Carbon Emissions from Land Use, Land Use Change and Forestry (LULUCF) in

Berau District East Kalimantan, Indonesia

"Are conditional and realistic REDD mechanisms feasible in Berau district, East Kalimantan?"

Project Report

World Agroforestry Centre

Carbon Emissions from Land Use, Land Use Change and Forestry (LULUCF) in Berau District East Kalimantan, Indonesia

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Introduction:

Are conditional and realistic REDD mechanisms feasible in Berau District, East Kalimantan?

Emissions from agriculture, forestry and other land uses (AFOLU) in the tropics contribute about 20% of the global climate change. In tropical countries like Indonesia, the economic returns from converting forests to other land uses have been relatively low when expressed per unit CO_2 emitted. Therefore from the economical perspectives, opportunities to reduce emissions from deforestation and degradation are substantial if effective and efficient mechanisms can be established to offset real and legitimate opportunity costs. From three provincial case studies in Indonesia, 70 to 90% of carbon emissions during 2000-2005 were associated with low economic benefit (less than 5 USD/t CO_2-eq (van Noordwijk et al., 2007a).

However, development of mechanisms that provide economic incentives through REDD is hampered by a number of important issues:

- Lack of clarity in land tenure or land rights for many local stakeholders,
- A non-level playing field including uneven access to information and opportunities to influence decisions,
- A history of top-down decision making in spatial planning,
- Competition of REDD incentives with external, large scale drivers and interest groups in forest use,
- Lack of social capital between agencies, between local communities and local government and between layers of government,
- Widespread poverty that restricts options on investment,
- Lack of tested options for REDD implementation.

A pilot area for REDD implementation can help address the last issue and is very attractive, not only for gaining in-situ project experience, but also for the potential lessons learned and resultant multiplier effects.

In June 2008, the Ministry of Forestry, as the designated national lead institution on REDD and in anticipation of post-Kyoto protocol agreements, launched a draft decree regarding regulation of REDD pilot areas. However, the primary mandate of the Ministry of Forestry is to manage gazetted forest lands while the mechanism for REDD should be applicable of all areas with actual terrestrial C-stocks. Unpublished data from BAPLAN show that in several provinces, land outside the gazetted forest land has two-thirds the probability of having tree cover that meets the international forest definition, compared to gazetted forest land. Data that address existing land cover comprehensively, regardless of institutional forest definitions, are needed at this stage to get a realistic idea of the degree of emission reduction that is feasible.

In responding to the opportunity of developing REDD pilot areas, the district government of Berau has formed a task-force to discuss the potentiality of district-level involvement in developing pilot areas, supported by *The National Conservancy*. Berau as a district with high forest cover, 74% or 1.5 million hectares of land is covered by degraded and undisturbed forest (Landsat interpretation 2005) has a long history of forest management with a complex network of stakeholders involved. More recently, there have been some changes in the drivers of land cover changes and forest management. While in the past most forest exploitation was in the form of selective logging, recently logged forests have been converted to oil palm and timber plantations. More than half of the total area is gazetted as production forest and 17% as protection forest. The remaining area (roughly 25%) is designated as non-forest area. According to the hotspot map produced by JICA, about 38% of the total area has medium to high fires risk. From 1990 to 2005, forest degradation was a greater problem than deforestation, especially within the production forest area. (ICRAF, 2008, unpublished data).

Analytical approach

Three main criteria for judging whether a compensation and reward for environmental services (CRES) is fair and efficient are: realistic, conditional and voluntary (van Noordwijk et al., 2007a). The 'realistic' criterion is defined as "effectively mitigates, reduces or avoid threats to environmental services for all parties involved". In the context of REDD, driver analysis of land use changes is essential in order to identify cause-effect relations of emissions from deforestation and degradation and relevant actors, and potential activities to reduce these threats. Further, opportunity costs for actors are economically feasible to be off-set or access limit can be overcome without major leakage.

The 'conditionality' criterion is defined as "measurable delivery of service that is transparently linked to actions of seller". Five levels of measured conditionality are identified. The highest level is with the strictest requirement of demonstrable additionality and the lowest level relies on trust as a basis to evaluate the conditionality. For REDD mechanism, the second level of conditionality is deemed to be necessary and sufficient, i.e., 'the actual condition of the agro-ecosystem is taken as a basis for conditionality'. Remote sensing analysis coupled with plot level C-stock measurement could be acceptable if the interpretation is highly accurate (van Noordwijk et al., 2007).

For REDD, conditionality embraces the additionality, permanence and leakage aspects that relate to the accuracy of carbon accounting and monitoring system. Uncertainty is an issue and is an integral part of REDD conditionality. The smaller the magnitude of additionality (reduction of emission) is, the higher the accuracy of accounting and monitoring systems that are required to assess additionality.

The revised 1996 IPCC Guidelines for National GHG Inventories estimated 60% overall uncertainties at national reporting from LULUCF. This level of uncertainty is unacceptable if REDD pilot areas at sub-national level are to show additionality (reduction in emission from the agreed baseline). Among the methods suggested by IPCC GPG (IPCC, 2003) to assess uncertainty, Monte Carlo simulation is the most widely applied (Monni et al., Ogle et al., Larocque et al., 2008).

In the humid tropic, the productivity of the systems is high. Especially in the area where population density is relatively low and forest cover is extensive, shifting cultivation remains to be common agricultural practices among small holder farmers. The dynamics of carbon stock is therefore high, often in small patchy areas. Timber plantation also has a relatively short life cycle, which also produces a highly dynamic carbon stock over time but in a relatively extensive area. This accounts to the difficulty in monitoring. In addressing this, ICRAF under ASB project proposed time-averaged carbon stock of land use systems that captures the dynamics quite accurately. By regression modeling, biomass estimation from the plot level measurement taken for different age classes for each land use systems will result in time-averaged carbon stock of each of the land use systems.

Through a look-up table that provides a matching between land use systems as practiced on the ground and the land cover classes as 'seen' by the satellite and differentiated through statistical analysis, this bottom-up method allows us to take into account the specific land management systems practiced by land owners or managers in estimation carbon stock at the large area without losing the comparability power if it is conducted in proper hierarchical ways (ref ASB lecture notes). Three main sources of uncertainties are: plot level measurement, satellite image analysis and the matching/upscaling from plot to landscape level.

The higher disaggregation level we take for defining land use systems, the more accurate the plot level carbon stock estimates are, but at the same time the lower accurate the land use/cover change results derived from remote sensing are. As an example, different logging practices (e.g., conventional, reduced impact logging) can result in significantly different carbon emissions among them, however such differences cannot be picked up from the remote sensing data. Some good ancillary data might help but it reduces the accuracy of the land use/cover change results. The uncertainty analysis of this method has not been rigorously performed beyond empirical experiments using different levels of classification schemes (Lusiana et al., 2007, Dewi et al., 2007).

The 'voluntary' criterion in CRES is based a 'free and prior informed consent' agreement on the nature and level of deliverables in reward agreement. Both market and multilaterally funded REDD should ensure this voluntarity in the beginning of any stakeholder discussions.

Particularly for CRES in REDD, we identified the following essential activities in defining the REDD value chain:

- Actual emission reduction on the ground (Conditionality)
- Provision of sustainable livelihoods that reduce local threats to the carbon stored in the landscape (Realistic)
- Protection against 'leakage' by providing local income opportunities (Realistic)
- Securing 'additionality' over 'baselines' in a context of local development planning (Conditionality)
- Accounting for changes in C stock in a consistent national framework (Conditionality)
- Provision of institutional framework (e.g. by signing international agreements and reviewing legal context of 'rights to pollute') (Voluntary)

- Independent verification of emission data (Conditionality)
- Marketing capacity in linking potential supply and demand for emission reduction (pre-condition)

The scoping study for a REDD pilot area should test the feasibility of REDD from all three criteria: conditionality, realistic and voluntary criteria. For the conditionality criterion, historical baselines of C-stock should be derived from accounting and monitoring C-stock along with uncertainty analysis. A driver analysis for land use changes and profitability analysis of land use systems should be conducted to answer whether realistic criteria could be achieved.

In the case of Berau, the task-force will address the voluntary criterion of the REDD pilot areas to be set up. The other two criteria require that the accounting and monitoring systems are compliant to the national and international levels, and developed in partnership between the Berau task-force and independent agencies.

The study and its objectives

Depart from the above, a leading question to be addressed in the study is: Are conditional and realistic REDD mechanisms feasible in Berau district, East Kalimantan?

The study, namely 'Carbon emissions from LULUCF, uncertainty analysis and REDD opportunity costs' addresses the two criteria of CRES: conditionality and realistic, with the following specific objectives in Berau district, East Kalimantan:

(1) To estimate overall forest carbon emissions, and estimates for individual forest carbon loss components;

(2) To assess overall uncertainty levels of those forest carbon emissions estimates, and individual uncertainty levels associated with each relevant component of the forest carbon loss calculation;

(3) To identify drivers of land use/cover changes;

(4) To calculate opportunity cost for reducing emissions from deforestation and degradation; and

(5) To identify priority research needs to reduce uncertainty to acceptable levels (e.g., <20%).

The study components

The study comprises of three study elements: (1) Carbon Accounting and Monitoring, (2) Driver analysis of land use/cover changes, and (3) Profitability analysis and REDD opportunity. The first element covers objectives 1,2 and 5, while the second and the third elements covers objective three and four respectively.

In implementing the study, as much as possible, they use the best secondary data available through a meta-analysis and literature review including an evaluation of their reliability. Whenever there are gaps among the available, reliable data with our data requirement, we will collect essential primary data within available resources.

Carbon stock accounting and monitoring

This study element include four components of the forest carbon loss calculation: area deforested and/or degraded, biomass, combustion completeness, and the fate of cleared or degraded forests over time. The activities were done by ICRF and Centre for Social Forestry-Universitas Mulawarman (CSF) consists of:

(1) Primary data collection of plot level carbon stock measurement.
This activity led by CSF supported by ICRAF from methodological and training sides. Tool for Rapid Appraisal of Carbon Stock Assessment (RACSA) that has been developed by ICRAF and applied consistently in different landscapes in Asia, Africa and Latin America will be applied here. Combustion completeness from slash and burnt activities will also be recorded based on interview about local practices and secondary data (CSF and ICRAF)

(2) Data entry and analysis (CSF)

(3) Grountruthing for the satellite image interpretation (CSF)

(4) Spatial analysis to derive land use cover changes during the period of 1990-2005. For satellite image interpretation we will use hierarchical, object-based classification techniques (ICRAF), followed by the assessment of dynamics of carbon stock at the district level (ICRAF)

Driver Analysis of Land Use/Cover Change

Driver of land use/cover changes and the dynamics of the drives identified for each stakeholder in the district as well as external factors, including actors, intermediate and ultimate/underlying drivers. For this analysis ICRAF has developed a tool, namely DriLUC (Rapid Appraisal of Drivers of Land Use Change) which aims to provide a systems-level understanding of the way local drivers of land use change in a landscape relate to external conditions and the types of local/regional/national feedback that currently relate impacts on livelihoods and the provision of goods and services through focus group discussions, interviews with key informant and literature surveys. CSF lead this activity with support from ICRAF in methodology.

Profitability analysis and REDD Opportunity Cost

Profitability analysis of each major land use systems in the district is conducted using Policy Analysis Matrix (e.g., Monke and Pearson, 1995). Primary data to support the analysis will be collected. We will prioritize the primary data collection of carbon stock measurement, so depending on the gaps identified in the beginning of the study; we might cover spatially explicit profitability analysis. The district area is spatially stratified into zones in which input and output factor of land use systems are different, and therefore there are variabilities in profit of the same land use systems of different zones. This will reduce uncertainty of the opportunity cost analysis of REDD.

Outputs, deliverables and report organizations

Besides this Full Final Report that, the study produced three study reports and carbon stock database of Berau District. This Final Report contains Synthesis based on the three study report.

The three study reports are: (1) 'Estimation of LULUCF carbon emissions of Berau district, East Kalimantan', prepared by Spatial Unit of ICRAF and CSF ; (2) Identification of Drivers of Land Use/Cover Changes in Berau District (East Kalimantan, prepared by CSF; and (3) Profitability Analysis of Berau Main Land Use systems, prepared by Economic Functional Unit of ICRAF.

This report is organized as followed. The following Chapter will be a Synthesis entitled "Conditionality, Realistic, Voluntary and pro-poor in REDD". The Synthesis is based on the three Study reports. The three study reports will be included in this report as three sections following the synthesis.

