LBNL-61463

Assessment Of Carbon Leakage In Multiple Carbon-Sink Projects: A Case Study In Jambi Province, Indonesia

Rizaldi Boer[1], Upik R. Wasrin[2,3], Perdinan[1], Hendri[1], Bambang D.Dasanto[1], Willy Makundi[4], Julius Hero[3], M. Ridwan[5] And Nur Masripatin[6]

[1]*Climatology Laboratory, Department of Geophysics and Meteorology, Faculty of Mathematics and Natural Sciences, Bogor Agricultural University*, [2]*Land Management Grand College,*

[3]*Ecology Laboratory, Faculty of Forestry, Bogor Agricultural University,*

[4]*Lawrence Berkeley National Laboratory,* [5]*Lestari Hutan Indonesia*

[6]*Departement of Forestry, Republic of Indonesia*

*(*Corresponding author: rizaldiboer@hotmail.com)*

Abstract. Rehabilitation of degraded forest land through implementation of carbon sink projects can increase terrestrial carbon stock. However, carbon emissions outside the project boundary, which is commonly referred to as leakage, may reduce or negate the sequestration benefits. This study assessed leakage from carbon sink projects that could potentially be implemented in the study area comprised of eleven sub-districts in the Batanghari District, Jambi Province, Sumatra, Indonesia.

The study estimates the probability of a given land use/cover being converted into other uses/cover, by applying a logit model. The predictor variables were: proximity to the center of the land use area, distance to transportation channel (road or river), area of agricultural land, unemployment (number of job seekers), job opportunities, population density and income. Leakage was estimated by analyzing with and without carbon sink projects scenarios. Most of the predictors were estimated as being significant in their contribution to land use cover change.

The results of the analysis show that leakage in the study area can be large enough to more than offset the project's carbon sequestration benefits during the period 2002-2012. However, leakage results are very sensitive to changes of carbon density of the land uses in the study area. By reducing C-density of lowland and hill forest by about 10% for the baseline scenario, the leakage becomes positive. Further data collection and refinement is therefore required. Nevertheless, this study has demonstrated that regional analysis is a useful approach to assess leakage.

Keywords. carbon leakage, carbon-sink projects, logistic modeling, mitigation,

1. Introduction

In the past few decades, forest cover in Indonesia has declined significantly due to increasing rate of deforestation in the larger islands (Kalimantan, Sumatra, Sulawesi and Irian Jaya), extensive forest destruction by wild fires and a declining rate of reforestation and afforestation. The forest estate is generally classified into several main types (ITTO, 2002): (i) conservation forest - for scientific reserve and nature reserve, wild life sanctuaries, national parks, grand forest parks and nature recreation parks, (ii) protection forest - usually on very steep slopes and vulnerable to soil erosion and water degradation, and not made available for logging, (iii) production and conversion forest - for logging and also for conversion to other land uses, (iv) critical forest - former forest land severely damaged by excessive harvesting of wood and/or non wood forest products, poor management, repeated fires, grazing, and disturbances or land uses that damage soils and vegetation to a degree that inhibits or severely delays the re-establishment of forest after abandonment, (v) degraded forest - primary forest that has been adversely affected by the unsustainable harvesting of wood and/or non wood forest products. It has lost the structure, function, species composition and/or productivity normally associated with the natural forest type expected at that site, (vi) unproductive lands - lands with reduced capability to produce goods and services that are economically and socially viable such as fallow land, bare land, bush and thickets, and (vii) plantation forests - a forest stand that has been established by planting or seeding. To illustrate the rate of decline of forest cover, in 1997, the area classified as critical land and degraded forest was estimated to be about 30 million hectares (Mha) (Boer, 2001). By 2000, the area of critical and unproductive lands in the state forestland had increased to 54.6 Mha (MoF, 2001), an increase of 82 percent over 3 years.

This study is based on analysis done for potential carbon sequestration projects in Jambi province. Based on a 1986 vegetation map and 1992 satellite imagery (Landsat TM), the mean annual rate of deforestation in the province was estimated at 106,700 ha/year. The annual rate of forestation (re-greening, reforestation, and timber estate plantations) was significantly lower, estimated at about 14,000 ha per year between 1988 and 2000, with the difference representing the annual increase in critical land area. In 1989, the total area of critical land inside and outside forest area was 194,000 ha, and by 1999, this area had increased to 716,000 ha. Total critical land in Jambi at the end of 2000 was about 887,500 ha, distributed in four districts, i.e., 77,100 ha in Batanghari 96,400 ha in Kerinci, 321,400 ha in Bungo Tebo and 329,500 ha in Sarko. About 61% of the critical land is grassland, while the remaining is shrubs or fallow or shifting cultivation.

Funding sources for restoring forests are very limited. The Forest Rehabilitation Fund ('*Dana Reboisasi*') is only enough for restoring 3-4 Mha of degraded lands and forests (Boer *et al.*, 2001), while total degraded lands and forest of Indonesia in 2000 reached 49 Mha (MoE, 2003). Thus in order to reforest the remaining degraded lands other sources of funds must be sought, including other domestic sources, and bilateral and other international funding mechanisms. The clean development mechanism (CDM) of the Kyoto Protocol provides one likely source of investment for reforesting these areas.

In addition to carbon benefits from the rehabilitation of degraded lands such projects may have other benefits, including biodiversity, quality of life, watershed and water quality, and adaptive capacity to climate change. However, accounting for the carbon that is actually saved by the projects poses a number of challenges (Brown *et al.* 1997).

First, most carbon sequestration projects involve multiple point sources of emissions or sequestration and they are spread over a wider geographic area. This leads to complexities arising from the variations in data, biomass and soil properties as well as in land-use classification. Second, projects that sequester carbon may carry some risk of unintended release of the carbon (e.g. in forest fires) or the duration of carbon storage may only be temporary. Third, the implementation of these projects in a given location may lead to carbon emission or sequestration in another area outside the project location - commonly referred to as <u>leakage</u>. Various suggestions have been put forth on approaches to address leakage (IPCC, 2000) but so far there has not been clear acceptable methodology which can resolve all the major associated technical problems.

The two key elements in accounting for GHG benefits are the (i) setting of a baseline against which a change in GHG emissions or removals are to be measured, and (ii) determination of additionality (the additional amount of carbon stored or emissions reduced by the project). In addition, the baseline needs to be adjusted against leakage, i.e., for the loss or gain of net GHG benefits beyond the project boundary. This study develops an approach for the determination of the baseline and measurement of leakage in multiple potential forestry projects in Batanghari District, Jambi Province, Indonesia.

2. Carbon Leakage

Leakage is defined as loss or gain of net greenhouse gas benefits outside a project boundary. According to a COP9 decision, leakage refers only to the increase of all greenhouse gases outside the project boundary, measurable and attributable to the project. CIFOR (2001) stated that leakage in sinks projects might occur when one of the following phenomena occurs outside the project boundary:

- Unallocated forested lands are harvested
- Protected areas are converted into production forest areas
- Illegal logging increases in protected and production forests
- Land is converted to lower C stocking rates due to emissions reductions elsewhere

Furthermore, establishment of community woodlots may result from protection of an area which previously was the source of timber and woodfuel for a community.

In order to predict whether leakage will occur or not, Auckland *et al.* (2001) stated that *baseline drivers*, *baseline agents*, *causes and motivations*, and *indicators* that exist in the project sites should be understood. *Baseline drivers* are defined as activities predominantly taking place in the absence of the project, and that the project will replace. *Baseline agents* are actors who are engaged in those activities. *Causes and motivations* refer to factors that drive the baseline agents to do the activities and these can be represented by *indicators*. By knowing the interrelationship between these factors, we can predict whether leakage would occur or not. The following example illustrates the definitions mentioned above.

Suppose that the type of activity proposed involves the establishment of timber estate plantation – Hutan Tanaman Industri (HTI). The establishment of HTI in Indonesia normally takes place on state-owned land carried out by state enterprises or private forest companies. At present only a few of the degraded production forests in Batanghari district in Jambi have been converted into HTI. The idle degraded forest-lands are normally left as unmanaged land (fallow) or used by local community for ranching, agricultural activities or as a source of fuel wood. Fallow, ranching or agricultural activities are *baseline drivers*, while local communities that engage in these activities are the *baseline agents*. One of the main reasons for the local community to engage in these activities on this land is to get additional income, and this factor is taken as *cause and motivation*. The next question is, what indicator can be used to measure the leakage?

