Flexibility of multi-agent system models for rubber agroforest landscapes and social response to emerging reward mechanisms for ecosystem services in Sumatra, Indonesia

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ABSTRACT

Payments for ecosystem services (PES) have been widely recognized as an innovative management approach to address both environment conservation and human welfare while serving as a policy instrument to deal with the ecosystem service (ES) trade-offs resulting from land-use/ cover change (LUCC). However, there is no solid understanding of how PES could affect the synergies and trade-offs among ES.

This research focuses on the LUCC and its inherent ES trade-offs in the context of social-ecological systems (SES) that incorporates key feedbacks and processes, and explores the possible impacts of management regimes, i.e., PES schemes (e.g., eco-certification and reduced emissions from deforestation and degradation (REDD)). To address the complexity of this research, a multi-agent simulation (MAS) model (LB-LUDAS - Lubuk Beringin - Land Use DynAmics Simulator) was applied in which process-based decision-making sub-models were incorporated in the decision-making mechanism of agents. The model was developed to explore policy scenarios by quantifying the potential ES trade-offs resulting from the agents' land-use choices and preferences. It was first implemented for the rubber agroforest landscape in Jambi Province (Sumatra), Indonesia. Species richness, carbon sequestration, opportunity costs, and decision processes such as PES adoption and future land-use preferences sub-models were incorporated to capture as much as possible the real SES of a rubber agroforest landscape. Three scenarios were simulated over a 20-year period, namely the PES scenario, the scenario land-use preference if supported by financial assistance/subsidies (SUB), and the current trend as the baseline scenario.

From the simulations, the key findings show that there was a minimal land-cover change under the PES scenario, where an estimated 22% of the species richness in rubber agroforests could be conserved and 97% of the carbon emissions reduced compared to the baseline scenario. For the SUB scenario, an estimated 6% of the species richness could be conserved and 47% of the carbon emissions reduced. With regard to livelihoods, only under the PES scenario was wealth inequality reduced up to 50%. Regarding the return for land investment, the profitability of a land-use type depends considerably on each scenario; however, rubber agroforests would be highly profitable (20%) if a price premium were to be implemented under an eco-certification scheme. The main conclusions of this study are firstly, that PES schemes for rubber agroforests could offer synergies among carbon emission reduction, biodiversity and livelihoods, thus reducing the trade-offs resulting from possible land-use/cover change, and secondly that the LB-LUDAS model as an integrated and MAS model is a useful tool to capture the ES trade-offs as an emergent property of the dynamic social-ecological systems at the same time serving as a negotiation-support system tool to support the design of land-use policies.

The use of process-based decision making in the LB-LUDAS model is recommended in order to incorporate intended decisions of agents in various situations. In this way, the triggers, options and temporal and spatial aspects of agents' reactions are captured in a relatively realistic way.

Flexibilität agenten-basierter Modelle für Kautschuk-Agroforstsysteme und soziale Reaktion auf Anreizmechanismen für Ökosystemdienstleistungen in Sumatra, Indonesien

KURZFASSUNG

Finanzielle Anreize für Ökosystemdienstleistungen (PES) sind ein weit verbreiteter und anerkannter Managementansatz sowohl im Hinblick auf den Umweltschutz als auch auf das Wohlergehen der Menschen. Gleichzeitig dienen sie als politisches Instrument für den Umgang mit den durch die Veränderungen in der Landnutzung/-bedeckung (LUCC) bedingten Trade-offs der Ökosystemdienstleistungen (ES). Es gibt jedoch kein solides Wissen darüber, wie sich PES auf die Synergien und Trade-offs zwischen den ES auswirken könnten.