Synthesis

Conditionality, realistic, voluntary and pro-poor in REDD

Meine van Noordwijk, Sonya Dewi and Suseno Budidarsono

Three main criteria for judging whether a compensation and reward for environmental services (CRES) is fair and efficient are: realistic, conditional and voluntary (van Noordwijk et al., 2007a). These criteria should be applied under a pro-poor perspective for local communities.

The 'conditionality' criterion is defined as "measurable delivery of service that is transparently linked to actions of seller". Five levels of measured conditionality are identified. The highest level is with the strictest requirement of demonstrable additionality and the lowest level relies on trust as a basis to evaluate the conditionality. For REDD mechanism, the second level of conditionality is deemed to be necessary and sufficient, i.e., 'the actual condition of the agroecosystem is taken as a basis for conditionality'. Remote sensing analysis coupled with plot level C-stock measurement could be acceptable if the interpretation is highly accurate (van Noordwijk et al., 2007). For REDD, conditionality embraces the, permanence and leakage aspects that relate to the accuracy of carbon accounting and monitoring system. Section discusses the emissions estimation from LULUCF in Berau.

The 'realistic' criterion is defined as "effectively mitigates, reduces or avoid threats to environmental services for all parties involved". In the context of REDD, driver analysis of land use changes (Section 2) is essential in order to identify cause-effect relations of emissions from deforestation and degradation and relevant actors, and potential activities to reduce these threats. Further, opportunity costs for actors are economically feasible to be off-set or access limit can be overcome without major leakage.

This section incorporates the three components of the study, namely C-stock change estimation from LULUCF, driver of land use and cover changes and profitability analysis of land use systems in Berau (Section 3). The aim is to estimate the opportunity costs for reducing emissions through a retrospective analysis.

In analyzing the abatement cost for carbon emission from land use and land cover changes, one has to consider at least 3 different cost components, namely:

1. Opportunity costs for reducing emissions
2. Transaction costs for awareness raising, contractual costs, monitoring and evaluation cost, brokerage
3. Operational cost of agreed actions

The implications and options for policies and interventions to reduce emissions are then discussed.

Methods

Within this study we only cover the first component of the abatement cost estimation. We incorporate the results of Estimation of LULUCF carbon emissions of Berau with the results of profitability analysis of Land Use Systems above. Figure 1. shows the schematic diagram of the calculation, which is a more comprehensive scheme compared to that of Figure 1.1. For each pair of changes in land use and land cover categories per unit area per year, time-averaged C stock differences can be estimated. Correspondingly, the differences in NPV per unit area (can either be private or social profitability) can be calculated. Therefore changes in NPV per ton of C emitted can be calculated by dividing up changes in NPV with changes in C-stock, which is the opportunity cost of the avoiding the particular changes in land use and land cover. Table 2.3. summarizes plausible trajectories dan drivers.

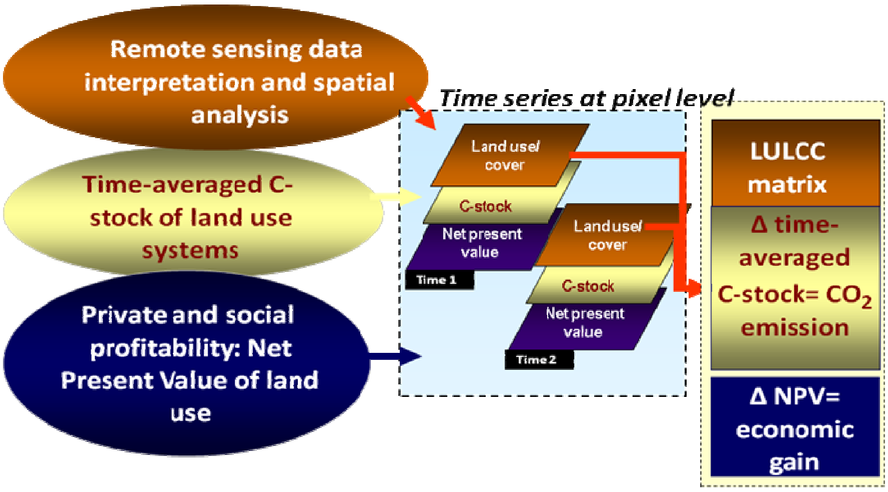

Figure 1. Schematic diagram of opportunity cost estimation

Due to time limits and technical difficulties in conducting profitability analysis, not all of land use systems in Berau are covered (Section 3). Therefore we need to take some assumptions in assigning NPV in each of the land use and land cover systems that is a stand-alone class within the legend categories from satellite image interpretations, but not covered by profitability analysis. Vice versa, those land use systems that are studied by profitability analysis but cannot be separated through satellite imageries, e.g., pepper and annual crop, or cannot be separated regarding their plot level C-stock, e.g., high density and low density logged over forests, are aggregated when assigning the NPV. Table 1. presents the NPV of each of the land use and land cover classes along with the descriptions of assumptions we take.

Table 1. NPV at private prices of land use and land cover types in Berau district

Land use and cover	NPV at private prices ($/ha)	Assumptions
Undisturbed forest	-	No management as undisturbed forest per se; the benefit of logging is attributed to the conversion rate
LOF	1,081	Average of low and high density logging (398 and 1,765 respectively)
Undisturbed mangrove	-	No management; treated like undisturbed forest
LOF mangrove	398	Same as low density logging on mineral soil
Undisturbed swamp	-	No management; treated like undisturbed forest
LOF swamp	398	Same as low density logging on mineral soil
Old shrub	-	No management
Mixed garden	302	Same as mixed cacao
Old rubber	302	Same as mixed garden
Teak	575	Same as acacia, since field observation show poor management and poor quality of standing stock
Acacia	575	Timber plantation
Other Forest Plantation	575	Same as Acacia
Rubber	1,260	Monoculture rubber
Oil Palm	3,424	Oil palm companies
Coconut	352	Monoculture coconut
Shrub	-	No management
Cacao	302	Monoculture cacao
Annual Crop	2,900	Pepper; according to Statistics data, the extent of pepper is about 2000 ha
Ricefield	(2,871)	Average between wet and dry system in coastal area (-2,563 and -3,179 respectively)
Grassland	-	No management
Cleared land	-	No management
Burnt forest	-	No management
Road and settlement	5,785	Same as cost of developing transmigration settlement in West Kalimantan (KOMPAS, June 27, 2006: Rp 14M per 2500 sq m)

Results

The overall emission and proportion of emission that is associated with negative, low and high opportunity cost is presented in Figure 2. Conversions to oil palm is shown to be in the high end both in the opportunity cost curve of emissions, due to its NPV which by far is highest compared to any other land use systems. The proportion of emission from conversion to oil palm increases over time. Logging is the single activity that causes the highest proportion of emissions with lower benefit than oil palm conversion per unit C emitted, especially if the conversion is from logged over forest. From ICRAF study on carbon footprint from oil palm plantation development, when the land cover of C-stock lower than 40 t/ha, e.g., grassland, shrubs, is converted to oil palm, there is no C-debt in the long run (assuming 25 years rotation). It is interesting to note here is the large portion of emission that is associated with establishment of forest plantation, which seems to be increasing in the more recent period. The forest plantation to supply raw materials to pulp and paper industry has been established in logged-over forest and undisturbed forests.

Both oil palm plantation establishment and logging are associated with higher than $5 increase in NPV/ton CO_2-eq emitted. The results suggest that logging in high density forest on dry land and conversions to oil palm do generate profit that is much larger than $5 and therefore costs for abating them might be substantial. However, a closer look show some variation in logging, i.e., logging in mangrove and swamp forest generates much lower profit such that the opportunity cost per t C emitted is close to $5. Even lower is the conversion of natural forest to forest plantation, e.g., Acacia, in Berau.

The potential of getting local people involved in reducing emission is evident. Conversions of forest to mixed garden or cocoa, which was conducted by local people, do not seem to bring any real economic benefit (< $5/ t C emitted). The paddy rice cultivation even associated with economic loss (negative NPV) but a purely economical consideration cannot be justified since paddy as staple food is produced for subsistence. Especially for remote areas, the activity is part of strategy to achieve food security. The pro-poor principle to reach fairness in the Locally Appropriate and Mitigation Action (LAMA) should be applied.

The results in Table 2 indicates that proportion of emission from land use and cover changes that are associated with increases in NPV less than $ 5 (opportunity cost < $5) sharply increases more recently, from below 50% in the period of 1990-2000 to 70% between 2005-2008.

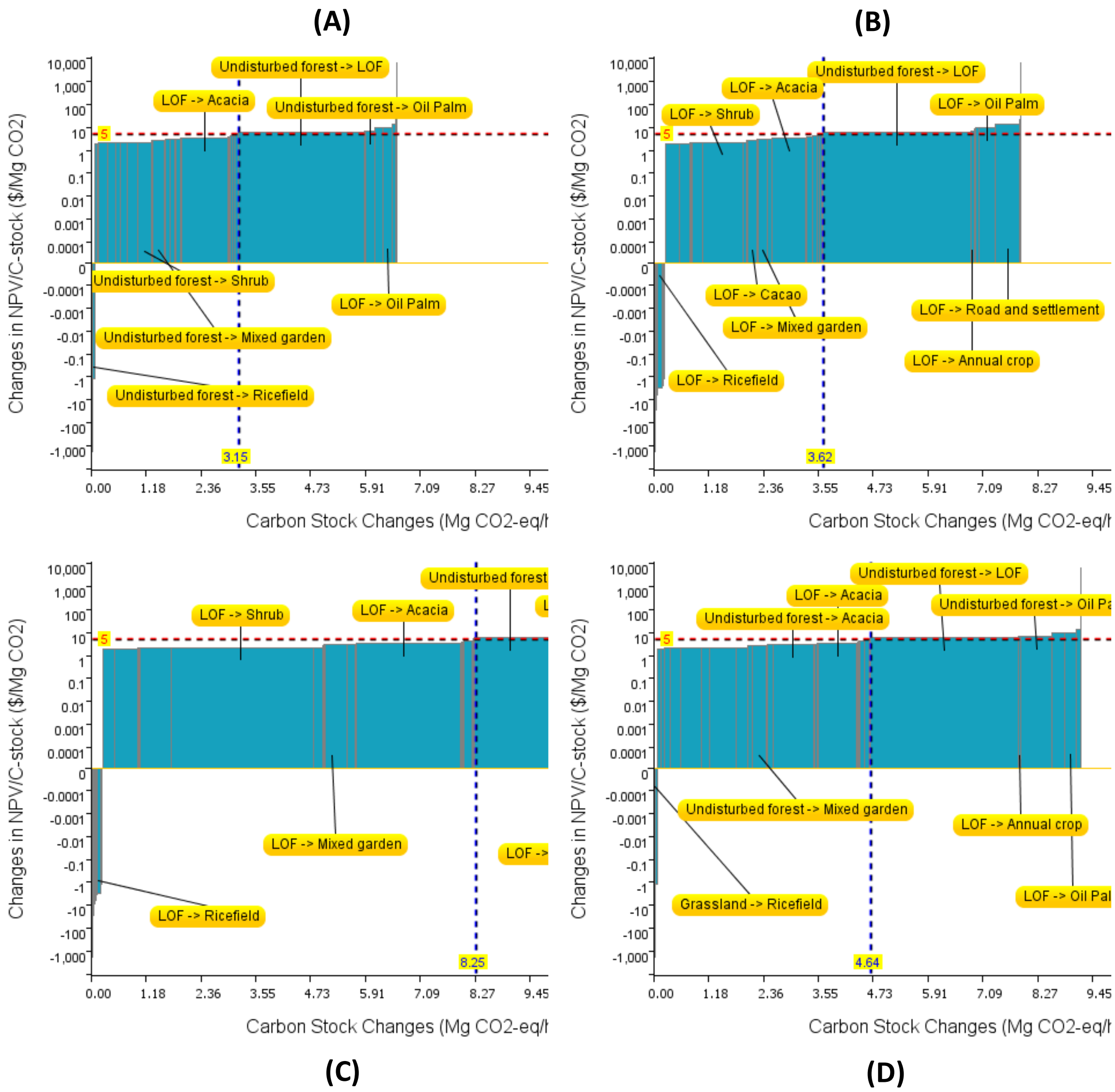

Figure 2. Opportunity cost of Berau emission in 1990-2000 (a), 2000-2005 (b), 2005-2008 (c) and 1990-2008 (d)

Table 2. Summary of emissions, removal and opportunity cost over the period of analysis

	90-'00	00-'05	05-'08	90-'08
Average Emission(Mg CO_2-eq/(ha.y))	6.57	7.9	11.65	9.2
Total Emission(Mg CO_2-eq/y)	14,390,171.73	17,316,980.72	25,537,545.04	20,165,036.23
Average sequestration (Mg CO_2-eq%/(ha.y))	0.02	0.13	0.35	0.02
Total sequestration (Mg CO_2-eq/y)	50,101.15	295,041.87	762,227.05	39,416.79
Emission at $5 threshold (t CO_2-eq/ha)	3.15	3.62	8.25	4.64
% of emission associated with < $5	47.9	45.8	70.8	50.4

Discussion

The opportunity cost analysis that is conducted here, in tandem with driver analysis and existing regulation and plans, can be used as a tool in identifying policy and intervention options across Berau district. Table 2 provides qualitative summaries of 4 main categories of opportunity cost from land use and land cover changes. This tool and collaborative GIS can help stakeholder negotiations and spatial planning process. Furthermore, activities, actors, and locations can be specifically identified, targeted and quantified using the data we produced. Under each scenarios that are built in participatory discussion, the amount of reduction of C emission from particular actions can be estimated, along with the level of funding necessary for compensating opportunity cost of such actions at particular extents in specific location within Berau district.