To answer the above question, further information from related stakeholders in the project site needs to be sought (see Figure 1). The responses to the questions in Figure 1 help to determine whether leakage is likely to occur or not.

[INSERT FIGURE 1]

There are two main types of leakage - primary and secondary leakage (Moura Costa *et a*l., 1997; SGS, 1998). Primary leakage occurs when the GHG benefits of the project cause an increase or decrease of GHG emissions elsewhere. For example, if the degraded forest-land allocated for HTI is already used by the local community for agriculture, the implementation of the HTI project may displace the agricultural activities to other areas or may cause the community to engage in other income generating activities such as logging, which would increase emissions elsewhere (negative leakage). Secondary leakage occurs when a project's outputs create incentives to increase or to decrease GHG emissions elsewhere. For example, the project increases economic activity in the project area that creates additional income for the local community thus leading to a reduction in deforestation or illegal logging outside the project area (positive leakage). The project can also lead to negative leakage if the increase in income leads to activities that increase GHG emissions such as conversion of forest areas to rice cultivation. Thus, both primary and secondary leakage can be positive or negative depending on the nature of their causes, and the agents involved.

The above examples show that change in forest cover and carbon density outside the project area can be an indicator of leakage. In order to know whether the deforestation rate is altered by the project activities, we may need to track historical series of deforestation surrounding such projects, before and after the initiation of the project. Other external factors that may affect deforestation such as rate of population growth, agricultural prices, demand for timber/fiber/fire wood, road density, change in forest law, and enforcement policies also need to be assessed, as well as agents involved in baseline activities throughout the project timeframe and the activities they engage in.

Considering that leakage may cover very wide areas away from the project area, the use of satellite imagery for assessing the leakage can be very useful (*e.g*. Chomitz and Gray, 1995; Hall *et al*., 1995). The potential extensive area of leakage impact is one reason put forth advocating the use of regional baselines (IPCC, 2000). In this study, we utilized satellite imagery for assessing leakage and setting up a regional baseline for future sinks projects.

3. Project Site Characteristics

Location of Carbon-Sink Projects. The available maps could not be used to identify the critical lands, as such the analysis assumed that the critical/degraded lands are generally to be found in the lowland logged-over forest and secondary re-growth areas.

Satellite Images. In this study, satellite images for the analysis were from Landsat TM 1986 and 1992, which were obtained from Wasrin *et al.* (2000). The study area in Batanghari district has 12 sub-districts, and it is assumed that carbon sequestration or avoidance projects will be implemented in eleven sub-districts excluding the sub-district of Kodya Jambi.

Land-Use Change and Forest Cover in Project Site. The total area of the study district is about 1.1 million ha. The district's forest cover is estimated to have declined by 117,000 ha in the period between 1986 and 1992. Most of these forests were converted into small-holder rubber plantations (75%) and estate plantations (24%), with a small forest area converted to agriculture and resettlements (Figure 2).

[INSERT FIGURE 2 HERE]

Socio-Economic Condition of Project Site. Shrinking forest due to deforestation causes degradation of land and water resources, decline of food production capability, and decreasing availability of wood for fuel, shelter, and timber products. The future of world forestry is therefore not just dependent on appropriate management of forests themselves but also management of conflicts that forests face from outside. To understand these conflicts and learn how to deal with them, it is not enough to learn how the forest ecosystem functions but it is vital to understand the social system in which the forest in embedded (CIFOR, 1995).

To understand the socio-economic conditions in the study area, a survey of five villages in the district, namely *Aro*, *Terusan*, *Olak*, *Jambi Kecil* and *Sengeti* was conducted. Results of the survey indicated that in Sengeti and Olak the level of community dependency on the forest was very high, with 75% of the families engaged in illegal logging, while the other three villages had less than 10% involvement. Most families in Sengeti and Olak villages have experience in working with concession companies.

Most of the forests near the five villages are already degraded and abandoned. Loggers from the five villages harvest wood mostly from state forests in other villages, where they have to travel about 40-150 km. The loggers sell the illegal logs to sawmills in their villages or in other villages. Evaluation of village statistical data and result of the survey indicated that the rate of illegal logging is highly correlated with the number of sawmills and population density. Sengeti with the highest rate of logging (more than 150,000 m^3 per year) has 20 sawmills and a population density of about 266 persons/km^2, while the rest of the villages combined have a logging rate of 22,000 m^3 per year, l5 sawmills, and a population density of less than 158 persons/km^2.

The main agricultural activities in the five villages include lowland and upland rice-based farming systems and rubber-agroforestry system. Farmers also get their income from selling fruit such as oil palm, durian (*Durio zibenthinus*), duku *(Lansium domesticum)*, pinang *(Arenga pinanga)*, rambutan *(Nephelium spp)*, macang *(Mangifera spp.)* and aren. Based on discussions with village loggers, they are willing to stop logging, if the income from their agriculture land is high enough to support their livelihood. Since the 1997/98 economic crisis, however, income from their agricultural land has been inadequate to meet their needs. Optimizing the use of community land for agricultural activities (high value crops and trees) may be able to reduce the pressure on forests.

- The investment cost for fruit-tree-based agroforestry system in these villages is not very high. The survey results from the villages, indicate that investment cost for developing one hectare of fruit-trees-agroforestry system varied from US$67 for pinang up to US$136 for oil palm with an area average of US$104 per ha compared to US$400 per ha for establishing timber estate plantation. This is because, land preparation, cultivation and planting practiced by villagers for agroforestry is simple and inexpensive. Villagers mostly use the slash-and-burn system, while forest companies use hole-in-line (*cemplongan)* system, where land is tractor ploughed (turning up the soil) 1-2 times before line planting.

4. Methodology

Different approaches have been tried to estimate the rate of forest cover change, each with varying degree of reliability given the underlying assumptions. The two main types of models on deforestation processes are broad area versus local models (Turner and Meyer, 1991). The broad scale models use factors that operate globally to drive land cover change, where as the local area approaches focus on human activities at the landscape level that vary significantly from place to place or by region. The Markov chain model is a local area model that describes land cover change processes through a sequence of steps in discernible states. This type of model describes ‘the conditional probability of land use at any time, given all previous uses, depending at most upon the most recent use and not upon any earlier land uses’ (Bell and Hinojosa, 1977). Though in this study we used the local area approach, we specifically focused on the use of another class of models – logistic function models.

A logistic function is a mathematical formulation of a ‘growth curve’, commonly referred to as the S-curve. This curve is typical of growth functions for ecological systems under constraints where the growth is slower in the beginning and then rapidly increases and slows down as exhaustion is approached (Hutchinson, 1978). Many studies have used the logistic function to model deforestation rates (Esser, 1989, Grainger, 1990, Palo et al, 1987, Reis and Margulis, 1991). The applicability of this functional form in predicting land cover change (deforestation) arises from the fact that a forest area is a limited resource and the rate of its conversion will eventually be slowed by scarcity as increasingly more area is converted. The theory of spatial diffusion of innovation also provides a basis for the application of the logistic model to deforestation (Casetti, 1969; Cliff and Ord, 1975). In this sense, deforestation is seen as a process of human activity across a landscape, especially as it relates to people moving into new areas to undertake land clearing. In its primary form, the model predicts the impact of socio-economic and ecological mechanisms on land cover.

Inclusion of socio-economic factors as independent variables in the model allowed for the extension of the model to predict land cover change in small areas, such as the application by Grainger (1990) to simulate future trends converting forests to farmland. In another study on deforestation in the Amazon at municipal level (Reis and Margulis, 1991), land cover change was found to increase with population density that tailed off at high population densities. Their model was specified in a logarithmic form and used cross-sectional data of various municipalities. The fraction of deforested area at municipal level was specified as a function of population density, road density, agricultural area, cattle density, amount of timber extraction, distance from major economic centers (state capital) and dummies to account for differences among states. The results showed a good explanatory power of the model, with farm area, population and road density accounting for the lion's share of the variation in deforestation.

Development of Land/Forest Conversion Model. In this study, the logistic model is used to predict deforestation under a baseline scenario. As was mentioned above, leakage can be measured by estimating changes of land use cover/forest (and carbon stock) pattern in a region, with and without the mitigation project.

