is almost flat beyond 20 plots. Fig 3 illustrates very clearly the relationship between precision of measurement and the amount of C credits that can be claimed, but it says nothing about the optimal sampling strategy. The optimal sampling strategy will be affected by the cycle length, prices, costs and discount rate. This is explained below.

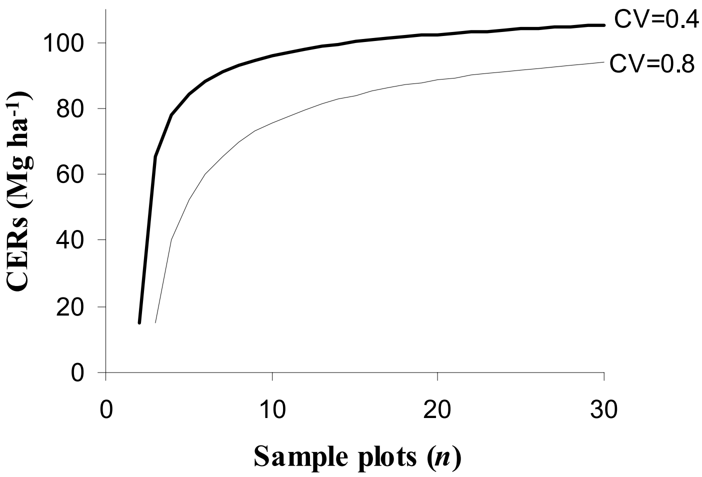

Figure 3. The relationship between number of permanent sample plots and the amount of CERs claimed (based on RME) in simulated *A. mangium* plantation in South Sumatra; two coefficients of variation (CV) are shown.

The NPV of profits obtained over a series of *A. mangium* rotations is illustrated in Fig 4; a fixed number of sampling plots (10) was used to obtain these figures. The year at which NPV reaches a maximum is the optimal rotation length (indicated by arrows in Fig 4). The optimal rotation length decreases from 16 years when the discount rate is 5% (Fig 4A), to 12 years when the discount rate is 15% (Fig 4B). As with all long-term investments, the actual profitability of the plantation is very sensitive to the discount rate, decreasing from about \$6,000 ha^{-1} at 5% to about \$600 ha^{-1} at 15%.

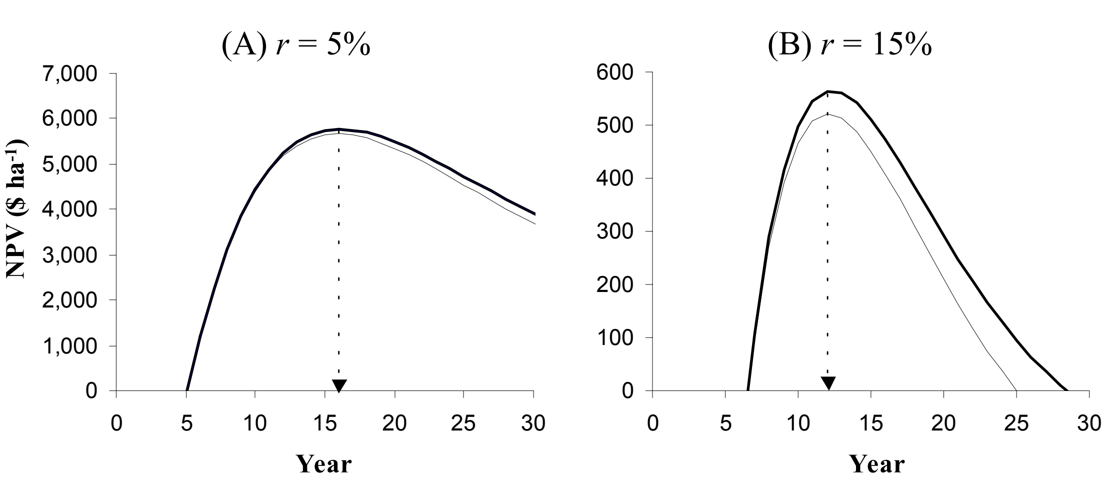

Figure 4. Trajectories of net present value (NPV) of simulated *A. mangium* plantation in South Sumatra; two discount rates (*r*) are shown. In each chart the top line represents a coefficient of variation (CV) of 0.4 and the bottom line a CV of 0.8. Arrows show the optimal cycle length.

Fig 4 illustrates how the optimal cycle length can be estimated for any given combination of discount rate, coefficient of variation and number of plots sampled. The next step is to estimate the optimal number of sample plots to use in a project. This can be accomplished by performing the analysis illustrated above for a range of values of *n* and selecting the maximum NPV (Fig 5).