C-stock and C emission monitoring systems should be conducted in an integrative manner with the assessment of socio-economic impacts of climate change mitigation action for different actors. This will make Measuring, Reporting and Verifying (MRV) climate change mitigation actions in terms of emissions and finance, which is agreed by parties and reflected in Bali Action and Copenhagen Accord, can be achieved efficiently.

Wall-to-wall district analysis, rather than smaller projects, offers some advantages in terms of integrated actions across landscape such that institutions and payment distribution are easier to set up, and also addressing double counting and leakage. Accounting for LULUCF rather than forest C-stock and emissions is appropriate such that baseline and REL can be determined in a fair and efficient ways and monitoring can be conducted holistically. Treating the MRV actions in the entire landscape rather and register them under Locally Appropriate Mitigation Actions (LAMA) rather than treating specific actions separately will also enable the establishment of a nested structure of LAMA within Nationally Appropriate Mitigation Actions (NAMA).

Section 1

Estimation of Land Use, Land Use Change & Forestry (LULUCF) and carbon emissions of Berau district, East Kalimantan

Sonya Dewi, Andree Ekadinata, Zuraidah Said, Subekti Rahayu, and Fadjar Pambudhi

Introduction

TNC and partners are launching Reduced Emissions from Deforestation and Degradation (REDD) demonstration activities in Berau, Indonesia in support of Berau district government interest in REDD. Critical research needed to set the stage for, and design, REDD activities include:

- Estimation of historic rates of forest carbon emissions from deforestation and forest degradation with acceptable levels of uncertainty;
- Identification of drivers of land use/cover changes; and
- Calculation of opportunity costs for reducing forest carbon emissions.

High, or poorly defined, levels of uncertainty can both (a) reduce the likelihood of access to future REDD markets by undermining the credibility of avoided emissions, and (b) reduce the monetary value of future REDD credits since credits will likely be calculated using a "conservativeness factor" as the bottom end of the 95% confidence interval (GOFC-GOLD, Sourcebook, 2008; Grassi et. al. 2008).

The need for estimations of LULUCF carbon emissions is induced by the recognition of potential mitigation actions which embraces large areas beyond project boundaries. This broad approach being seen as suitable for REDD/REDD+ schemes is led by the followings:

- Lessons learnt from the failures of CDM A/R with complicated set of rules with high transaction costs;
- Small project area is prone to leakage problems;
- Co-benefit is feasible to be set;
- Less risk, more buffering capacity to increase higher probability of sustainability and successes;
- Nested systems and baseline are necessary to guarantee real reduction in emissions at the country level;
- Government endorsement and roles are stronger;
- Easier to get synergy with spatial land use planning and cross-sectoral policies

It is important to address elements within the land use sector holistically rather than one in isolation to others for the following reasons:

- There are dependencies and interconnectedness among land uses, e.g., through interactions among the land managers, in a landscape. Isolating some land use types from the landscape will fail to acknowledge these dependencies and therefore will be sub-optimal in addressing the landscape issues

- There are varying processes and proportions of land use types in different landscapes such that excluding some in the rules will cause inefficiency in reducing emissions from land use sectors and unfairness in rewarding people for climate change mitigation

In line with that we therefore propose LULUCF accounting rather than forest carbon accounting for the following reasons:

- Addressing all land use/cover types, rather being restrictive to and applying artificial boundaries through ambiguous definitions (Figure 1.1). Baselines of emissions for land uses can be developed, in whatever reward schemes that might be implemented in the future
- Current inconsistencies and changing schemes between planned and unplanned emissions and eligible and non-eligible reduced emissions can still be addressed
- Achieving compliance of reporting at the national level within a nested system

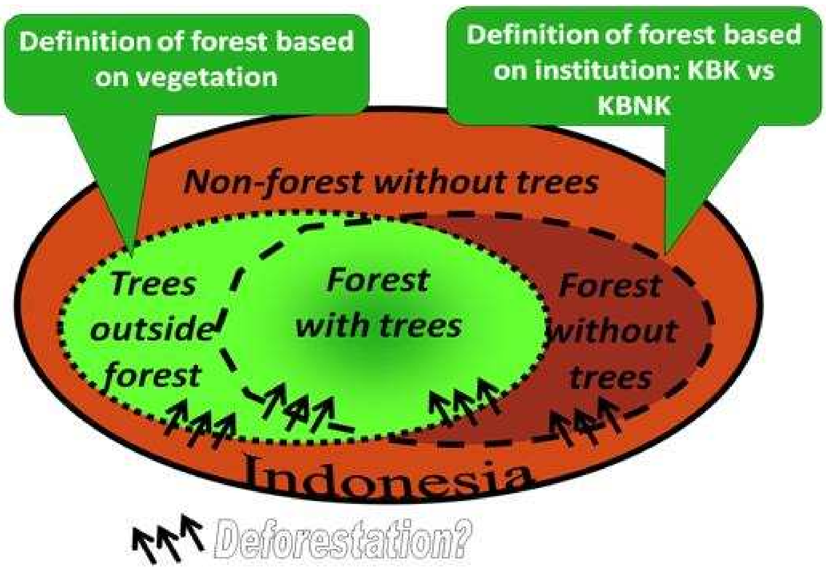

Figure 1.1. Institutional forests versus tree covers

This component of study addresses the methodological issues and attempt to produce highly accurate data for emission estimates from LULUCF at relatively low cost, in terms of time and resources. The report describes in details the materials, methods and resulted data and is accompanied by a CD of data files. Lessons learnt and research gaps are identified.

Materials

Two main materials compiled, used and produced during this study are: (i) spatial data to quantify area of changes (activity data), and (ii) measurement of all carbon pools in the land to quantify C-stock and C-stock differences at plot level (emission factor). The source of dynamically spatial data is time series of satellite imageries that cover the period of study between 1990 to 2008. Other than those, all other spatial data are static: Digital Elevation Model, thematic maps of administrative boundaries, topography, spatial land use plan at provincial level (Rencana Tata Ruang dan Wilayah Provinsi – RTRWP), and peat map, and GPS points of land use/cover. The best available DEM is still quite low in terms of resolution and accuracy. The number of GPS points to help with the interpretation of satellite imageries, especially in different forest density, is quite low and not well distributed over Berau landscape due to time and access constraints.

We used 5 sources of plot level datasets; 4 of them are secondary and only 1 is primary data to this study. The other four secondary datasets are: (i) compiled primary and secondary data by ICRAF (ii) STREK data, (iii) National Forest Inventory data, (iv) periodical forest inventory (Inventarisasi Hutan Menyeluruh Berkala – IHMB) data by one logging company in Berau. The size of primary plot dataset collected by our team is small compared to the secondary data that have been compiled during this study. For forest plot data, most are collected from Berau district by different institution, while for agroforestry plot data and other agricultural land, most data were collected from different places. The plot measurement in the virgin forest areas in Berau is extremely few due to accessibilities. Among the database, only the 62 primary plot data contains measurement of biomass/C from all carbon pools as specified by IPCC (above ground biomass (living and dead) and soil carbon).

Appendix I presents the spatial data used in this study and Appendix II provides the summary of plot level data from each sources, along with description of the plot sizes relative to tree diameter sizes for each dataset. The database of plot level, in raw and analyzed formats, is provided as a companion of this report, except for secondary data which is non-public domain.

Methodology

The overall methodology adopts the Rapid Carbon Stock Appraisal (RaCSA) developed by ICRAF which has been consistently used by ICRAF team and different NGOs and institutions in collecting their plot level data. The materials have also been used for trainings in 5 regions in Indonesia. The completion of the manual is currently at the final stage (Hairiah et al., 2009, draft).

RaCSA embraces multi-disciplinary approaches in order to reconcile local ecological knowledge, scientifically valid methodology and political spheres of land uses in addressing multiple level issues of emission estimation from land use sectors, namely tree, plot, land use systems, stratum within a landscape and landscape levels. At the tree and plot level, the field measurement is quite similar to standard forest inventory with the exception of the inclusion of necromass and litter measurement, and soil sample collection to estimate soil carbon.

IPCC refers to two types of methods in calculating emissions: (i) gain-loss method, which accounts the detail of fluxes due to both human activities and natural processes at a relatively short time scale, (ii) stock-difference method, which accounts for changes in stock due at a coarser time scale. The first method, if done appropriately, can be more accurate especially within a short time scale and within a small area. However, this method is very tedious and quite expensive. For an accounting of large areas using this method, default values at national or global level are commonly used, which in itself becomes a major source of error if applied to a specific area. We adopt the second method, which makes accounting feasible at a large-scale, such that emission can be estimated with a reasonable accuracy at a relatively low cost.

In our approach, the emission factors are defined as the stock differences between original and subsequence land use systems. Time-averaged C-stock is defined as a land use system specific measure. Land use systems capture the combination of land cover (vegetation density and composition that cover the earth surface), land use (human activities conducted on the land and the vegetation on it) and the periodic cycle attached to those particular human activities that relate with a specific sequencing of various land cover. The concept of land use systems and time-averaged C-stock are particularly developed to suit the common patterns of land use trajectories in the tropical landscapes with a definite and relatively short rotation. As an example, the traditional shifting cultivation cut across several different sequences of land cover types (e.g., secondary forest- cleared land- annual crop-shrub-agroforestry) and different land use and activities (e.g., non-timber forest product gathering-slashing and burning-planting and harvesting of paddy-rubber tapping, rattan harvesting) within a particular rotation period (e.g., 40 years, 60 years).

Land use systems should be able to capture the temporal dynamics of C-stock such that the typical or average C-stock across a system can be calculated, which is known as time-averaged C-stock. In a landscape, ideally spatial variation is also addressed by conducting field measurement across different age and location of each land use systems. In a system which is relatively stable or in equilibrium stage for a long period of time (hundreds of years) like in natural forest, time-averaged C-stock is basically equivalent to space-averaged C-stock. The approach of quantifying differences of time-averaged C-stock between original and subsequence land use systems are sensitive to emissions due to changes among land use systems but not to variations within the dynamics of a particular land use system. The method does not attempt to assign an accurate value of C-stock in each pixel of the landscape at a particular time, but rather the typical value across a life cycle of the land use system of the particular pixel, and hence the changes in stock due to the changes in land use systems across the landscape.

The choices of list of land use systems to be explicitly covered in a study should be made by considering the following criteria:

- Time-averaged C-stock within a land use system should be homogeneous enough, i.e., variation among land use systems should be higher than within a land use system
- The sequences of land cover within each land use systems are known and can be differentiated from the spectral signatures of the satellite imageries
- Activities that affect biomass or C-stock in each of the land use systems are known
- Rotation period of each of the land use systems are quite uniform across the landscape of interests

This choice made has consequences in the resulted overall uncertainties. Choosing very detailed list of land use systems will reduce uncertainties of time-averaged C-stock at land use system level. However that also means that the satellite image interpretation has to produce a very detailed legend, which often is not possible or doable to achieve with high accuracy, depending on the resolution (spatial, temporal and spectral) and quality of the imageries, the technical skills of interpreter and the amount of ground information that are available. A trade-off is to be made to optimize error from the two technical steps (which often co-vary) and therefore minimize uncertainties. We design the legend of the land cover mapping and the plot sampling based on the list of existing major land use systems that we learn from key informants, focus group discussions and/or field visits. As the data are collected and analyzed, the list might need some revision, i.e., some disaggregation or aggregation of land use systems might be needed, to accommodate the data.

Aside from land cover and land use types, depending on the extent of areas of interests and their spatial heterogeneity, there might be factors that immensely affect biomass accumulation, and therefore C-stock. Example of this is biophysical factors such as soil types (e.g., peat areas known to deposit a huge amount of soil carbon), elevation and climate. Ignoring these factors will result in high uncertainties of C-stock estimation of a land use system. Therefore stratification in sampling is necessary in reducing uncertainties.