Model specification: To evaluate the change, equations for estimating the probability of certain land use being converted into other uses were developed, specified, and estimated following Aldrich and Nelson, (1984):

$$\mathrm{Logit}(P_i) = a + \Sigma(b_j.x_j) \quad (1)$$

where

P_i = probability of land cover change-i,

a = intercept

b_j = coefficient of independent variable $x_{j.}$

In the general form of the model, the coefficient b_j and variable x_j can be used as vectors B and X of coefficients and independent variables respectively. The functional relationship between P_i and Logit(P_i) is expressed as:

$$P_i = e^{\mathrm{logit}(Pi)}/(1+e^{\mathrm{logit}(Pi)}) \quad (2)$$

Since the result of this equation is a continuous value between 0 (no land cover change) and 1 (land-cover change occurs), a lower limit to accept land cover change event probability needs to be defined. In this study we used a value of 0.5 as a lower limit (Murdiyarso *et al*., 2000). Thus, if the probability of an area moving from current status to another state exceeds 50%, then we assume that land-cover change occurred. It is noteworthy that this fraction is not the strict definition of deforestation as per FAO, which will keep degraded forest under forest classification until it loses at least 90% of its crown cover (FAO/UNEP, 1999). The 50% threshold is more appropriate for a study covering all types of land-use change, including abandoned agricultural land to forests.

Factors crucial to the selection of the independent variable x_j (predictors) are data availability and result of previous studies. In Indonesia, a study at Pelepat - a sub-watershed of Batanghari watershed indicated that the important predictors influencing the change of land use pattern are distances of land to road, river, settlements, and logging area, slope, soil organic matter, population density, and profitability (net present value) of agroforestry (Murdiyarso *et al.*, 2000). Other studies indicate that population density is strongly correlated with deforestation rate, with the correlation increasing with the number of rural landless families (Ludeke *et al.*, 1990; Reis and Margulis (*op cit*), 1991, Adger and Brown, 1994; Harrington, 1996; Sisk *et al.*, 1994; Kaimowitz, 1997; Ochoa-Gaona and Gonzales-Espinosa, 2000). It was also found that agricultural prices, regional per capita income, access to markets, better quality of soil and flatter lands were in general associated with higher deforestation rates (Adger and Brown, 1994).

Studies in other tropical countries also show that population density, poverty, international economics such as debt and macroeconomic adjustment, policy failure such as subsidies for land use conversion, and failure to capture public good aspects of forests were significantly related with deforestation in broader areas or at national level (Adger and Brown, 1994). From the above studies, it was found that population density consistently appeared to be a significant variable that can explain the deforestation rate, followed by income (expressed in GDP/GNP per capita), agricultural productivity and external indebtedness. Other factors that affected the deforestation rate in a few studies were wood price, length of road and road density, price of kerosene, per capita wood fuel consumption, per capita food production and value of agricultural exports.

Considering the availability of data and results of the previous studies, eight predictors (independent variables) were selected for this study for developing the probability equation. These predictors could be divided into two types namely physical predictors and socio-economic predictors. Data for the physical predictors were extracted from landsat images, while socio-economic data were collected from the statistical bureau (BPS 1987-2000). The physical predictors used were:

- Distance from a pixel centre of a given land use (1 pixel = 1 ha) to the pixel center of a adjacent land use (X1) - represents the closeness to the frontier of conversion
- Distance from a pixel centre to a pixel centre of adjacent main-road (X_2) – represents ease of access and road transport
- Distance from a pixel centre to a pixel centre of adjacent main river (X_3) – represents access and ease of log transportation
- Total area of agriculture land (X_4) – represent demand for land for key economic activity

While socio-economic predictors were:

- Job seeker (X_5) – demand for employment opportunities
- Job opportunity (X_6) – availability of employment
- Population density (X_7) - number of people per pixel
- Income (X_8) – represents ability to make a livelihood

The population density is assumed to decrease exponentially the farther away the pixel is from the center of the resettlement area.. In this study the population density was estimated using Equation (3), adapted from Murdiyarso *et al.*, 2000:

$$P_t = [0.2402e^{-0.9464D}]*P \qquad (3)$$

where

P_t is the population density in a given pixel,

P is total population in the sub-district, and

D is distance of a pixel to the defined center of the resettlement area (km).

Same equation was also applied to estimate the changes in the number of job seekers, job opportunities, and incomes in each pixel. In this case, the number of job seekers in a given pixel was assumed to decrease exponentially as it moved away from the center of the resettlement area. Job opportunities and incomes decreased as they moved away from the center of activities. The center of activities was defined as pixels located in the center of smallholder rubber, paddy field, mosaic fruit trees, mosaic upland rice, estate plantation, and the project areas.

Estimation procedure: When parameters of the logit regression equations are developed, the probability of a given land use being converted into other land use can be estimated using the defined predictors. Thus, the change in land use pattern in the future with and without carbon-sink projects can be predicted by estimating the change in predictors (or by making projection of the predictors) under both conditions. The physical predictors, X_1, X_2, and X_3 remain unchanged under both scenarios. For estimating land use changes from 1992 to 1999, the model uses physical data for 1992, while the socio-economic data is the average for the periods 1992 to 1999. In the case where probabilities of change across land uses, say A to B, A to C and A to D are all more than 0.5, the change being considered is the one that has the highest probability. For example, when the probability of land use A to be converted into land use B was 0.55, A into C was 0.60, A into D was 0.72, the path of the change would be from A into D. Figure 3 illustrates the steps in the analysis.

For estimating land use changes up to 2012, the models were run with two-year steps. Land use change in year 2002 was estimated based on predictors and land use for 2000, then the resulting land use for 2002 was used to predict the land use change for 2004 and so on. Two rules observed for the analysis were: (i) once an area has a C-sink project underway it could not be converted to other land uses, and (ii) conservation/protection forests were not allowed to be converted to other uses other than forests but they could change to other forest types, in this case they might become secondary forest or logged forest as a result of illegal logging.

[INSERT FIGURE 3]

Projection of Predictors. The projection of the values of the predictors to the future is based on scenarios. There are three scenarios used in the analysis, i.e. *baseline scenario, and two mitigation scenarios (*one involving about 40,000 ha and the second one covering 90,000 ha of critical land that will be used for project implementation). In the baseline scenario, the projection of the socio-economic predictors is based on historical data (1986-1999) and government plans (target). Since the long historical data and government plan are not available at the sub-district level, the changes in socio-economic variables at the sub-district level were assumed to follow the trend of the Batanghari district for which government plans do exist. In order to capture the variation between the sub-districts, the projection was done in two steps. The first step was to estimate the changes in the socio-economic variables for the Batanghari district using historical data (1986-1999) and a regression. The second step was to estimate the future values of the socio-economic variables for the sub-districts. This was done using the formula:

$$GF_i = GP_i/GP_B * GF_B \qquad (4)$$

where GF and GP are future and past values of socio-economic predictors respectively, and sub-script-*i* indicates sub-district-*i*, and B is Batanghari District. This approach was used since the sub-districts do not have as much historical data as the Batanghari district. The sub-districts only have data for one or two particular years. In the case where sub-districts do not have job-seekers and job-opportunity data, these data were assumed to be the same as the proportion of the corresponding sub-district population with the Batanghari district population multiplied by the number of job seekers or job opportunities in the district.

In mitigation scenarios, the projection of the socio-economic values was done in the same way as in the baseline scenario. However, the total area of agricultural land (rice paddy and agricultural plantations), job opportunities and income changes in the scenario depended on the total land allocated for the implementation of the mitigation project.

The type of mitigation options considered in this analysis involves planting trees on lands classified as degraded and unproductive. Based on practices from similar land use areas elsewhere in the province as well as other non-project sites in the district, the selected species for projects were: Albizia (*Paraserianthes falcataria*), meranti (*Shorea spp.*), rubber (*Hevea braziliensis*), palm oil (*Elaeis guineensis*), kemiri/candle nut (*Aleurites molluccana*), pinang (*Arenga pinanga*), durian (*Durio zibenthinus*), duku (*Lansium domesticum*), rambutan (*Nephelium* spp.), mangga (*Mangifera indica*), and macang (*Mangifera* spp.). Cost effectiveness of the options and the annual carbon stock saved by each mitigation option was assessed using the COMAP model (Sathaye *et al.*,1995). Total area allocated for the implementation of the different options under the baseline and mitigation scenarios is presented in Table 1 below.