Der Schwerpunkt dieser Studie liegt auf den LUCC und ihren inhärenten ES Trade-offs im Kontext von sozial-ökologischen Systemen (SES), die wichtige Feedbacks und Prozesse berücksichtigen. Die Studie untersucht die möglichen Auswirkungen von Managementregimen, d.h. PES-Systemen (z.B. Ökozertifizierung und reduzierte Emissionen von Entwaldung und Degradation (REDD)). Um die Komplexität des Themas zu erfassen, wurde ein Multi-Agentensimulationsmodel (MAS; LB-LUDAS - Lubuk Beringin - Land Use DynAmics Simulator) eingesetzt, bei dem prozessbasierte Entscheidungs-Submodelle im Entscheidungsmechanismus der Agenten berücksichtigt werden. Das Modell wurde entwickelt, um verschiedene Szenarien durch die Quantifizierung der potentiellen ES Trade-offs, die durch die Wahl bzw. Vorlieben der Agenten hinsichtlich der Landnutzung entstehen, zu untersuchen. Es wurde zuerst für die Kautschuk-Agroforstsysteme in der Provinz Jambi (Sumatra), Indonesien, eingesetzt. Sub-Modelle wie Artenvielfalt, Kohlenstoffspeicherung, Opportunitätskosten und Entscheidungsprozesse wie die Anwendung von PES und zukünftige Präferenzen wurden berücksichtigt, um so weit wie möglich die tatsächlichen SES von Kautschuk-Agorforstsystemen zu erfassen. Drei Szenarien wurden über eine Periode von 20 Jahren simuliert, nämlich das PES-Szenario, das Szenario der Landnutzungspräferenzen, im Fall der finanziellen Unterstützung bzw. Subventionen (SUB), sowie der aktuelle Trend als Grundszenario.

Die wichtigsten Ergebnisse der Simulationen zeigen eine minimale Veränderung der Landnutzung im PES-Szenario, wobei im Vergleich zu dem Grundszenario ca. 22% der Artenvielfalt in den Kautschuk-Agroforstsystemen erhalten und die Kohlenstoffemissionen um 97% reduziert werden konnten. Bei dem SUB-Szenario konnten ca. 6% der Artenvielfalt erhalten und die Kohlenstoffemissionen um 47% reduziert werden. Hinsichtlich der Lebensgrundlagen wurde nur beim PES-Szenario die Wohlstandsungleichheit um bis zu 50% reduziert. Was die Renditen für Investitionen ins Land betrifft, hängt die Wirtschaftlichkeit der einzelnen Landnutzungstypen sehr stark vom Szenario ab; Kautschuk-Agroforstsysteme wären jedoch sehr profitabel (20%), wenn eine Preisprämie in einem Ökozertifizierungsprogramm eingeführt würde. Die wichtigsten Schlussfolgerungen dieser Untersuchung sind erstens, dass PES-Programme für Kautschuk-Agroforstsysteme zu Synergien zwischen Reduzierung von Kohlenstoffemissionen und

Erhaltung der Biodiversität sowie zur Verbesserung der Lebensgrundlagen führen und damit die Trade-offs reduzieren, die durch mögliche Veränderungen in der Landnutzung/-bedeckung entstehen können, und zweitens, dass das LB-LUDAS-Modell - als integriertes sowie als MAS-Modell - ein nützliches Instrument darstellt, um die ES Trade-offs als eine wichtige Eigenschaft der dynamischen sozial-ökologischen Systeme zu erfassen. Gleichzeitig dient das Modell als Instrument zur Unterstützung von Verhandlungen bei der Planung von Landnutzungsmaßnahmen.

Der Einsatz prozessbasierter Entscheidungen im LB-LUDAS-Modell wird empfohlen, um geplante Entscheidungen von Agenten in verschiedenen Situationen zu berücksichtigen, Auf diese Art können die Auslöser, die Optionen sowie die zeitlichen und räumlichen Aspekte der Reaktionen der Agenten auf relativ realistische Weise erfasst werden.

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List of Abbreviations

ABM	Agent-based model
ASB	Alternative-Slash and Burn
CA	Conservation agreement
CHES	Coupled human environment systems
DBH	Diameter breast height
DEM	Digital elevation model
ES	Ecosystem services
FALLOW	Forest, Agroforest, Low-value Land or Waste
FSC	Forestry Stewardship Council
IBM	Individual-based model
ICRAF	World Agroforestry Centre
KCA	*K*-means Cluster Analysis
LB-LUDAS	Lubuk Beringin – Land Use Dynamic Simulation
LUCC	Land-use and cover change
LUDAS	Land-Use Dynamics Simulator
MA	Millennium Ecosystem Assessment
MAS	Multi-agent system
masl	meters above sea level
MDG	Millennium Development Goals
NDVI	Normalized difference vegetation index
NSS	Negotiation support system
NTFP	Non-timber forest products
ODD	Overview, Design concepts and Details
P/RES	Payments/ Rewards for environmental services
PCA	Principal Component analysis
PES	Payments for ecosystem services
REDD	Reduced emissions from deforestation and degradation
RUPES	Rewarding Upland Poor for Environmental Services they provide
SAR	Species-area relationship
SES	Social-ecological system