Depending on the purpose of the emission estimation or the accounting activities, we may or may not want to further zoning the landscape of our interests. Within policy spheres in mitigation action strategies, often a landscape should be disaggregated based on different criteria for attribution, and/or allocation in the spatial planning. There may be many other different ways of cutting or zoning the landscape. The sub-landscape level accounting and the whole landscape level accountings might both need to be done.

Four main steps of the estimation (Figure 1.2.) are:

A. Estimation of time-averaged C-stock of each land use systems to determine the emission factors, i.e., differences between time-averaged C-stock of original land use systems with subsequences land use systems;
B. Quantification of activity data, i.e., areas of each transitions of land use/cover types;
C. Calculation of emission estimation based on the activity data from step B and emission factors form step A;
D. Uncertainty analysis of the estimates.

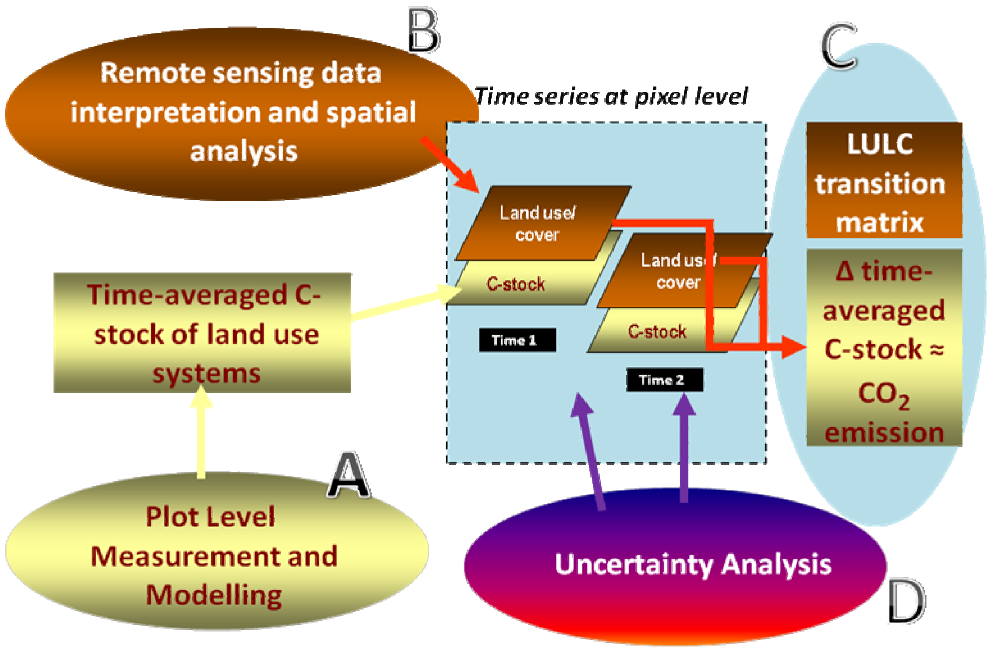

Figure 1.2. Four main steps of the C-stock-difference estimation from land use/cover changes

Time-averaged C-stock estimation

Sampling design

We draw lessons from decision tree models applied by Saatchi et al. (2007) in designing the plot samples to reduce plot-level uncertainties by spatial stratification based on climate, vegetation types and other environmental variables. In particular for Berau district we used accessibility, topography and spatial land use plan laid out at the Provincial level (Rencana Tata Ruang dan Wilayah Propinsi–RTWTP) which refers to national level land allocation (Penunjukan Kawasan) as stratification factors. Accessibility was indicated from road density and classified as: low, medium and high. Topography was classified as: flat, hilly and mountainous. Land use plan or zones are differentiated among protection forest, production forest and non-forest.

Based on interviews and the first iteration of land use/cover mapping, we found that Berau land cover is dominated by natural forest, especially in the hinter land, of various quality and density. Other than that, common land use systems in Berau are: forest plantation (*acacia*, *paraserianthes*, *teak*, *gmelina*), oil palm, rubber, coconut, mixed garden, cacao, fallow or traditional shifting cultivation systems, shrubs, annual crop land, grassland. In estimating time-averaged C-stock of a land use systems, sample plots to be measured should cut across different age class of the land use systems so sequences of land use/cover types, and therefore variances in C-stock, within a particular land use system can be covered.

Plot sample selection for land use and cover types other than natural forests were done by first gathering information from TNC colleagues and local communities about the areas where particular land use and cover types dominate in terms of extents. Once the areas are identified, plot was positioned in the centre of the local communities managed lands; the size of the land has to be large enough to develop a plot and to avoid edge effect. For selecting of plot samples in the natural forest, information about logging year, density, topography and accessibility is necessary. This information was gathered from the currently active logging companies. Due to the time limitation, sample plots were selected in the areas which can be accessed.

Ideally a full factorial design between land use systems (across different age classes) and stratifying factors should be implemented for the sampling, however due to the following problems, the sampling design for the primary data collection is restrictive:

- Not all combination can be found due to huge covariation among the 3 factors, e.g., protection and protected forest are mostly found in low accessibility and mountainous area;
- Land use systems across different age classes are often not easy to find, especially in relatively new emerging land use systems in the area, e.g., old oil palm plot cannot be found since it was just recently started;
- Low accessibilities makes it hard to reach the areas within the time frame and these two factors drove the pragmatic sample selection within the strata rather than random or systematic sampling;
- Larger number of sample plots should be measured to reduce uncertainties, in terms of random error, and to cover the full cycle within land use systems. A second field measurement should be conducted to fill data gaps that are identified after the

analysis of the (first) field measurement, however due to time and resource constraint, these could not be done;

- Out of the 3 stratifying factors, topography can represent accessibility and land allocation based on spatial analysis and the ground work. The composition of sample plots is provided in Table 1.1., and the location in Figure 1.3. Table 1.2. summarizes characteristics of different plot sampling systems.

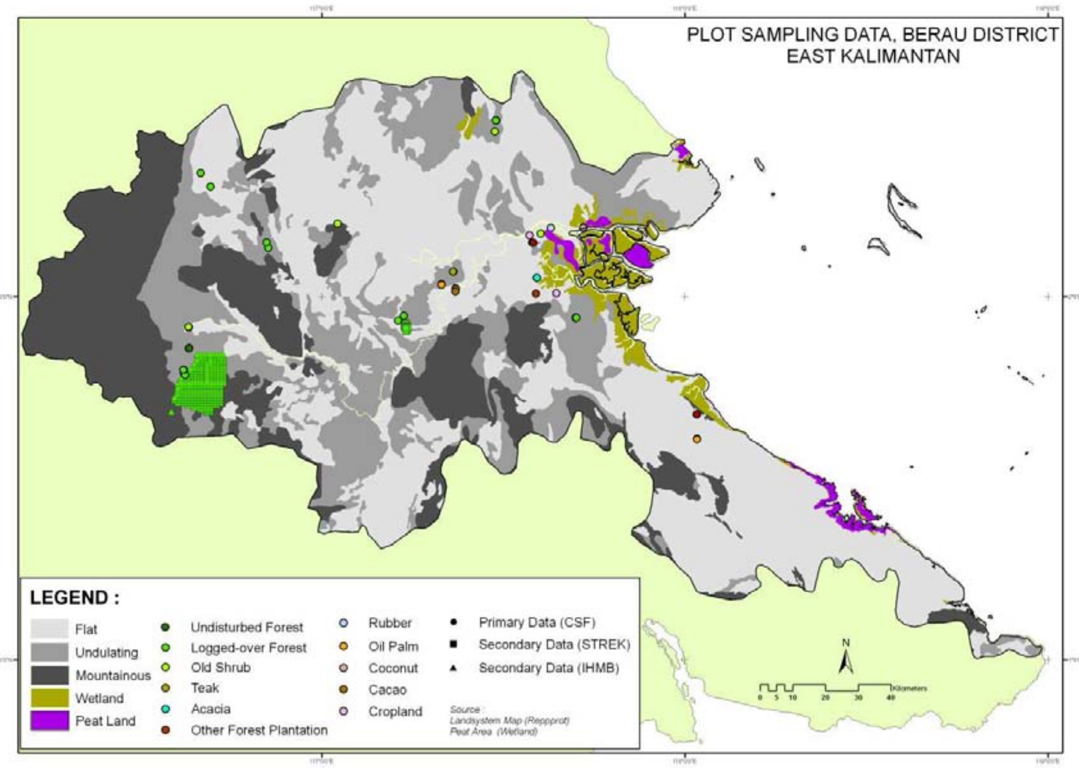

Figure 1.3. The location and distribution of sample plots

Table 1.1. Sample plots measured in different categories of topography in Berau district

Land cover type	Topography			
	Flat	Undulating	Montaneous	Total
Forest (undisturbed)			2	2
Forest (high density)	1	5	2	8
Forest (medium density)		6	2	8
Forest (low density)	1	3	2	6
Acacia	3			3
Gmelina	3			3
Paraserianthes	3			3
Teak	3			3
Old shrub		2	2	4
Oil palm	3			3
Cacao	3			3
Rubber	3			3
Coconut	3			3
Coffee	3			3
Upland paddy	6	1		7
Total	35	17	10	62

Table 1.2. Plot sampling systems of different data sources

Sources	Permanent/Temporary Sample Plots	Plot size (m)	Min tree size cut off	Allometric equitations
Primary data	Temporary	20 x 100	30 cm	dependent on tree species
		40 x 5	5 cm	dependent on tree species
Periodic Forest Inventory (Logging concessions)	Permanent	20 x 20	10cm	Ketterings et. al. 2001 and Basuki et. al. 2009
		20 x 125	20 cm	Ketterings et. al. 2001 and Basuki et. al. 2009
STREK	Permanent	100 X 100	10 cm	Ketterings et. al. 2001 and Basuki et. al. 2009

National Forest Inventory	Permanent	Circle with 5 cm radius	10 cm	Ketterings et. al. 2001 and Basuki et. al. 2009
		Circle with 12.5 cm radius	20 cm	Ketterings et. al. 2001 and Basuki et. al. 2009

Each of the secondary dataset we use in this study was collected for specific purposes and objectives, and therefore applied different ways in designing the sampling. STREK data were collected to monitor the impact of different practices of logging (i.e., Reduced Impact Logging (RIL) and conventional logging) in the long run. They study is done in a small geographical extent which is quite homogeneous in terms of the above stratifying factors and permanent sample plots were developed. Four replicates of each treatment plus one control (virgin forest) were taken in the measurement. The first measurement was conducted before the logging activities took place and then biannually for the period of 1994 to 2008.

National Forest Inventory (NFI) data were collected across the country with systematic sampling of interval 20 km x 20 km. The inventory was targeted to assess forest resources at one particular time, through the temporary sample plot measurement, and also to monitor the changes, through the permanent sample plot measurement. For Berau, only the first measurement has been done in 20 plots. The periodical forest inventory is a new requirement for logging companies enacted by the Ministry of Indonesia since 2009. The purpose of the inventory is to monitor forest potential, in terms of standing stock, and the regenerations. The sampling is conducted systematically, i.e., at 1 km interval, longitude-wise, and less than 1 km interval, latitude-wise, depending on the size of the logging companies. ICRAF data collection was conducted through different series of projects; they mainly focused on seeking the understanding of the roles of agroforestry systems in providing environmental services, including climate change mitigation. The measurements were conducted in different geographical areas, each are relatively small homogeneous areas, rather than applying any systematic or stratified samplings.

Plot level measurement

Within plot, the individual tree measurement was conducted in similar manner across the 4 sources of dataset, except for the detail in terms of cutoff points of size with associated plot or sub-plot sizes (Appendix II). Of many variables observed on individual trees, the two most important ones for biomass estimation are common across the 5 dataset: diameter at breast height (dbh) and species (or genus at the very least if species cannot be identified). In contrast to the most forest inventory for logging purposes, every individual trees of particular diameter class within the specified plot size, are enumerated, despite of the economic values.

The species identification is often done in local names in the field and then translated into scientific name as part of the desk work, in order to assign wood density to the individual trees. Wood density is known as an important variable in estimating biomass, and therefore C-stock (Chave, 2007). ICRAF has so far compiled wood density of approximately 3600 species in its database, which is used in this study.

In addition to the tree measurement, our field activities also included dead wood measurement, litter data collection, and soil sample collection. These measurements were not taken for the other four datasets. Soil samples were then analyzed for the soil carbon and the bulk density.