[INSERT TABLE 1 HERE]

Method for Quantifying Leakage. The amount of leakage is the change in carbon stock outside the project boundary caused by the implementation of the projects. In a COP9 decision, leakage was defined as the increase in greenhouse gas emissions by sources which occurs outside the boundary of project activities under the CDM which is measurable and attributable to the project activity, while project boundary geographically delineates the project activities under the control of the project participants and the project activity may contain more than one discrete area of land. In this study, the project boundary was set to be the same as the edges of the project area, and the leakage was confined to the change in carbon stock that might occur within the Batanghari district. Thus, this study assumed the area that will be affected by the projects was limited to the Batanghari district. It should be noted that the increase in GHG emissions from other sources might also occur due to project implementation, for example, the increase in transportation intensity etc. However, for this study, the emissions from these sources were not accounted for. The change in carbon stock in the project areas would be the direct carbon benefit of the projects. If over a given time (e.g. *n* years after planting), the carbon stock in the project area was X t C, and that of the degraded lands was Y t C, then the net carbon benefit due to the project would be Z = (X-Y) t C. Suppose under the absence of the project, the projected land use and forest cover in the rest of Batanghari district in the given time has carbon stock of R t C, while under the presence of the project it has carbon stock of S t C, the leakage would be T=(R-S) t C. Following COP9 decision, leakage occurs only when value of S is lower than R. Thus the carbon benefit from the project after considering leakage would be (Z-T) t C.

5. Results and Discussion

5.1 Logit Regression Equations and Validation

From the analysis, most of the predictors (independent variables) were found to be statistically significant in influencing land use/cover change in Batanghari district. The adjusted coefficient of determination (R^2adjusted) of the equations ranged from 0.08% to 95% with average of about 36%. For verification, the equations were applied using the physical predictors of 1986 and mean of socio-economic predictors of 1986-1992. It was found that the equations were able to predict the land use change pattern of Batanghari very well. The percentage of matching between predicted and actual land use was about 83%.

5.2 Mitigation Potential and Cost Effectiveness of the Options

Among the 11 tree and fruit tree species, it was found that meranti is the species with the highest mitigation potential, i.e. more than 200 t C/ha, while oil palm, duku, rambutan, mangga, macang, kemiri, rubber, and durian have mitigation potential of between 100 and 200 t C/ha; albizia and pinang less than 100 t C/ha (Table 2). Investment costs required for implementing these options range from US $16 to 90 /ha or equivalent to about US $0.06 to 0.79 per t C. Anther earlier study (Boer *et al.*, 2001) found that investment costs for establishing timber estate plantation using short rotation species were between US $23 and 33/ha (equivalent to US $0.42

and 0.88/t C), while those using long rotation species were between US $42 and 77/ha or equivalent to about US $0.19 and 0.42/t C.

The life cycle cost varies among the options, with plantation trees at the lower end (meranti, kemiri, and pinang) and fruit trees at the upper end (Table 2). This is because the initial seedling cost, and first three years maintenance cost, of fruit trees are higher because in the fruit-tree plantations food crops are also planted. All options gave positive monetary benefit, with most of the options that use fruit tree species resulting with higher benefits than the other options, in particular Durian since products of these options are not only from wood but also from the fruits. By including the carbon revenue, these options will become more attractive.

[INSERT TABLE 2]

5.3 Projection of the Predictors

In the long-term Development Plan of Batanghari district, its population density is projected to increase by about 2% per year, job opportunity by about 7.5% per year, job seekers by 9.2% per year, and agricultural land by about 3.3% per year for rice paddy, 11.0% for tubers, 5.9% for vegetables, and 4.0% for estate plantations (*PEMDA Batanghari*, 2000). In the period 1986-1998, the annual growth rates of agricultural land were 1.3% for rice paddy, 1.1% for tubers, 3.6% for vegetables, and 5.1% for estate plantation. Growth rates of job seekers and job opportunities during this period fluctuated from year to year, and tended to decrease. Considering this historical trend, the growth rate of agriculture land for annual crops as well as job seeker and job opportunity was assumed to be half of the government target. Income of the district (gross domestic regional income, PDRB) is projected to increase by about 25% per year, much higher than historical trend. This assumption was adopted considering the change from a centralized government system to a decentralized one (local autonomy system). In the new system, most of the revenues from mining, agriculture, industries, etc will now be retained in the local areas instead of being sent to the central government. Recently, Batanghari district has started exploiting natural gas, while crude oil is being explored and it is expected in the next 3-5 years this resource will be exploited.

Implementation of C-sinks projects under the two mitigation scenarios will require land and labor (about 4 person-years per ha). The projects will also generate new income for the sub-districts. Thus, the implementation of the projects will affect job opportunity, income, total land use for agriculture etc. As these predictor variables are affected, the probabilities of a given land use to be converted into other land uses will also be affected.

Other physical parameters such as X_2 (distance from a pixel centre to a pixel of adjacent main road), X_4 (total area of agriculture land), X_5 (number of job seekers), and X_7 (number of persons per pixel) may also change in the future. In the Five-year Development Plan, the government planned to develop new roads, however, length and location of the new roads were not provided in this plan. Thus, in this study the predictors X_2, X_4, X_5 and X_7 for the two mitigation scenarios were set to be the same as those for the baseline scenario.

5.4 Prediction of Land Use Change/Forest Cover and C-Stock from 2000 to 2012

The results of the analysis suggests that under the baseline scenario, the areas of secondary regrowth, small holder rubber plantations, mosaic upland rice, and estate plantations increase from 2000 to 2012. As shows in Figure 4, the increase in above types of land uses occurs at the expense of areas under lowland logged over forest, lowland and hill forest, and mosaic fruit trees. The largest absolute change in area occurs in lowland logged over forest which loses 29 thousand ha while secondary regrowth, and smaller holder rubber and estate plantations each increase by about 9 thousand ha. One of these trends is intensified in the mitigation scenarios and more of the lowland logger over forest, is converted to other uses such as mosaic fruit trees and upland rice, and estate plantations. At the same time, the baseline increase in secondary regrowth, and small holder rubber plantation, decreases in the mitigation scenarios.

Under the mitigation scenarios, the pattern of land use changes outside the project areas is not the same as that of the baseline scenario (Figure 4 and Table 3). Under these two scenarios, many of areas of mosaic fruit trees outside the project boundary are converted into mosaic upland rice and residential areas. Table 3 shows that the area of mosaic upland rice and residential areas in 2012 under the mitigation scenarios are much higher than the baseline. The increase in conversion rate of forest to mosaic fruit trees and to residential areas under the two mitigation scenarios is in part due to the higher increase in income. Income has statistically significant positive correlation with the probability of mosaic fruit trees being converted to residential areas. Similarly, the increase in income also increases the probability of this land being converted into mosaic upland rice areas.

[INSERT FIGURE 4]

The results of this study also suggest that some of the smallholder rubber area would be converted into mosaic fruit trees. In 2012 the area of smallholder rubber plantations in the mitigation scenarios is much lower than in the baseline scenario (Table 3) as the rate of development of fruit trees under the mitigation scenarios is high. Our logit model analysis indicates that conversion of a given land use to another type of use is affected by land uses adjacent to it (represented by the predictor X_1). Similar to the changes within the project area, more areas are converted to fruit trees from smallholder rubber plantations that are adjacent to mosaic fruit trees in the surrounding areas.

5.5 Estimated Carbon Benefit from Project

Changes in the carbon stock within and outside the project boundary but inside the Batanghari study area are shown in Figure 5 for the baseline and two mitigation scenarios. In each panel, the baseline refers to the trend in carbon stock in the study area from 1999 to 2012. Figure 5 shows that carbon-stock in the study area under the baseline remains unchanged until 2008 and then increases slightly afterwards due to the increasing rate of the establishment of timber plantations. Each panel also shows the trend in carbon stock in the study area due to the mitigation planting in the project area (Figure 4), and the trend in carbon stock in the study area when the leakage activities are accounted for. Figure 6 shows the same mitigation trends in a bar chart for 2008-2012. Without accounting for leakage the net carbon sequestration amounts to 430 thousand and one million t C and the leakage amounts to 1.2 million and 1.75 million t C for the two mitigation scenarios respectively. Taking leakage into consideration the net sequestration amounts to -770 and -750 thousand t C respectively for the two mitigation scenarios.

[INSERT FIGURES 5 AND 6]

As this study shows income and job opportunities are two important factors that affected the dynamics of land use projects. The scale of the project, however, would be critical in determining whether significant leakage would occur. If the project were small enough, leakage might not occur. This is one of the areas that need to be studied further as a basis of determining the minimum scale of LULUCF-CDM project below which leakage could be assumed negligible.