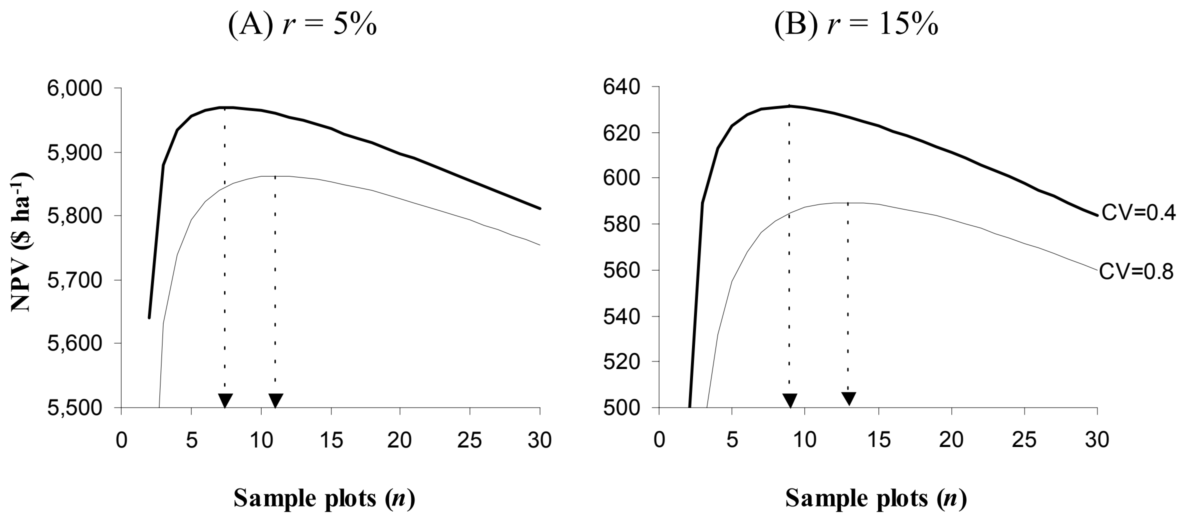

Figure 5. The net present value (NPV) of simulated *A. mangium* plantation in South Sumatra at different sampling intensities; two discount rates (*r*) and two coefficients of variation (CV) are shown. Each point in these lines was taken from the optimal cycle length for the given number of plots (see Fig. 4). The arrows indicate the optimal sample size.

For the given assumptions regarding prices and costs, at a discount rate of 5%, it is optimal to establish 7 permanent sampling plots if *cv* is 0.4 or 11 plots if *cv* is 0.8 (Fig 5A), as the discount rate increases to 15%, the number of sampling plots increases to 9 and 13 for *cv*s of 0.4 and 0.8 respectively (Fig. 5B). This is because, with higher discount rates, the value of carbon increases relative to the value of timber, which is harvested far into the future and heavily discounted, so more effort is put into measuring carbon.

4.2 Sensitivity analysis

The previous section presented results under base-case assumptions and illustrated how the optimal management of a plantation can be determined, in terms of cycle length and number of permanent sample plots, to maximise the net present value of a forestry cycle managed for both timber and carbon credits. In this section, a sensitivity analysis is performed on three critical variables: the cost of carbon monitoring (β_m in \$ per plot), the coefficient of variation (*cv*) and the discount rate (*r*). The optimal results are shown in Table 2 for a number of combinations of these variables, with a project of 1,000 ha.

There are several obvious trends in Table 2. First, the maximum NPV decreases as *r*, *cv* and/or β_m increase, and NPV is most sensitive to the discount rate. Second, the optimal cycle length decreases as *r* increases, but is generally not affected by *cv* or β_m, with one exception to be discussed later. Third, the optimal number of sampling plots is directly related to *r* and *cv*, but inversely related to β_m. Fourth, the number of CERs obtained by the project decreases as r, cv or β_m increase, and the average cost of carbon monitoring varies inversely with the values of these variables.

Table 2. Results of sensitivity analysis with a project of 1,000 ha in size.