Biomass and C-stock estimation

Allometric modeling is to be applied to estimate the biomass, and therefore C-stock, of each individual tree in the plot. Based on the specific area factor (depending on the plot and sub-plot sizes), the total C-stock per unit area (in this case hectare) can be estimated from each individual trees in a plot. Several allometric equations have been derived from past studies for various tropical tree species (see Hairiah et al., 2009, Chave et al., 2005, for compilation of allometric equations developed in for tropical forests). Some of these equations embrace tree diameter, height and wood density and some are subset of the three variables. Some equations are developed specifically for particular climatic zones. In selecting the allometric equation, therefore we need to consult our datasets at the plot level and site level.

In this study, we assume that Berau district is relatively homogeneous in terms of climate and therefore we will only apply one common allometric equation for the same group of species. There are two particular allometric equations which we think best suit the Berau case, in terms of species composition and climate. One equation was developed by Ketterings et al. (2001) from destructive sampling in Sumatra and the other from Basuki (2008) from study in Berau. Kettering's and Basuki's results are similar, and since we use datasets from other location as well, we decided to use Kettering's for consistency.

The application of the allometric equation results in the estimation of dry weight biomass of individual trees, which then is converted into C-stock by multiplying it with the carbon content factor of 0.46 (van Noordwijk et al., 2002). The total aboveground living C-stock of each plot of particular age or stage of a particular land use systems is calculated from the total C-stock from individual trees in each plot calibrated into C-stock per unit area (ton C/ha) by appropriate area factors, depending on the plot size associated with the diameter class. To calculate the time-averaged C-stock, we fit the curve of plot level C-stock with age, and take the fitted value of C-stock at the midpoint of the length of rotation period. However, often our dataset does not allow us to follow the above procedure due to the number and distribution of the plot data in each of land use systems. In this case we do space-averaging instead of time averaging. Also, as mentioned above, for land cover that has been reaching equilibrium over a long period of time (hundreds of year) as in primary natural forest, we do space averaging.

Sources of uncertainties of time-averaged C-stock

In each of the steps toward the calculation of time-averaged C-stock of land use systems, there are specific risk or potential sources of uncertainties which will eventually accumulate in the final estimates. These sources of uncertainties are:

- At the tree level: errors in species identification, error in measuring tree diameter and heights, error in enumeration, error from allometric modelling
- At the plot level: errors in plot and sub-plot setting, error in enumeration, error in defining and applying area factor, error in soil sampling, error in estimating percentage of decay of dead wood, error in estimating percentage of combustion, error in litter sampling, error in the estimate of proportional storage of C as off-site timber products
- At the plot level: changes in below ground biomass, especially in the peat soil, which can be high, is not measured
- At the land use system level: error in identifying stratifying factors, errors in determining the sample location and sample plots, error in estimate of growth rates, and error in applying assumption of average stocks, to extent this differs from actual spatial average during 5 year performance period

Analysis of land use/cover trajectories (ALUCT)

Before any technical steps are designed and conducted, the most crucial decision to be made is the legends or classification schemes of the land cover mapping. The legend must connect ALUCT with the time-averaged C-stock measurements through the land use system definition. We use hierarchical classification which is meaningful in terms of separating variations of C-stock of different land use/cover types within specific land use systems and at the same time in addressing variations of spectral signatures in satellite imageries of different land use/cover types. The hierarchy accommodates the iterative and interactive process between land use/cover mapping and the plot level C-stock estimation. Figure 1.4. shows our hierarchical scheme of classification to produce land use/cover maps of Berau.

Appendix III provides the description of each of the land use/cover classes of the Level 3 classification scheme. Some classes, like primary forest, do not have any representative photos because the groundtruthing team could not reach the areas.

Time coverage, spatial resolution, and *amount of cloud cover* are three main criteria used in selecting the best satellite images for this study. Within REDD+ discussion in Indonesia, the period of 1990, 2000 and 2005 are seen to be most relevant in terms of the historical dynamics of land use trajectories. For Berau case, the interview with key informants and focus group discussions, and the analysis of driver of land use change (DriLUC) suggest that rapid changes are occurring during the most recent years, therefore we add 2008 in the study period. Even though there are extensive areas covered by cloud in 2008 data, we include it in the report with considering the particular importance of the most recent information on the rapid changes.

Spatial resolution, as the smallest size of object in earth surface that can be recognized in satellite image, also should be a considering factor when designing a study to address specific objectives. Since the size of study area is quite large, medium resolution satellite of Landsat (30m resolution) image is chosen for this study.

The results of ALUCT based on this time coverage, temporal resolution and spatial resolution of Berau should be able to address the data requirement for setting Reference Emission Level of REDD+. However for performance monitoring, for some mitigation action hotspots, e.g., monitoring Improved Forest Management (IFM), a set of higher resolution imageries will be needed in the analysis with shorter time interval. Cloud cover is a serious obstacle if highly accurate performance monitoring system is to take place. A combination between optical and radar imageries should be explored.

Analysis of land use and cover trajectory (ALUCT) was conducted on the basis of time series land cover maps produced from satellite images. In the context of quantifying C emissions from LULUCF with possibility of linking/attributing the emissions to drivers and agents in particular period in the past, we produce three main outputs from the analysis:

- Time series land cover maps in 1990, 2000, 2005, 2008;
- Land cover change quantification of the district area and zone-specific areas within the district;
- Landcover trajectories for the period of analysis.

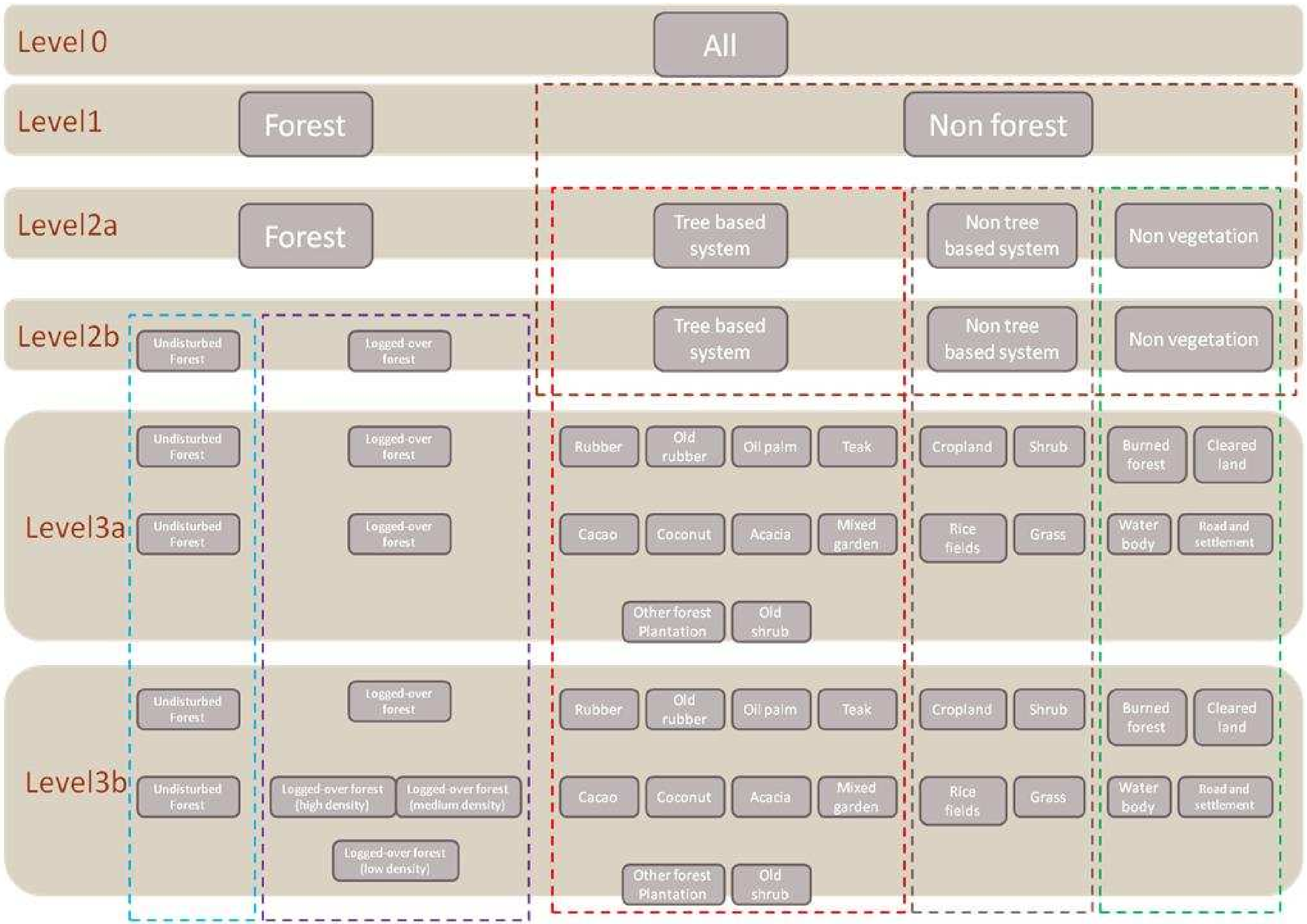

Figure 1.4. Hierarchical scheme of land use/cover classification for Berau

Field geo-referenced data are collected during groundtruthing; they cover variations of land cover types across the district, recorded using global positioning system (GPS) receivers. This data serve two purposes, as guidance in image interpretation process and as a reference to calculate accuracy of the land cover map produced. In the case of Berau, the distribution of the points is limited by the accessibility of the areas. However, some considerable efforts have been put to cover some core forest area. In addition to our groundtruthing, we compiled secondary groundtruth data collected by colleagues (see Appendix I).

ALUCT workflow (Figure 1.5.) can be classified into three stages: (1) *Image pre-processing*, (2) *Image classification*, and (3) *Post interpretation analysis*. The first stage, *Image pre-processing,* aims to rectify geometric distortion in satellite images using ground control point (GCP) collected from reference datasets. In this case, orthorectified Landsat ETM from United States Geological Survey (USGS) in each study sites is used as reference data. Minimum of 20 GCP were used in geometric correction, ensuring geometric precision of 0,5 pixel (<15m) for all images.

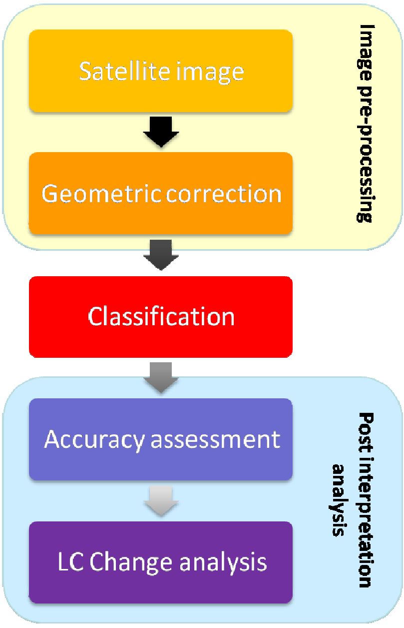

Figure 1.5. Overall workflow of ALUCT

The second stage of ALUCT is *image classification*. The objective is to produce time series land cover maps through satellite image interpretation. *Object-based hierarchical classification* approach is used at this stage. In this approach, image classification steps begin with a series of image *segmentation* process. The purpose is to produce *image objects*, a group of pixel with a certain level of homogeneity in term of spectral and spatial characteristics. Image objects had to be able to represent actual features on satellite image, therefore several phases of segmentation process were conducted to get the required levels of detail. The result of these phases is called *multiresolution image segments* which serve as a basis for the hierarchical classification system (Definiens, 2007). Illustration of segmentation process is shown in Figure 1.6.

Following the segmentation processes, image classification is conducted using hierarchical structure shown in Figure 1.4. The hierarchy is divided into three levels, where objects are classified into land use/cover types based on spectral characteristics and spatial rules. As we move from the simplest legend categories (higher level) to finer and more detailed legend categories (lower level), the spectral characteristics become more similar and harder to be separated into classes, and therefore spatial rules play increasingly important rules. *Level 1* differentiates between forest and non-forest classes, which can be easily distinguished using combination of visual inspection, spectral transformation and simple vegetation index. Tasseled cap image transformation (Kauth & Thomas, 1976) was used to summarize spectral signature in Landsat images into three transformed layer: *brightness, greenness, and wetness.* Combined with Normalized Difference Vegetation Index (NDVI), greenness and brightness value were used to differentiate forest and non forest classes, while wetness value were used as a basis to identify wetland area from satellite image. Vegetation index is a ratio of spectral value between vegetation-sensitive channel (near infra red spectrum) and non vegetation-sensitive channel (visible spectrum) in the satellite images. Result of *Level 1* is further classified in *Level 2,* in which forests are differentiated into undisturbed and logged-over classes, and non-forests into tree, non-tree and non-vegetation. For this level, reference data is required to develop spectral and spatial signature of each land cover classes. *Nearest Neighborhood* approach is then used in the classification stage. The approach is conducted in two steps: (1) Feature space optimization and (2) Classification. The first step is conducted to calculate combination of object features that produces the largest average minimum distance between the samples of the different classes. The combination of object features is used in the second steps to classify all objects into land cover classes in level 2 (Definiens, 2007).