Sensitivity to assumption about change in carbon density: It should be noted that this analysis assumed that C-densities of all land uses and forests outside the project boundary are constant. It is very likely that illegal logging does occur to some level and this will affect the carbon-stock of the forests outside the project boundary. It is conceivable that the rate of illegal logging in the mitigation scenarios would be lower than that in the baseline as the project creates more job opportunities. Our logit model analysis indicates that the probability of lowland and hill forest being exposed to illegal logging would decrease as job opportunities increased. Thus, the C-density of forest outside the project boundary would be higher under the mitigation scenario. To illustrate, if the C-density of lowland logged over forest in the baseline were reduced by 10% (or from 90 t C/ha to 81 t C/ha), the impact of the implementation of C-sink projects on the total C-stock in the project boundary would be positive. The C-stock outside the project boundary would increase significantly. This means that the loss of carbon due to the increase in forest conversion to upland rice and resettlement areas could be compensated by the decreasing rate of illegal logging in the lowland logged over forest. In other words, by implementing a carbon mitigation project, carbon stock outside the project boundary would be higher than that without the project. Therefore, for the improvement of the analysis, the change in C-density of standing forests outside the project boundary should also be taken into account in particular for forest area closed to project sites.

The results of this analysis suggest that satellite imagery can be used in conjunction with other data to assess and estimate the extent of leakage in mitigation projects in the land use, land-use change and forestry sector However, some improvements are still needed. The analysis should be able to provide more detail classes for a forest type covering wide areas according to their C-density. This is particularly important if illegal logging or encroachment is a common practice surrounding the project site. The approach used here highlights the usefulness of using a single leakage assessment whose results are used for a number of C-sink projects located over a wide area. However, the analysis requires good database which is necessary for developing reliable land –use/cover change prediction equations. Additional analysis is required to test how far out the prediction equations could reliably be used for land use change prediction. The logit regression equation may not perform well if the equation is used to estimate the probabilities of land use conversion in a point of time that is far from the time of prediction due to changes in the underlying factors used to support the structure of the equation. Refining of the equations after a certain period may be needed.

6. Conclusions and Recommendations

Important conclusions and recommendations that can be drawn from this study are:

- The use of satellite imagery for assessing leakage can be effective for multiple mitigation projects distributed over a wide area. However, there is a need to define the acceptable level of error and to increase the precision of analysis by considering the likely changes of C-density of dominant forests outside the project area.
- The main constraint of using this approach is the availability of data for projecting socio-economic predictors (non-physical variables), and also the identification of the key factors driving the land use change in the specific area of study over time.

- The logit regression equations may not perform well if these are used for predicting forest/land conversion in a point of time far from the time of for which the data are relevant. Additional analysis to find appropriate timeframe for the use of the equations is required.

Acknowledgement

This work was supported by the U.S. Environmental Protection Agency, Office of Atmospheric Programs through the U.S. Department of Energy under Contract No. DE-AC02-05CH11231. Disclaimer: The views and opinions of the authors herein do not necessarily state or reflect those of the United States Government or the Environmental Protection Agency. The Authors also acknowledged the inputs given by Jayant Sathaye, N.H. Ravindranath, Kenneth Andrasko, Ben de Jong, Rodel Lasco in workshops on 'Forestry & Climate Change: Emerging Opportunities-Status and Perspectives' held in Bogor September 7, 2001 and in workshop on 'Forestry & Climate Change: Assessing Mitigation Potential-Lesson Learned' held in New Delhi 23-24 September 2002.

References

Adger WN, Brown K (1994) Land use and the causes of global warming. John Wiley and Sons, New York, pp: 133-163

Aldrich JH, Nelson FD (1984) Linear, probability, logit and probit models, in Series L. Quantitative application in the social science, Newbury Park, Sage University Publication

Auckland L, Moura-Costa P, et al (2001) A conceptual framework for addressing leakage on avoided deforestation projects, Winrock International, Arlington

Bell EJ, Hinojosa RC (1977) Markov analysis of land use change: continuous time and stationary processes. Socio-economic Planning. Science 11:13-17

Boer R, Masripatin N, et al (2001) Greenhouse gases mitigation technologies in forestry: status, prospect and barriers of their implementation. In: MoE, identification of less greenhouse gases emission technologies in Indonesia. pp: 6.1-6.28

Boer R (2001) Economic assessment of technology options for enhancing and maintaining carbon sink capacity in Indonesia, Mitigation and Adaptation Strategy for Global Change 6:257-290

BPS (1987) Batanghari dalam angka 1986, Biro Pusat Statistik Kabupaten Batanghari, Batanghari

BPS (1988) Batanghari dalam angka 1987, Biro Pusat Statistik Kabupaten Batanghari, Batanghari

BPS (1989) Batanghari dalam angka 1988, Biro Pusat Statistik Kabupaten Batanghari, Batanghari

BPS (1990) Batanghari dalam angka 1989, Biro Pusat Statistik Kabupaten Batanghari, Batanghari

BPS (1991) Batanghari dalam angka 1990, Biro Pusat Statistik Kabupaten Batanghari, Batanghari

BPS (1992) Batanghari dalam angka 1991, Biro Pusat Statistik Kabupaten Batanghari, Batanghari

BPS (1993) Batanghari dalam angka 1992, Biro Pusat Statistik Kabupaten Batanghari, Batanghari

BPS (1994) Batanghari dalam angka 1993, Biro Pusat Statistik Kabupaten Batanghari, Batanghari

BPS (1995) Batanghari dalam angka 1994, Biro Pusat Statistik Kabupaten Batanghari, Batanghari

BPS (1996) Batanghari dalam angka 1995, Biro Pusat Statistik Kabupaten Batanghari, Batanghari

BPS (1997) Batanghari dalam angka 1996, Biro Pusat Statistik Kabupaten Batanghari, Batanghari

BPS (1998) Batanghari dalam angka 1997, Biro Pusat Statistik Kabupaten Batanghari, Batanghari

BPS (1999) Batanghari dalam angka 1998, Biro Pusat Statistik Kabupaten Batanghari, Batanghari

BPS (2000) Batanghari dalam angka 1999, Biro Pusat Statistik Kabupaten Batanghari, Batanghari

Brown P, Cabarle B, et al. (1997) Carbon Counts: Estimating Climate Change mitigation in Forestry Projects. World Resources Institute, Washington DC

Casetti E, (1969) Why do diffusion processes conform to logistic trends? Geographical Analysis 1:101-105

Chomitz K, and Gray DA, (1995) Roads, land, markets, and deforestation: a spatial model of land use in Belize. World Bank Economic Review 10:487-512

CIFOR (1995) A Vision for forest science in the twenty first century, Centre for International Forestry Research, Bogor, 49p

CIFOR (2001) Developing a shared research agenda for LUCF and CDM; Research needs and opportunities after COP 6. Centre for International Forestry Research, Bogor

Cliff AD, Ord JK (1975) Model building and the analysis of spatial pattern in human geography. Journal of Royal Statistical Society 37:297-348

Esser G (1989) Global land use changes from 1860 to 1980 and future projection to 2500. Ecological modeling 44:307-316

FAO/UNEP (1999) Terminology for Integrated Resources Planning and Management. Food and Agriculture Organization/United Nations Environment Program. Rome, Italy & Nairobi, Kenya

Grainger A, (1990) Modeling deforestation in the humid tropics. IN: Palo M, Mery G (eds) Deforestation or development in the third world? Vol III, Helsinki. Division of Social Economics of Forestry. Metsantutkimslaitoksen Tiedonantoja 272, pp 51-67

Hairiah K, Sitompul SM (2000) Assessment and simulation of aboveground and belowground carbon dynamics. Report to Asia Pacific Network (APN). Brawijaya University, Faculty of Agriculture, Malang, Indonesia

Hall CS, Thian H, et al (1995) Modeling spatial and temporal patterns of tropical land use change, Journal of Biogeography 22:753-757

Harrington LMB, (1996) Regarding research as a land use, Applied Geography 16:265-277

Hutchinson GE, (1978) An introduction to population ecology. Yale University Press, New Haven

IPCC, (2000) Special report on: land use, land use change and forestry. Cambridge University

ITTO, (2002) ITTO guidelines for the restoration, management and rehabilitation of degraded and secondary tropical forest. ITTO Policy Development Series No. 13. ITTO, CIFOR, FAO, IUCN, WWF International

Kaimowitz D (1997) Factors determining low deforestation: the Bolivian Amazon', Ambio 26: 537-540

Ludeke AK, Maggio RC, et al (1990) An analysis of anthropogenic deforestation using logistic regression and GIS, Journal of Environmental Management 31:247-259

MoE (2003) National strategy study on cdm in forestry sector. Ministry of Environment, Jakarta

MOF (2001) Forestry statistics of Indonesia 1999/2000, Agency for Forest Inventory and Land Use Planning, Jakarta