1 MODELING LAND-USE CHANGE AND ECOSYSTEM SERVICE TRADE-OFFS: A SOCIAL-ECOLOGICAL SYSTEMS APPROACH

1.1 Background

Earth's life support systems and society have entered an era of massive change. In the past 50 years, the global population has doubled, and by 2050 the global population is projected to grow by 50%. The Millennium Ecosystem Assessment (2005) reported that there is an increasing trend in both harvested area (area expansion) and cereal yields (a proxy of increased intensification). Over the past 40 years, cropland area has expanded globally by 15% (from 1.3 to 1.5 billion ha), while the area for pasture has increased by 11% (from 3.14 to 3.48 billion ha) (FAOSTAT 2004). And yet, the number one target of the Millennium Development Goals (MDG) is to halve hunger by 2015. Doubling and at the same time sustaining food production demands environmental integrity.

Conservationists are alarmed that the impact of agricultural change, e.g., intensification, on nature is now greatest in developing countries (Green et al. 2005). For instance, an analysis of the world bird database of the Birds International conducted by Green et al. (2005) shows that farming is the single biggest threat to endangered bird species (accounting for 37% of threats) and is substantially important in developing countries. It is also frequently observed that the biodiversity value of farmland declines with increasing yield (Pain and Pienkowski 1997; Krebs et al. 1999; Donald et al. 2001). Green et al. (2005) suggested that maintaining high biodiversity on farmland often requires foregoing opportunities for high yields. Balancing these conflicting demands is a major challenge to all ecologists as well as policy makers.

The Millennium Ecosystem Assessment mainstreams the concept of ecosystem services (ES). It describes how humanity benefits from ES and how human actions alter ecosystems and the services provided. The ES concept has been widely adopted among the scientific and policy communities and created new approaches for research, conservation and development (Daily and Matson 2008; Carpenter et al. 2009). However, there is a growing body of literature about the challenges of integrating and understanding the relationships of ES and human well-being (Bennett et al. 2009; Mooney 2009). Among these challenges are how to analyze trade-offs involved in land-cover and land-use change, particularly with respect to the spatial analysis and dynamic modeling tools, scale, development and challenges regarding the inclusion of ecosystem services in integrative landscape planning and decision-making tools (De Groot et al. 2010). Basic science (i.e., including the basic information on the dynamics of social-ecological systems) is needed to assess, project, and manage the flows of ecosystem services and human wellbeing. Carpenter et al. (2009) listed some major research challenges:

1. Management of ecosystems services is based on assumptions that have not yet been vetted by evidence, and thus evaluation of assumptions, policy instruments and practices is sorely needed.
2. Explicit models of coupled social-ecological systems (SES) are essential for research, synthesis, and projection of the consequences of management actions.
3. Research is needed to build the empirical base for understanding thresholds of massive persistent changes in social-ecological systems, the factors that control probabilities of such changes, and leading indicators of incipient thresholds.

1.1.1 Land-use /cover change (LUCC) and ecosystem services (ES) trade-offs

Humans have transformed significant areas of the Earth’s land surface (land cover) (Vitousek et al. 1997; Agarwal et al. 2002; Foley et al. 2005). These land-use/ cover changes (LUCC) are intertwined in many ways with global environmental issues such as climate change and carbon cycle, loss of biodiversity, sustainability of agriculture, and provision of safe drinking water (Foley et al. 2005; Lepers et al. 2005). Though some of these changes are absolutely essential for human survival, other forms of land use are degrading the ES (Figure 1.1).

According to Foley et al. (2005), confronting the global challenges of land use will require assessing and managing inherent trade-offs between meeting immediate human needs and maintaining the capacity of ecosystem to provide goods and services (DeFries et al. 2004; MA 2005b). Management systems differ in the way people extract goods, in the level of production, in the intended and unintended provision of services, and in the level and quality of biodiversity. Hence, there is a need to identify novel management systems and practices that facilitate desirable transformations (Folke 2005; Mooney 2009).