Some of the classes in *Level 2* are classified into more details in *Level 3.* In this level, spectral value is not the only parameters used. The context and surrounding of image objects is utilize as an important parameters to develop classification criteria in this level. As described in (Blumberg & Zhu, 2007), aside from spectral value, criteria of contextual classification in object based approach can be developed from spatial characteristic such as distance to settlement, proximity to logging road, forest concession, and plantation map was used as a rule in classification. Logged-over forest is classified further into low, medium and high density based on proximity to observed logging road, forest concession map, and estimated vegetation density derived from vegetation index value. Using the same approach, *Swamp forest* is classified into *undisturbed swamp forest* and *logged-over swamp forest.*

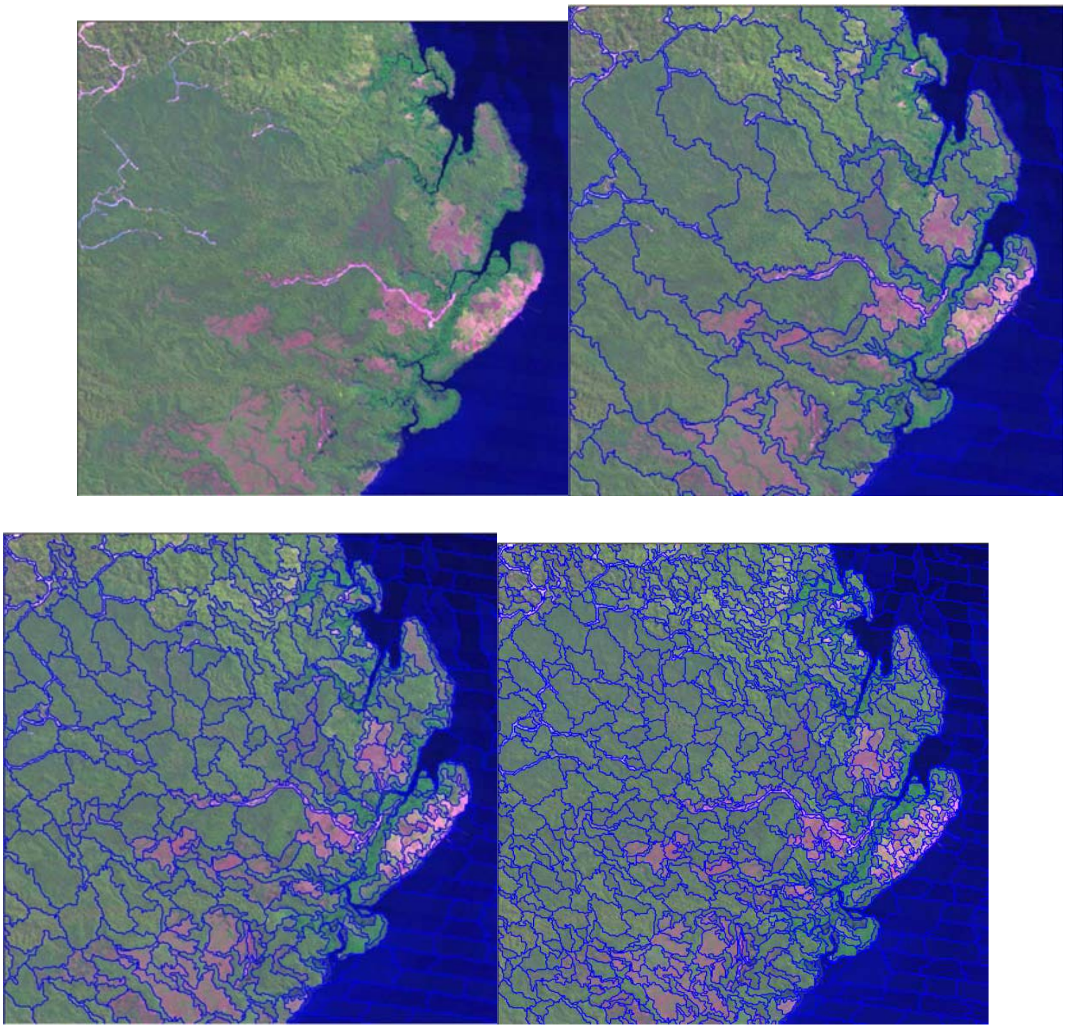

Figure 1.6. Segmentation process

The ground knowledge about land use/cover types and changes from key informants and also from groundtruthing are used as supplementary information during the interpretation. GPS points collected by the team and compiled from other sources are the main data to help with the interpretation and to assess accuracy of the results. Google maps are also consulted whenever it is feasible as an ancillary data. Key informants are local people from whom we gain information about current and historical land uses, past drivers and the current trends of land use and land cover changes. They can be land owners, local transport operators, NGOs and local government officials. The accuracy of the satellite image interpretation will be evaluated against the groundtruthing data, and will only be conducted on the result of the most recent image interpretation. The rationale behind this is because the GPS points collected during this study recently is closest to the most recent imageries such that the possibilities of changes happening in between the acquisition time and the field visit are minimized. If we have a long term study or GPS data for the area of Berau that match closely the acquisition year of the earlier imageries, the accuracy assessment can also be conducted for the earlier land use/cover maps. Once all land use/cover maps are produced for each acquisition dates, we do final consistency check across the time series by putting highest confidence in the most recent maps, or by applying some expert judgements when the quality of the most recent imageries are not adequate, and do some necessary editing.

Post classification analysis process is the last stage of ALUCT. It consists of two processes, *accuracy assessment* and *land cover change analysis.* The objective of *accuracy assessment* is to test the quality of information derived from image classification process. It is conducted by comparing field reference data with the most recent land cover map. The last step in ALUCT is the land cover change analysis.

Two final forms of output are resulted from ALUCT: (i) *area- based changes analysis* and (ii) *trajectories analysis. An area-based change* analysis is a simple analysis conducted by comparing total area of land cover types in each time period. The result shows a clear indication of overall trend of land use/cover changes in the area. However, there are no information on the location and trajectories of changes provided. The analytical power offered from this is tremendously affected by the intensity of cloud cover, or the extent of no-data areas in the map. *Trajectory analysis* summarizes sequences of changes in land use/cover of each pixel in the map within the study period. The extent or area of each occurrence or sequence of changes can then be quantified. The second component of the study, namely the Driver analysis of Land Use Changes (DriLUC) (see Section 2 of this report), is an immense source of qualitative data that are very crucial in interpreting and discussing the results.

In the context of mitigating emissions from LULUCF, understanding the footprint of dominant land use/cover changes in the region and the driving factors are necessary. In this context, we group sequences of land use/cover changes into the following types:

1. Natural forest conversion to:
    a. Forest plantation
    b. Agroforest
    c. Tree crop
    d. Shrubland
    e. Traditional shifting cultivation
    f. Permanent cropland
2. Natural forest degradation, i.e., from higher stocked C natural forests to lower stocked
3. Agricultural intensification, including:
    a. From tree-based systems to annual crop or others
    b. From shrubland to permanent crop land
4. Conversion from land based activities to non-land based activities, i.e., changes to settlement, road, etc.

Along the same line, in helping to link and understand ways to mitigate emissions better, we look deeper into differences in trajectories of land use/cover types, and therefore their emission contribution to total landscape emissions from LULUCF, within different zones of land use plan, laid by the government. The planned and unplanned amount of emission in the past can be used further for determining the Reference Emission Level (REL) for any mitigation action that can be compensated in the future, e.g., REDD+.

Sources of uncertainties of ALUCT products

As shortly mentioned above, we need to select a point of reference, where we know best of the ground reality, either because it is the most recent one, or it coincides with the largest set of groundtruthed data collection. Uncertainties in a single map product are defined as the discrepancy between the map produced by the image interpretation and the reality. In most cases reality is represented by groundtruthed data collected prior to the interpretation or reality check after the maps are produced. Analysis of land use and cover changes which involved multiple maps produced from satellite interpretation have additional source of uncertainties. In general, the sources of uncertainties of ALUCT products are:

1. The error of GPS receivers in recording the coordinates of a location, human subjectivities in deciding the land use and cover of the points;
2. Sampling error in grountruthing; sample points are not representation;
3. Image interpretation error (assessed using ground truth plots for accuracy assessment);
4. For change analysis, which involves overlaying more than one map, error in georeferencing leads to imperfect multi-layer rectification, meaning that change analysis does not compare exactly the same pixels across temporal gradients?

Emission estimate at the landscape level

Within a particular period of time, area of land use/cover changes is quantified, as activity data, and time-averaged C-stock of each land use systems are used to determine the differences in C-stock between any two land use systems, taken as emission factors. Combining total activity data for some particular time period and the emission factors for the whole landscape across all land use/cover types, we can estimate the emission (in CO_2-eq) from LULUCF through stock difference method. Box 1.1. shows the formula of emission estimation used in this study.

Box 1.1.

$$\Delta C = \sum_{ij} A_{ij} [\Delta C_{ij\ LB} + \Delta C_{ij\ DOM} + \Delta C_{ij\ SOILS}] / T_{ij}$$

where:

ΔC is the annual change in carbon stocks in the system, tonnes C yr-1

A_{ij} is the area of land use/cover type *i* that change to *j*, in ha, or known as activity data. This is resulted from satellite image interpretation and spatial analysis

$\Delta C_{ij\ LB}$ is the annual change in carbon stocks in living biomass from changes of land use type *i* to *j* , tonnes C ha-1

$\Delta C_{ij\ DOM}$ is the annual change in carbon stocks in dead organic matter from changes of land use type *i* to *j* , tonnes C ha-1

$\Delta C_{ij\ SOILS}$ is the annual change in carbon stocks in soils from changes of land use type *i* to *j* , tonnes C ha-1

$\Delta C_{ij,}$ which is the total differences in C-stock of each component (above ground biomass (living and dead) and soil carbon stock) for each change in land use types, is known as emission factor. C-stock of each land use system is estimated from field measurement, laboratory analysis and allometric equation

T_{ij} is the time period of the transition from land use type *i* to land use type *j*, yr.

The weaknesses of the approach are: (i) the insensitivity in counting emission when there are no changes in land use systems, (ii) it does not capture a short temporal dynamics, and (iii) some assumptions may not appropriately address some reality on the ground, and therefore might not achieve the purposes of the accounting, e.g., removal of biomass from the site are counted as emissions. The strengths of the approach are: (i) it is relatively time- and cost-effective, especially when the study area is quite large, (ii) for rapidly changed area in terms of land use/cover, like Berau, both in term of permanent changes and rotational changes, the approach can capture well the stock changes over time and over space, and (iii) it inherently embraces the driving factors and socio-politic-economic contexts of land use and land use changes such that integrating the results with practical actions and policies are relatively straight forward. As discussed briefly in the Introduction section, the approach using land use systems, together with Profitability Analysis of land use systems (component II of this study), enables us to derive the retrospective rough opportunity cost level at the farm gate. From the driver analysis of land use/cover changes (section II), the historical setting, conflicts, problems and opportunities, and likely actors and costs to mitigate climate changes, along with the institutional capacities, by reducing emissions from LULUCF can be analyzed and projected, as a preliminary feasibility study.

Overall uncertainty analysis

Uncertainty analysis - The uncertainty of plot level measurement collected in the project will be analyzed statistically in combination with the ICRAF database. Earlier analysis of uncertainty in the use of allometric relations (Ketterings et al., 2001) will be used to separate 'bias' and 'random error' components. Bias cannot be reduced by increasing replication of the measurements, while 'random error' can.

Analyses at multiple scales of assessment will consider all components in the equation. Let us revisit the formula presented in Box 1.1. Monte Carlo simulations are run with taking into account the error matrix in land cover classification, transition matrix and the time-averaged C-stock of LUS. Let us take LC1 as the land cover map produced from the imagery for t1, and LC2 for t2. The following steps apply:

- Generate a land cover map, LG1 for t1 by introducing random error with refer to the error matrix on LC1;
- Generate another land cover map, LG2 for t2 by introducing a joint random error that refers to error matrix and transition matrix on LG1;
- Generate a randomized set of time-averaged C-stock of each LUS based on the distribution of the compiled dataset (primary and secondary data);
- Calculate the emission estimates for the whole landscape;
- Repeat 100 times;
- Calculate the statistics

If we use hierarchical approach and do wish to see the optimal error due to aggregation-disaggregation, viz-a-viz different legends/classification scheme, repeat the steps for each level. If we would like to treat LC1 as independent from LC2 then replace step 2 by generating LG2 from LC2 by introducing random error based on error matrix.