Moura-Costa PH, Stuart MD, et al (1997) SGS forestry's carbon offset verification service. In: Riermer PWF, Smith AY, et al. (eds), Greenhouse gas mitigation. Technologies for activities implemented jointly. Proceedings of Technologies for AIJ Conference, Vancouver, Oxford, Elsevier, pp. 409-414

Murdiyarso D, Suyamto DA, et al. (2000) Spatial modeling of land-cover change to assess its impacts on aboveground carbon stocks: Case study in Pelepat sub-watershed of Batanghari watershed, Jambi, Sumatra. In: Murdiyarso D, Tsuruta H (eds), The impact of land-use/cover change on greenhouse gas emission in tropical Asia, IC-SEA and NIAES, pp:107-128

Ochoa-Gaona S, Gonzalez-Espinosa M (2000) Land use and deforestation in the highlands of Chiapas, Mexico. Applied Geography 20:17-42

Palo M, Mery G, et al, (1987) Deforestation in the tropics: pilot scenarios based on quantitative analyses. In Palo and Mery (eds) Deforestation or development in the third world? Vol I, Helsinki. Division of Social Economics of Forestry. Metsantutkimslaitoksen Tiedonantoja 272, pp 53-106

PEMDA Batanghari (2000) Rencana Pembangunan Kabupaten Batanghari Lima Tahun. Pemerintah Daerah Tingkat II Batanghari, Provinsi Jambi

Reis EJ, Margulis S (1991) Options for slowing Amazon jungle clearing in Dornbusch R, and Poterba J, Global warming: economic policy responses, MIT Press, 335-375. Cambridge, MA

Sathaye J, Makundi W, et al (1995) A comprehensive mitigation assessment process (COMAP) for the evaluation of forestry mitigation options, Biomass and Bioenergy 8:345-356

SGS (Société Générale de Surveillance) (1998) Final report of the assessment of project design and schedule of emission reduction units for the protected areas project of the Costa Rican Office for Joint Implementation, SGS, Oxford. 133 pp

Sisk TD, Launer AE, et al (1994) Identifying extinction threats: global analysis of the distribution of biodiversity and the expansion of the human enterprise, Bio Science 44:592-604

Turner BL, Meyer WB, (1991) Land use and land cover in global environmental change: considerations for study. International Soil Science Journal 130:669-679

Wasrin UR, Rohiani A, et al A.: (2000) Assessment of aboveground C-stock using remote sensing and GIS technique, Final Report, Seameo Biotrop, Bogor. 28p

Figure Captions

Figure 1. Diagram showing the decision tree for assessing leakage occurrence for HTI.

Figure 2. Land use change in Batanghari district between 1986 and 1992.

Figure 3. Flow of the analysis.

Figure 4. Predicted LULUCF (Land use, land use change and forest) in the period of 1999-2012. Growing light brown circles in the maps are locations where the estate plantations are established. Top, middle and bottom panels show Baseline, Mitigation-1 and Mitigation-2 scenarios respectively.

Figure 5. The change in C-stock outside and inside project area under the two mitigation scenarios. In each panel, the baseline refers to the trend in carbon stock in the study area. Each panel also shows the trend in carbon stock in the study area due to the mitigation planting in the project area (C-Project), and the trend in carbon stock in the study area when the leakage activities are accounted for (Adjusted Baseline).

Figure 6. Standing C-stock from Project and Leakage in the period between 2008-2012 under the two mitigation scenarios.

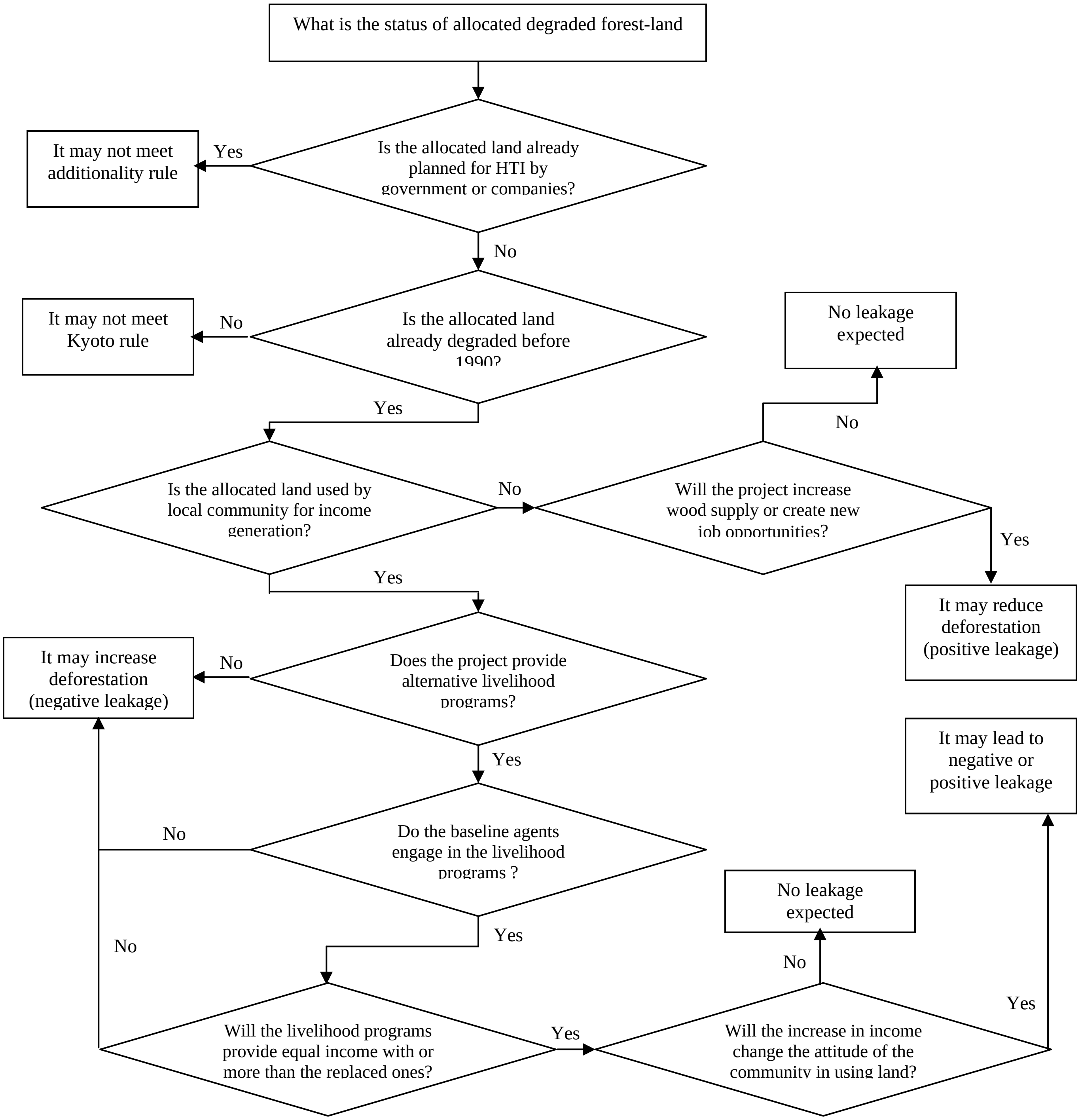

Figure 1. Diagram showing the decision tree for assessing leakage occurrence for HTI