	Discount rate			
Sampling	5%		15%	
cost (β_m)	Coefficient of variation		Coefficient of variation	
($ per plot)	0.4	0.8	0.4	0.8
	NPV of multiple cycle ($ ha^{-1})			
100	5,958	5,895	631	607
500	5,870	5,762	598	556
1,000	5,806	5,671	574	522
1,500	5,756	5,612	556	496
	Optimal cycle (years)			
100	16	16	12	12
500	16	16	12	12
1,000	16	16	12	12
1,500	16	15	12	12
	Optimal no. of sample plots			
100	19	30	22	30
500	8	11	9	13
1,000	5	8	6	9
1,500	5	0	5	7
	Time-averaged CERs sold (Mg ha^{-1})			
100	38.0	35.0	23.7	21.6
500	34.6	28.9	21.7	18.7
1,000	31.4	25.9	20.3	16.8
1,500	31.4	0.0	19.4	15.1
	Average Cost per CER ($ Mg^{-1})			
100	0.45	0.51	0.73	0.83
500	0.55	0.71	0.90	1.15
1,000	0.64	0.89	1.04	1.43
1,500	0.72	na	1.16	1.69

The reasons for the trends observed in Table 2 are mostly obvious, but there are a few cases that merit further discussion. In one case, it is better not to participate in carbon trading (optimal n is 0), this happens at the low discount rate (r = 5%), high variability (cv = 0.8) and high sampling cost (β_m is $1,500 per plot per year). This means that, given the low discount rate, it is better to harvest one year earlier (year 15 instead of 16) and obtain only the net benefits of selling timber, rather than delaying the harvest and paying a higher price per plot to measure carbon. In other words, the higher cv would require more plots to be sampled and this is not worth it.

The average cost per CER in terms of monitoring (the sum of fixed and variable costs divided by the number of CERs claimed), increases as cv and β_m increase (see last panel of Table 2), the reasons for this are that, either more sampling plots are required to reach a given level of accuracy (at high cv) or each plot is more expensive to sample (at high β_m). The reason for an increase in average cost of monitoring ($ CER^{-1}) with an increase in the discount rate is not immediately obvious. This result is caused by the larger number of sampling plots required; for example, with β_m = $500 and r =5%, the optimal values of n are 8 and 11 with cv= 0.4 and 0.8 respectively, these numbers increase to 9 and 13 as r increases to 15%. The other factor affecting this result is that the number of CERs obtained with a high r (15%) is lower than with a low r (5%) because of the shorter cycle length (12 vs. 16 years). So the combination of a larger number of plots and a smaller number of CERs, results in a higher cost per CER ($ Mg^{-1}) as the discount rate increases (Table 2). With β_m = $500 and r = 5%, the average costs per CER are $0.55 and $0.71 for cv= 0.4 and 0.8 respectively, and increases to $0.90 and $1.15 at r=15%.

Table 3. Results of sensitivity analysis with a project of 500 ha in size.

	Discount rate			
Sampling	5%		15%	
cost (β_m)	Coefficient of variation		Coefficient of variation	
($ per plot)	0.4	0.8	0.4	0.8
	NPV of multiple cycle ($ ha^{-1})			
100	5,808	5,729	574	543
500	5,687	5,612	529	482
1,000	5,612	5,612	494	482
1,500	5,612	5,612	482	482
	Optimal cycle (years)			
100	16	16	12	12
500	16	15	12	11
1,000	15	15	12	11
1,500	15	15	11	11
	Optimal no. of sample plots			
100	13	19	15	22
500	5	0	6	0
1,000	0	0	4	0
1,500	0	0	0	0
	Time-averaged CERs sold (Mg ha^{-1})			
100	36.7	32.7	23.0	20.7
500	31.4	0.0	20.3	0.0
1,000	0.0	0.0	18.0	0.0
1,500	0.0	0.0	0.0	0.0
	Average Cost per CER ($ Mg^{-1})			
100	0.89	1.03	1.43	1.66
500	1.12	na	1.78	na
1,000	na	na	2.11	na
1,500	na	na	na	na

The final step in the sensitivity analysis consisted of repeating the complete optimisation analysis just described for a project half as small as the base case (500 ha instead of 1,000 ha). The results are presented in Table 3. The general trends follow the same patterns as explained above, but the NPVs are lower because the fixed costs make profits per hectare lower. This means that there are more cases in which it is optimal not to engage in carbon trading. In 9 cases out of 16 the optimal n = 0 (Table 3) these cases are associated with high sampling costs and/or high variability. The smaller project size also results in higher average monitoring costs, with a range of $0.89 to $2.11 per CER (Table 3) compared to a range of $0.45 to $1.69 per CER (Table 2) with the larger project size.

5. DISCUSSION

Given the assumptions of this paper it appears that carbon-credit payments will provide incentives for forestry projects under certain conditions. The project size, monitoring costs, coefficient of variation and discount rate were all shown to have important effects on the incentives faced by an investor contemplating the establishment of a plantation for timber and carbon farming.