Results and discussions

As mentioned in the methodology section above, often we need to revise the original list of major existing land use systems identified earlier in the study to accommodate the data that have been collected and analyzed along the course of the study. In our case, the level 3 of classification hierarchy of land use/cover mapping from satellite imageries (Figure 1.4.), which comes up with 25 types of land use/cover, is modified into 23 types by aggregating different density classes of logged-over forests (low, medium, high) into one class of logged-over forest due to huge uncertainty of C-stock of each of the 3 logged-over forest class as measured in the field. The huge variation of C-stock within the logged-over forest of different densities should be represented by much larger number of replicates of sample plots than what we currently have. In the general discussion of land use and land cover changes in which trajectories and driver of land use/cover changes are also relevant, we shift to use the 25 legend categories. For the accuracy assessment, we calculate uncertainties of each of the level of classification in the hierarchy and its variants.

The primary data collection using RaCSA methodology is inclusive to all carbon pool. However because of the limited number of sample plots, which do not cover all land use systems in Berau, and more importantly the limited number of replications and geographical distribution of the forest plots, we also used secondary dataset which were collected for various purposes, mostly in forest plots. The secondary dataset mostly only cover aboveground living biomass, which in most cases are the dominant carbon pool, except for peat land. Since our purposes are to estimate emission (changes in C-stock with time) from LULUCF, rather than quantifying total C-stock at particular point in time, while soil carbon does not change drastically with most land use changes (except for drainage system development and burning activities on the peat land), our assumption that ignoring carbon pools other than above ground living biomass is justifiable.

Time-averaged C-stock estimation of land use systems

C-stock estimation of various land use types from primary data

Out of the 62 plots that were measured, we are not able to derive time-averaged C-stock for each of the land use systems because for some land use systems we did not find plots that represent different age group within the full cycle of a land use system, and therefore we refer to it as land use types rather than land use systems. We use Kettering's allometric equation for the forest tree species (Ketterings et al., 2001). The mean, standard deviation and the 95% confidence interval are presented in Table 1.3., while Figure 1.7., shows the bar chart of the components of aboveground and below ground C-stock for each land use types. The aboveground C-stock comprises of living and dead biomass; the below ground C-stock is from 0-30 cm top soil. There was no measurement taken on the peat land. Due to the lack of rigorous primary data, we use additional secondary dataset to reduce uncertainties and to calculate time-averaged C-stock of land use systems.

Table 1.3. C-stock estimation of various land use/cover types calculated from primary data collection in Berau.

	Aboveground stock (ton C/ha)			**Below ground (0-30 cm) stock (ton C/ha)**			
Land use/cover type (age)	Mean	Std dev	C Interval 95%	Mean	Std dev	C Interval	N
Undisturbed forest	159.02	23.06	31.96	41.60	7.75	10.74	2
LOF high density	216.26	107.47	74.47	67.01	19.84	13.75	8
LOF medium density	125.70	42.85	29.69	60.81	25.94	17.98	8
LOF low density	115.02	40.52	32.43	53.23	23.11	18.49	6
Gmelina (7)	37.57	7.40	8.37	51.05	11.42	12.92	3
Acacia (5)	59.71	41.08	46.49	64.20	10.78	12.20	3
Sengon (7)	77.84	17.45	19.75	69.84	11.57	13.09	3
Teak (7)	51.24	32.85	37.17	54.08	8.36	9.46	3
Rubber (3)	36.28	16.03	18.14	137.48	29.05	32.87	3
Coconut (40-50)	32.21	5.42	6.13	98.58	16.39	18.55	3
Cacao (10-20)	19.84	3.76	4.25	56.21	15.50	17.54	3
Oilpalm (7)	3.28	2.46	2.78	64.35	39.19	44.35	3
Coffee (3)	23.95	5.84	6.61	68.75	8.77	9.92	3
Shrub (3-10)	40.61	23.35	13.80	48.81	12.82	7.58	11

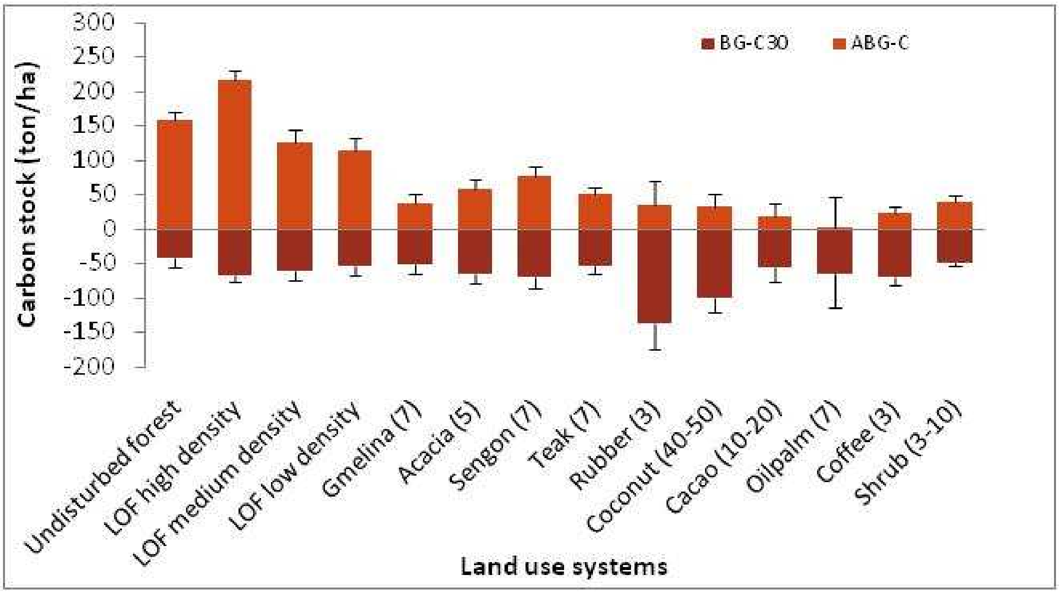

Figure 1.7. Aboveground and below ground C-stock in various land use types and the 95% confidence interval, estimated form primary data of Berau

All measurements were conducted on mineral soils. Forest plots of all types have higher average of C-stock compared to other land use/cover types. High density logged-over forests show highest C-stock in average, even compared to undisturbed forests. A closer look at the data shows that there is one particular plot with a stand out C-stock, i.e., 440 t C/ha from aboveground biomass, out of which 306 t C is from living trees. Half of the tree biomass comes from 3 individual trees of large diameter. In the field, this plot has been identified as high density logged-over forest. Due to the large variation within logged-over forest classes and the small number of sample plots, we therefore aggregate the logged-over forest classes into one class.

Mean C-stock of oil palm plots is low, because in this region, oil palm development just started recently. The measured plots are about 7 years of age, such that they have not reached the highest tree biomass. The below ground C-stock in the rubber plots are highest but the variability is highest among oil palm plots. This perhaps is due to the decay of necromass from original land cover prior to the plantation establishment. Piles of dead wood are often arranges as windrows in the oil palm plantation. Below ground C-stock in rubber and coconut plots are highest compared to others and even higher compared to the aboveground C-stock. With the minimum management of such systems, i.e., no fertilizer applied, the plausible explanation is the variations in soil types.

Estimation of time-averaged C-stock of various land use systems

Using the above primary data only, we cannot fill out the list of our land use systems with time-averaged C-stock. Therefore we combine the primary and the secondary data described under Material section, some measured in Berau and outside Berau. We did our best in selecting regions which are similar to Berau within our database but this is not always possible. We only address the aboveground living biomass from here on since most of the secondary data do not cover all carbon pool. Figure 1.8. presents the time-averaged C-stock of major land use systems in Berau, while Table 1.4. presents the additional information about the standard deviation and 95% confidence interval of C-stock of each of the land use systems.

Table 1.4. Time-averaged C-stock of various land use systems in Berau estimated from primary and secondary data

Land use systems	Time-averaged C-stock (ton/ha)	Std Dev	N	Allometric	CI 95%	Notes
Undisturbed forest	284.13	63.68	8	$DW=0.11\rho D^{2.62}$	44.12	From Berau and other places; Ketterings et al., 2001
Logged-over forest	189.64	82.55	34	$DW=0.11\rho D^{2.62}$	27.75	From Berau and other places
Undisturbed mangrove	123					Matsui's measurement in (Matsui, 1998)
Logged-over mangrove	38.26					No data; assume to be the same as swamp
Undisturbed swamp forest	123					Assume the same as mangrove
Logged-over swamp	38.26	16.18	22	$DW=0.11\rho D^{2.62}$	6.76	From Central Kalimantan (ICRAF study)
Mixed garden	37.93	52.78	25	$DW=0.11\rho D^{2.62}$	20.69	From West Java (ICRAF study) (Roshetko, et al., 2007)
Teak	51.61	25.35	24	$DW=0.20091D^{2.3}$	10.14	Hadi, 2007
Acacia	28.03	3.62	3	$DW=0.11\rho D^{2.62}$	4.09	Berau, measured by CSF (2009)
Other forest plantation	42.50	11.05	3	$DW=0.0272D^{2.831}$	12.50	measured by CSF and Sugiarto, 2002
Rubber	41.05	32.98	103	$DW=0.11\rho D^{2.62}$	6.37	
Oil palm	40.00			$DW=0.0976H+0.0706$		ICRAF study (Dewi, et al., 2009)
Coconut	30.77	58.65	4	$DW=0.3747H+3.6334$	57.48	FAO, 1997
Shrub	22.11	33.67	53	$DW=0.11\rho D^{2.62}$	9.07	
Cacao	29.30	22.22	7	$DW=0.1208^{D1.98}$	16.46	Yuliasmara, 2008
Cropland	0.72					
Ricefield	0.99	0.57	70		0.13	
Grass land	1.49	0.66	7		0.49	
Cleared land	1.49	0.66	7		0.49	
Burned forest	1.49	0.66				
Road and settlement	27.42	48.04	32		16.64	

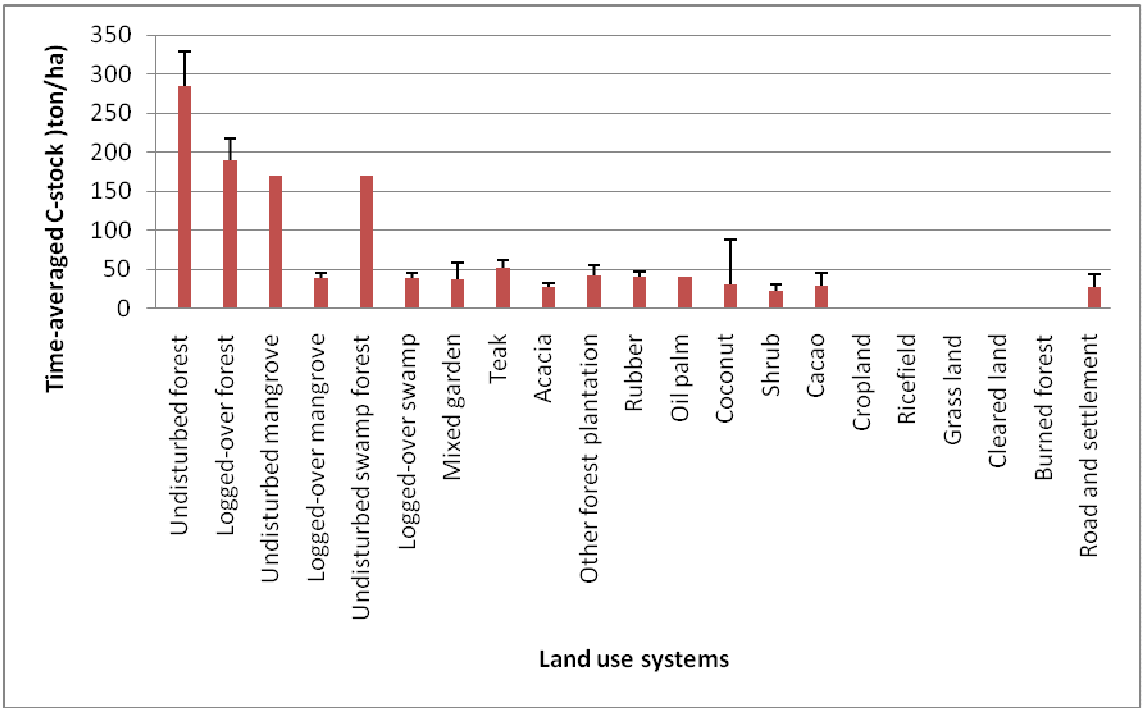

Figure 1.8. Time-averaged C-stock of various land use systems estimated from primary and secondary data with 95% confidence interval

The time-averaged C-stock of oil palm was taken from ICRAF recent study in Riau and Central Kalimantan (Dewi et al., 2009). Those of agroforesty land use systems were taken from other ICRAF study areas, mostly in Sumatra, while the forest are from different sources in Berau and other study areas. For the description of data, please see Appendix II.