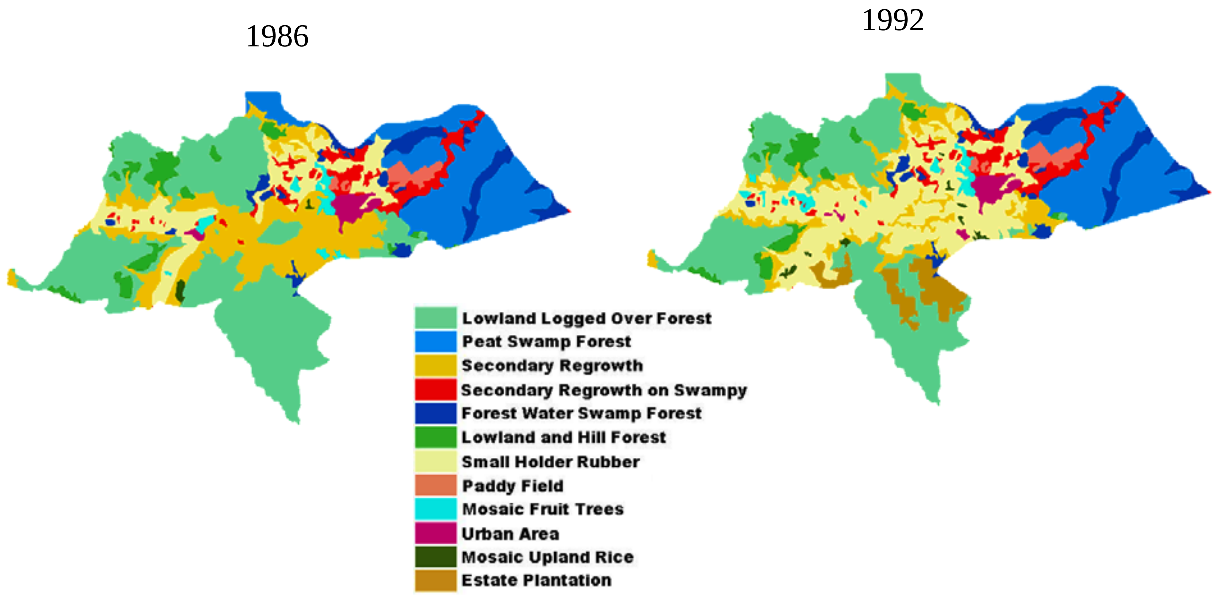

Figure 2. Land use change at Batanghari in 1986 and 1992 (Analyzed based on Wasrin *et al*., 2000).

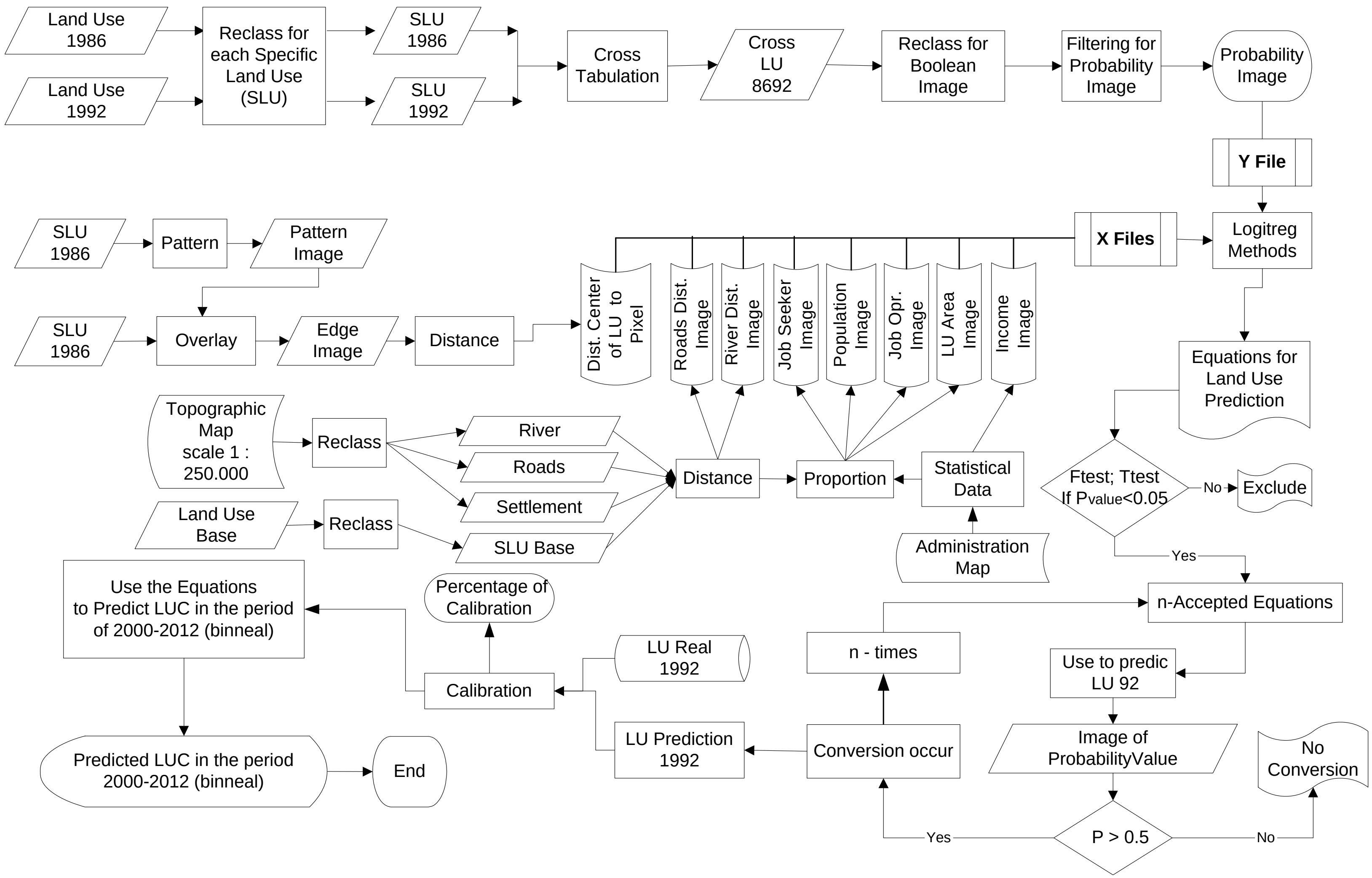

Figure 3. Flow of the analysis

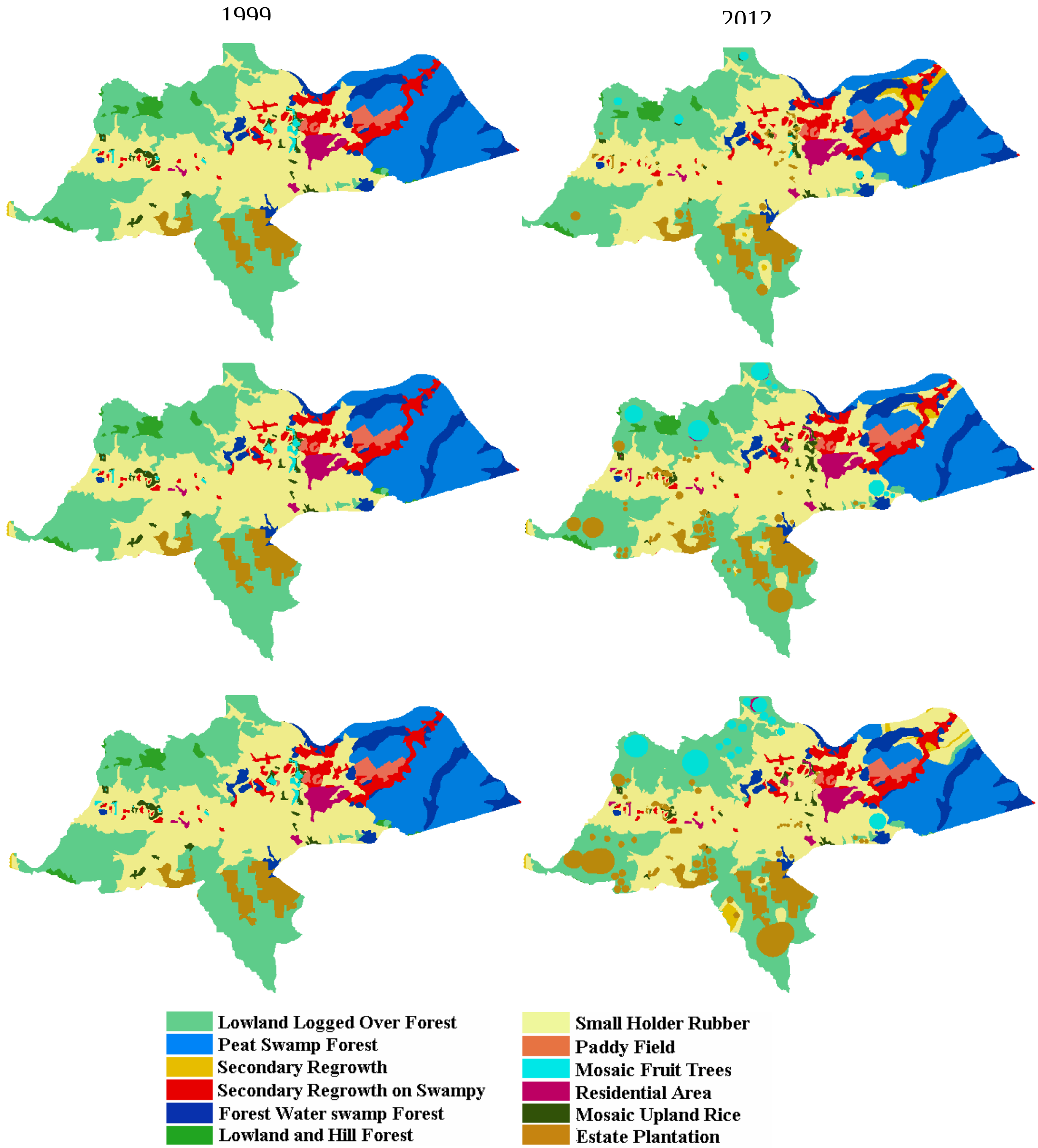

Figure 4. Predicted LULUCF (Land use, land use change and forest) in the period of 1999-2012. Growing light brown circles in the maps are locations where the estate plantations are established. Top, middle and bottom panels show Baseline, Mitigation-1 and Mitigation-2 scenarios respectively.