The results show that a 1,000 ha *A. mangium* plantation in South Sumatra may be able to claim between 15 and 38 Mg C ha^{-1}, provided that the costs of monitoring are kept within reasonable limits. These included \$10,000 to establish the baseline, sampling strategy, and project registration; plus annual fixed costs of \$5,000. Variable monitoring costs were varied between \$100 and \$1,500 per plot. Some of these costs may be optimistic for the current situation, but it is likely that, as the right institutions develop and agreement is reached for simplified baseline estimation, the costs will decrease overtime.

The price of carbon (p_C) was assumed to be \$20 (Mg C)$^{-1}$ throughout the paper; this is equivalent to a price of \$5.45 (Mg $C0_2$)$^{-1}$ and is on the conservative side of estimates presented in the literature. Obviously, increasing p_C will strengthen the incentives identified in this paper and decreasing p_C will have the opposite effect.

We abstracted away from the need to take stratified samples when the plantation is not homogeneous. This will add to the cost of monitoring but will not affect the general conclusions of the paper. Other simplifying assumptions included the omission of the baseline, soil carbon and underground biomass from the economic analysis. Soil carbon can be included by adding the simulation results from Fig 1 to the biomass estimates of Fig 2; given the small size of the former relative to the latter, this will have only a small effect on the results; this is discussed in more detail below. Underground biomass can be included by adding between 10% to 15% to the aboveground carbon estimate, whereas the baseline can be included by subtracting the carbon content of the area in the absence of the project (based on Roshetko *et al.* 2002, this could be 3.0 Mg ha^{-1} of biomass carbon and 40 Mg ha^{-1} of soil carbon for an *Imperata* grassland). The simplifying assumptions of ignoring both the baseline and underground biomass will not significantly affect the general conclusions of this study because they have opposite effects on the estimate of CERs.

It is not the total carbon stock but the change in the carbon stock relative to the baseline that is eligible for crediting in a LUCF activity. Our simulation results show that the net gain in soil carbon over the entire 40-year rotation is only 2.6 Mg C ha^{-1}, which involved a mean annual increase of approximately 0.25 Mg C ha^{-1}yr^{-1} for the first 30 years and then a decline of about 4 Mg C ha^{-1} over the last 10 years.

According to Brown (2001) the consensus is that the soil-carbon stock under a LUCF activity must to be measured and monitored if a decrease is expected, otherwise it need not be included. If the expected net change in soil carbon is expected to be positive (with 95% confidence), then the landholder/investor would wish to include it in the carbon inventory (within C_t in equation 3) only if the financial benefits exceed the costs of measuring and certifying the carbon in the soil. Under the assumptions of this paper, the net change is expected to be positive but small (2.6 Mg C ha^{-1} over 40 years).

These factors would have to be explicitly treated in designing a real forestry project, to obtain a more accurate estimate of CERs to be credited to the project. In this paper, the general assumptions are plausible and the modelling detail was kept to a level that provides realistic results but simplifies the exposition of the analytical procedures and the implication of variability, monitoring costs and discount rates on the incentives that investors in forestry projects will face.

LUCF projects consisting of a large number of landholders in a particular area may tend to have higher *cv* than commercial plantations, because of geographical dispersion, the need to continue producing food crops, and differences in the management ability of different landholders. This will tend to decrease the attractiveness of sequestration projects based on large numbers of smallholders. Variable monitoring costs (β_m) may also be higher for smallholder projects if they are geographically dispersed, because it will take longer to travel between sampling plots. Two other factors that may disadvantage smallholder projects may be their tendency to be smaller (resulting in higher average costs) and higher discount rates (resulting in shorter cycles and hence less CERs).

6. CONCLUSIONS

In this paper we show that some LUCF projects may benefit considerably from participating in the market for carbon offsets. Using a simulation model applied to an *Acacia mangium* plantation in South Sumatra we evaluate the magnitude of incentives faced by investors. Assuming that certified emission reductions (CER) are based on reliable minimum estimates (RME), which depend on the intensity of carbon monitoring, we show that between 15 and 38 Mg of CERs per hectare can be captured by the simulated plantation.

The effect of four important variables on the economic incentives faced by investors in LUCF projects can be summarised as follows: (1) project size is positively related to profitability per hectare; (2) the coefficient of variation and monitoring costs are both negatively related to profitability, and they both decrease the amount of CERs that can be sold under optimal management; (3) higher discount rates decrease the optimal cycle length and consequently decrease the amount of CERs claimed; and (4) there are important interactions between all these variables in the way they affect the optimal cycle length and the optimal number of sampling plots.

An important contribution of this paper is that it presents a simple methodology for evaluating the economic implications of project characteristics and carbon monitoring costs.

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