Whilst neglecting the below ground C-stock changes in mineral soil might be justifiable in terms of estimating emissions, the same justification is hard to make for the peat area, in general. In Lamandau, for example, with peat depth around 4.5 m, ICRAF unpublished data shows that C-stock can be as high as 80 ton C/ha. It is widely known that despite of the high stock of C in the peat soil, the uncertainty is extremely high; estimation of emissions due to peat fire and drainage rely heavily on assumptions and modellings rather than empirical data, which is very limiting.

In Berau, the extent of peat is about 21,000 hectares (calculated based on Wetland map), located in the swamp and mangrove ecosystems. About 16.74% of total area of mangrove forest has organic content meets the definition as being peatland, and 64.4% of swamp does. According to our classification, between 1990 to 2008, insignificant extent (117.27 ha) of forest on peat was converted to oil palm. While this suggests that our lack of carbon data in the wetland ecosystems will not be disastrous to our study, we do not imply whatsoever that filling the data gap on these areas is not necessary, especially with regards to future threat and the high C-stock of the wetland areas. A very recent mangrove study in Indo-Pacific find the total C-stock (aboveground and soil) ranges between 437 to 2186 t C/ha with remarkably little difference along coastal gradients, despite differences in mangrove/forest type (Murdiyarso, pers. Comm., 2010).

Analysis of land use/cover trajectories (ALUCT)

The results of the analysis are presented in the forms of graphical maps, GIS data and their accuracy assessed, tabular, transition matrices, and followed by series of discussions on the results. Transition matrices feed further analysis on estimating emissions for the whole landscape or per zones in the landscape (step C of Figure 1.2.). The main limitation of producing the land cover maps are in finding optical satellite imageries that are cloud and haze free. As can be seen from Figure 1.9., land cover map of 1990 is the only map within the time series that has minimum cloud, haze and shadow cover. Map of 2008 is the worst in terms of cloud cover (more than 40%) but that is the best available set of imageries we can find. This map was produced from Landsat 5 rather than Landsat 7 (for 2000 and 2005). The imageries of 2005 have different problems; namely the stripes due to the damage in some sensors of Landsat 7, which also causes difficulties in conducting automatic classification.

We tried to salvage the data of 2008 by combining the interpretation with ALOS PALSAR (radar imagery), which ideally should be able to fill the data gap caused by cloud, haze and shadow in the optical imageries. However this experimentation was not fruitful due to our lack of technical experiences using ALOS PALSAR and also due to limiting time to explore the data and the available techniques.

These data gaps in the wall-to-wall analysis result in inconclusive analysis of land use/cover changes. Ideally in all the analysis, we remove all no-data areas which are added from each map in the series to keep consistent total land area to enable us to draw conclusions on proportions and rates. However, if we apply this to our dataset, we will end up with less than 50% of total area of Berau district with data, due to the extensive distribution in various areas in the dataset. Therefore we decided to use the forest cover map produced by Daemeter based on Landsat 7 imageries of 2009 with legend categories: forest and non-forest only to fill the data gap due to cloud cover by inferring plausible transition between 2005 and 2009. However since this involves some inferences and also different method applied in image analysis, we only apply this for the calculation of Tables 1.5., while for the rest we use the original, non-gap filled maps.

Time series land cover maps in 1990, 2000, 2005, 2008

Figure 1.9. presents the land cover maps of Berau produced from Landsat imageries using object based image analysis. Compared to most land use/cover maps commonly derived for different purposes and extents, the legend we use here is quite fine and is designed to be meaningful in capturing the variation in C-stock associated with each land use/cover system. Above-ground living biomass characteristics that differentiate C-stock are the density, size and species composition of woody plant. Undisturbed, natural humid tropical forest undoubtedly has the highest C-stock of all other land cover types. Degraded natural forest and other tree-based systems might or might not have significant C-stock, whilst they are associated with completely different actors and drivers in terms of management and socio-politic factor, and plausible differences in terms of profitability. Therefore in order to address the three simultaneously, we make sure that those land use/cover types are separated as

different entities in the map, through hierarchical steps of classification described in the method section above.

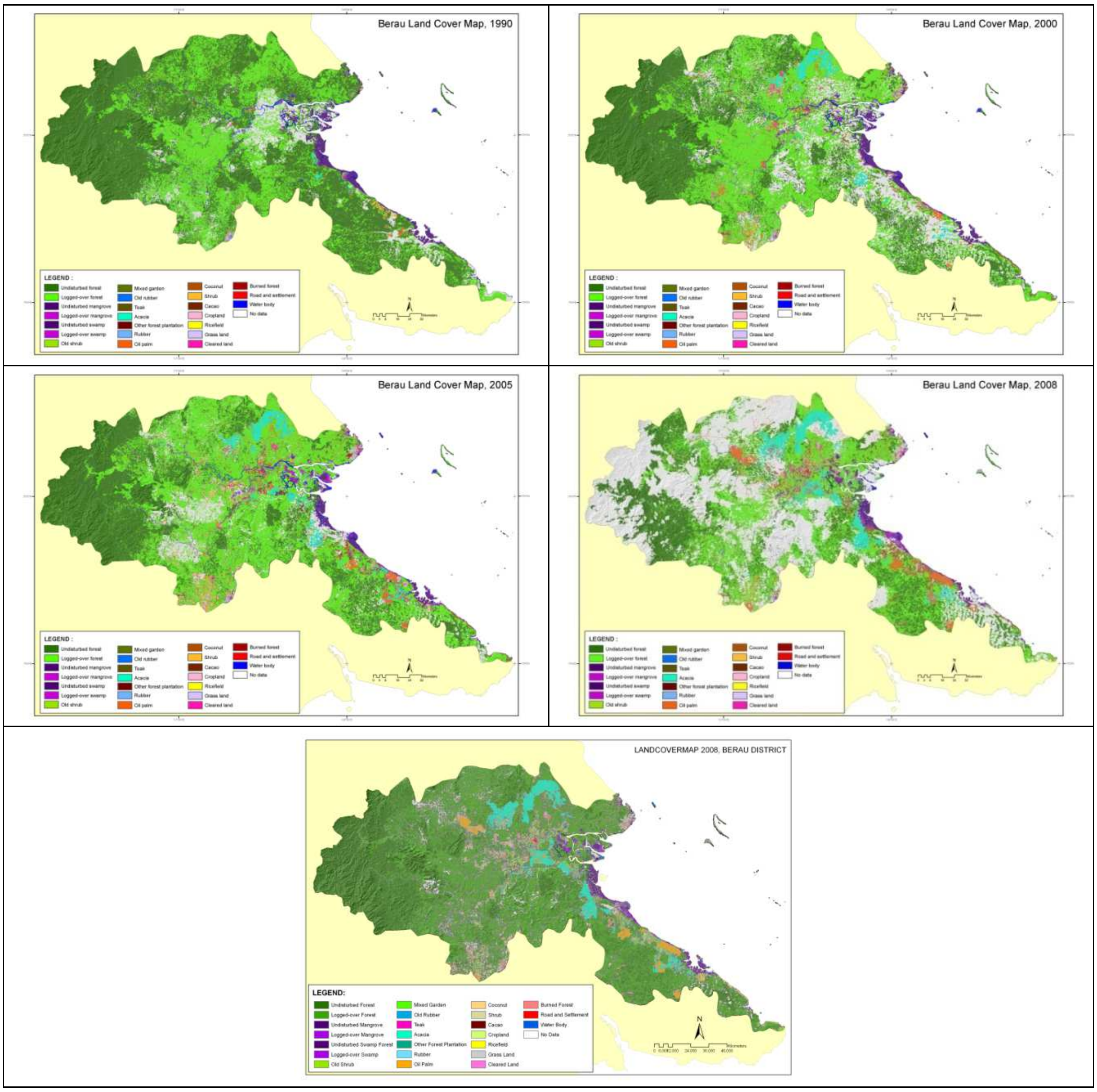

Figure 1.9. Land use/cover maps of Berau for 1990 and 2000 (top), 2005 and 2008 (middle) and 2008 (bottom) with data gap filled by 2009 forest cover map produced by Daemeter.

Starting in 2000, continuous expansions of acacia and oil palm have been taking places in the area of Berau especially in the coastal area (eastern part) toward the middle area across the southern to the northern part of Berau, where the topography is relatively flat. This is in line with the findings of the DriLUC analysis. Both of these major trends were initiated by large scale forestry and agricultural enterprises, namely timber plantation concessionaires, associated with pulp and paper industries, and oil palm industries, associated with Crude Palm Oil production. The transmigration program and spontaneous in-migration activities have been active since then in order to fulfill the labor demands generated by the industries. With capital accumulation and through partnerships with industries, farmers also actively establish small-scale forestry and tree crop plantations whenever accessibilities allow. Most of these plantation establishments involve conversions of natural forests of various densities, from very degraded to almost pristine natural forests. In addition to that, farmers and local people maintain their permanent and semi-permanent annual cropping of staple food (mostly un-irrigated rice) and vegetables, both for subsistence and for cash income. Some mangrove areas have been undergoing some changes as well, mostly to acacia.

The forest degradation is not evident visually from the maps but with a closer look we can see the spatial pattern of encroachment to large primary forest block starting from the side of higher access and flatter topography. This process is more rampant in the upper watershed hinterland areas and mostly associated with logging activities, which is another kind of large scale enterprise activities. As pointed out by DriLUC analysis, in this part of the region most small scale activities are associated with traditional shifting cultivation by indigenous communities. In some areas, even though it has been significantly reduced now after reaching its peak during the period of transition from the New Order, followed by the enactment of decentralization law (1998-2001) (Sardjono and Ibrahim, 2010), illegal logging activities have been prominent, resulted in the degradation of forests.

The results of accuracy assessment of the land cover map of 2008 by comparing the classification results and the GPS points can be seen in Figure1.10. The complete excel sheet of the accuracy assessment is provided in the database which is a companion of the report. Following the hierarchical method we described above, the accuracy of the resulted map of each of the level of classification are assessed. The accuracy of the most general legend (Level 1) is very high (97%) and these reduced to 85% for Level 2, and 81% for the most detailed legend (Level 3).

The accuracy assessment presented in Figure 1.10. consists of two accuracy measurement: (1) *User's accuracy* as an estimate of accuracy for each of land cover classes in one hierarchy level and (2) Kappa accuracy as an estimate of accuracy for each of the hierarchy level. Each of the measurement was produced by comparing classified image of 2009 to reference data that are independent from the datasets used in classification stage. User's accuracy is produce by dividing the number of correctly classified pixels in each class/category to the total number of sample pixels classified in that category. While Kappa accuracy is a measure of difference between the actual agreement between reference data and an automated classifier and the chance agreement between the reference data and random classifier (Lillesand & Kiefer, 1994). As the interpretation goes deeper in the hierarchical tree, the segmentation process produces smaller objects that contains pixels which are more uniform (high similarities among pixels within an object) and the distances among classes to be separated are smaller as we target finer legend categories (separating land use and cover classes that are more similar in spectral reflectances); this can lead to changes in accuracy of particular classes and therefore overall accuracy (ranges from 78% to 84%). The recent work by Mas et al (2010) also using object-oriented method shows that changes of values of similarity parameters during segmentation process leads to changes in overall accuracy but not significantly (ranges from 68.7% to 75.5%).

Most of the inaccuracy in classification is caused by the misclassification of oil palm to shrub. This cannot be avoided because most young oil palm, especially with the leguminous cover crops (LCC) planting, often mixed with imperata, in the first few years of the plantation has very similar spectral reflectance with shrub land. In the later stage when the oil palm canopy already dominate and the LCC and imperata cover have diminished, the spectral signature becomes unique and easily separable from those of other land use/cover types.

Another source of inaccuracy is the misclassification of cropland to other land use/cover types, mostly to grassland and rice field. This is understandable since with no extensive irrigation systems, most agricultural land are not planted during dry seasons and covered by grasses; similarly for rice field.

Other than this, the number of GPS point data that can be used (not under cloud cover) becomes very few and therefore reduces the statistical power of the analysis. Most of the misclassifications are within the neighboring classes in terms of C-stock, such that for the case of estimation of C-stock changes the land use/cover type misclassification is not directly scalable to the uncertainties in the loss estimates.