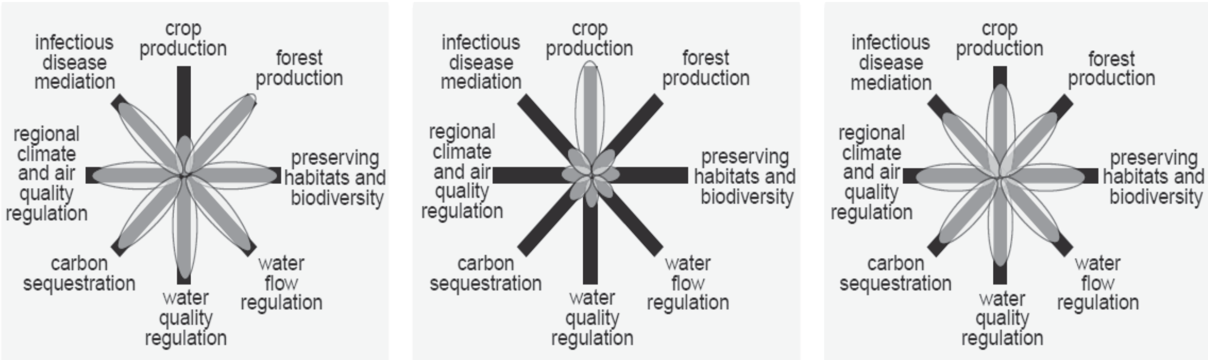

Figure 1.1 Comparison of land uses and trade-offs of ecosystem services (Source: Foley et al. 2005).

To make better decisions regarding the trade-offs among ES involved in LUCC, a systematic account of the relationships between ecosystem management and ecosystem services and the values that these generate is needed (De Groot et al. 2010). Although ES trade-offs are becoming a popular research topic in ecology, very few studies are available (Rodriguez et al. 2006), and an increased research effort is needed to quantify the capacity of various land-cover types and associated management strategies to provide a range (bundle) of ES.

1.1.2 Payments for ecosystem services (PES)

Payments for ecosystem services (PES) or payments/ rewards for environmental services (P/RES) have been widely recognized as an innovative approach to ensure sustainable ecosystem management. Bennett et al. (2007) defined management regime as the way the ecosystem is manipulated in order to obtain the desired ecosystem services. Nowadays, PES is one of the economic and market-based instruments seeking to support positive environmental externalities through the transfer of financial resources from beneficiaries of certain environmental services to those who provide these environmental resources. Over the last decade, the use of PES schemes for watersheds (e.g., downstream water users paying upstream farmers for adopting land uses that limit soil erosion), biodiversity (e.g., conservation donors paying landholders for creating set-aside areas for biological corridors), carbon sequestration and storage (e.g., car companies paying tropical farmers to plant or maintain trees) has gained popularity as it addresses the goal of both conservation and poverty alleviation (Wunder 2008). In the agricultural landscape, the main argument for creating PES schemes is that ecosystems such as natural or secondary forests, as well as human-interfered landscapes exploited for agriculture, provide mankind not only with marketed commodities, but also with additional services that create ecological benefits at complementary local, regional, and global scales (MA 2005b; Van Hecken and Bastiaensen 2010; Villamor and van Noordwijk 2011). Based on that premise, the land users are seen as ES providers who are assumed to take the opportunity to add ES to the portfolio of their production choices, and *positive externalities* of environmentally-sound land uses are assumed to be known, at best reflecting the full range of the provided ES. Therefore, there are at least two bottlenecks in the research efforts to determine successful PES: 1) understanding of land users' adoption of the introduced PES concept and schemes, and 2) evaluation of positive externalities, with respect to the ES bundle, that alternative land uses can offer. So far, too few studies examine how farmers adopt introduced PES schemes under a wide range of political, social, economic and ecological conditions (Pagiola et al. 2005; Zbinden and Lee 2005)

The growing demand to meet human needs causes a decline in other ES that are also crucial to human wellbeing. However, experience shows that the implementation of this instrument faces numerous challenges. There is a huge knowledge gap in the understanding of how management regimes affect bundles of ES, which are often interacting (Bennett and Balvanera 2007). Integration of the perceptions, knowledge and values of different stakeholders (e.g., conservation agents, local people, public/policy agents, existing tenure system) is seen as a crucial factor in the negotiation for any environmental compensation/reward scheme (van Noordwijk et al. 2007). Moreover, there is no solid understanding on how PES could affect the synergies and trade-offs among ES.