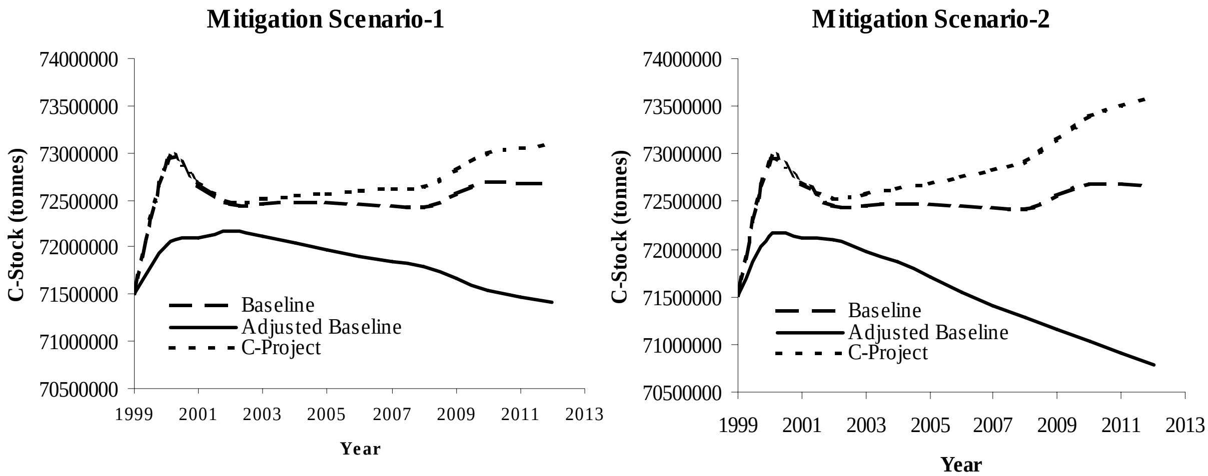

Figure 5. The change in C-stock outside and inside project area under the two mitigation scenarios. In each panel, the baseline refers to the trend in carbon stock in the study area. Each panel also shows the trend in carbon stock in the study area due to the mitigation planting in the project area (C-Project), and the trend in carbon stock in the study area when the leakage activities are accounted for (Adjusted Baseline).

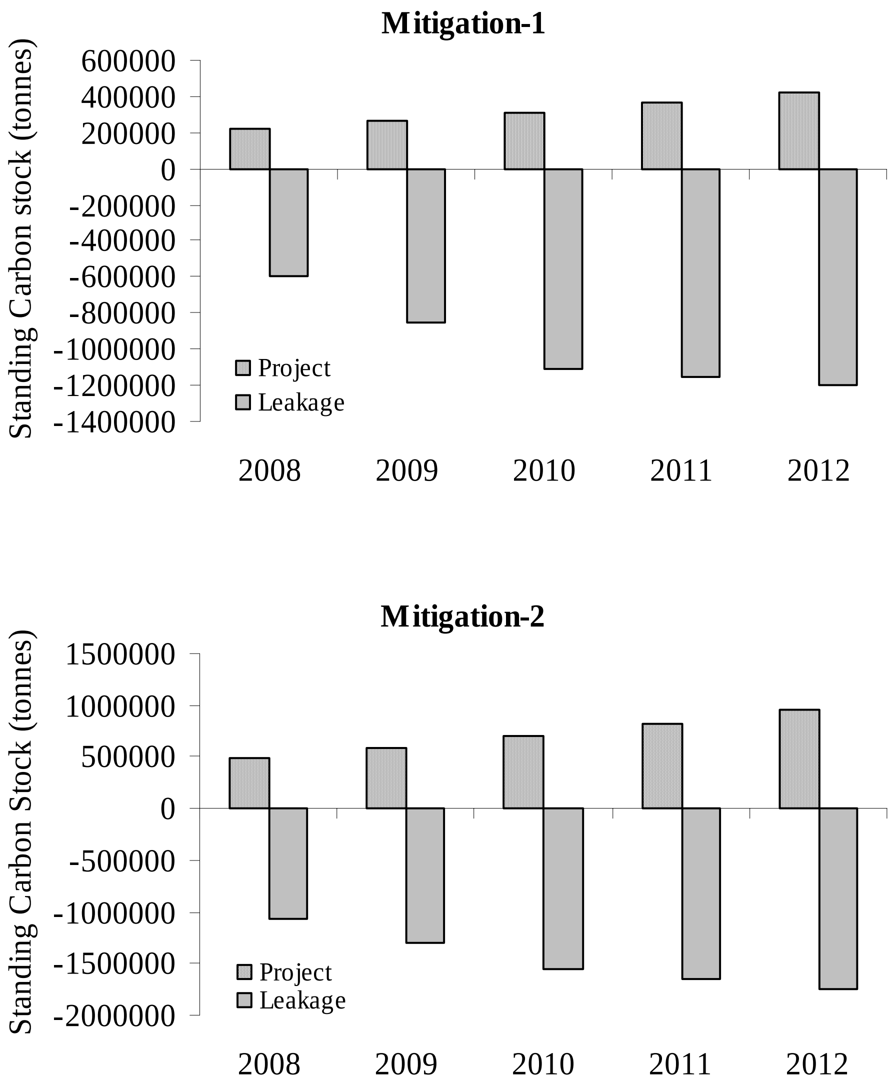

Figure 6. Standing C-stock from Project and Leakage in the period between 2008-2012 under the two mitigation scenarios

Table 1. Total available area for C-sink projects and total area allocated for each species

		Allocated Area (ha)		
Sub-Districts	Tree Species	Baseline	Mitigation-1	Mitigation-2
Sekernan	Mangga (*Mangifera indica*.)	1057	4369	9745
Kumpeh	Pinang (*Arenga pinanga*)	342	1414	3153
Pemayung	Durian (*Durio zibethinus*)	1120	4630	10327
Mersam	Rambutan (*Nephelium* sp)	883	3651	8143
Marosebo	Kelapa Sawit (Elaeis guineensis)	1162	4803	10713
Kumpeh Ulu	Duku (*Lansium domesticum*)	828	3421	7631
Jambi Luar Kota	Kemiri (*Aleurites mulluccana*)	555	2296	5120
Muara Tembesi	Meranti (*Shorea* spp.)	608	2512	5601
Muara Bulian	Karet (*Hevea braziliensis*)	1692	6995	15602
Mestong	Albizia (*Paraserianthes falcataria*)	658	2719	6065
Batin XXIV	Macang (*Mangifera* sp.)	866	3580	7986
Total		**9770**	**40390**	**90086**

Note: In this analysis the land allocation was determined based on farmers' preference (represented by total plantation area in year 2000 under each tree species

Table 2. Mitigation potential and cost effectiveness of the eleven species

Type of Mitigation Option	Mitigation Potential (tC/ha)	NPV Benefit ($/ha)[1]	Life Cycle Cost ($/ha)[2]	Investment Cost ($/ha)[3]
Rubber	128	21	131	73
Oil Palm	109	324	139	33
Rambutan	118	311	149	90
Meranti	254	13	94	16
Durian	133	948	149	90
Albizia	53	760	121	21
Duku	115	385	149	90
Mangga	121	927	149	90
Macang	121	478	149	90
Pinang	63	162	95	16
Kemiri	125	474	94	16

Note: Discount rate was assumed to be 10%.

[1] NPV = Net Present Value

[2] Life cycle cost refers to the discounted value of all costs to the end of rotation

[3] Investment cost = Initial cost including land acquisition cost, land preparation, planting and early tending.