1.1.3 Social-ecological systems (SES)

The challenge of the assessment of ES trade-offs lies in the complexity of ecosystem dynamics in which human and natural processes are coupled. The general problem of all ecological analyses and all environmental decision processes is the enormous complexity of the investigated ecosystems and landscape patterns (Müller et al. 2000; Rodriguez et al. 2006). Coupled social-ecological systems are characterized as non-linear (chaotic dynamics) with unpredictable behavior and interactions that span multiple levels of biological organizations or spatiotemporal scales (Folke 2006;

Norberg and Cumming 2008). Since complex systems violate the assumptions of reductionist techniques (Costanza et al. 1993), the need to work across all types of human boundaries at different geographic scales (including downstream and upstream relations) is required. Cumming (2011, p.59) describes that in "*the research on social-ecological systems the focal questions are likely to revolve around the maintenance of natural resources, the role of management in the system, and the requirements of different groupings within the human population.*"

Several general integrated modeling frameworks for the study of SES have already been proposed (Cumming 2011), e.g., multi-agent system/ or agent-based system models (MAS/ABM) (Holland 1992; 1995). These models lay out key elements or properties of complexity theory, e.g., aggregation, non-linearity, flows and diversity with mechanisms such as tags, internal models, and building blocks.

In recent years, multi-agent system simulation (MAS) has been receiving much attention in the research community mainly because it offers a way of incorporating the influence of human decision making on land use in a mechanistic, formal, and spatially explicit way (Matthews et al. 2007). It has been widely used to explore the decision-making processes of land managers in the context of spatial and social interactions (Parker et al. 2002; Parker et al. 2003; Evans and Kelley 2004; Veldkamp and Verburg 2004; Le et al. 2008; 2010; 2011). Matthews et al. (2007) reviewed the applicability and usage of MAS/ABM regarding the following aspects: (a) policy analysis and planning, (b) participatory modeling, (c) explaining spatial patterns of land use or settlement, (d) testing social science concepts, and (e) explaining land-use functions. Accordingly, MAS/ABM is promising as it can provide new insights into complex natural resource systems and their management that traditional approaches are not able to. Many MAS/ABMs have been widely explored to simulate LUCC (Bousquet and Le Page 2004; Le 2005; Parker et al. 2002). Developments in the use of this model led to incorporation of the human behavioral component that underlies the land-use change. Economic structural models of land-use decisions were developed within a spatially explicit framework of MAS/ABM (Irwin and Geoghegan 2001). Although it could be argued that land use in itself is not as important as its effects on the biophysical functioning of the landscape (e.g., provisioning of agro-biodiversity and maintenance of other ES), so far no studies using this model have been conducted to assess the ES trade-offs, mainly between food production and biodiversity, while simulating scenarios of management regimes like PES. To develop a comprehensive understanding necessary to assess and quantify the ecosystem responses to different types of land-use change in different ecological situations, DeFries et al. (2005) identify the key elements to be addressed:

1. driving forces behind land-use change including economics and markets,
2. human behavior,
3. international and national policies,
4. biophysical conditions and availability of technology to project future change,
5. observations and monitoring to identify patterns and locations of land-use change, and
6. analysis of the ecosystem consequenses of land-use change and the feedbacks to future land-use options.

1.2 Research questions and objectives

Taking into account the research challenges listed above, the aim of this study is to provide insights and clarity on the following research questions:

1. Can agricultural production and agro-biodiversity protection as two different perspectives be bridged?
2. How do specific management regime/policy intervention such as PES schemes affect the trade-offs and synergies among different ecosystem services?
3. How could the complexity of social-ecological systems be represented using multi-agent system (MAS) models?
4. How can the MAS model support the design of PES schemes?

The specific objectives are the following:

1. To parameterize and validate a multi-agent land-use dynamic simulator model (i.e., LB-LUDAS) to explore temporal and spatial impacts of PES interventions on the trade-offs between agro-biodiversity and food production as the main categories of ES;
2. To identify synergies and trade-offs between the main categories of ES using a MAS model;

3. To develop a tool-based approach using a MAS model to assess ES trade-offs and support the design of PES schemes.

1.3 Thesis outline

This thesis is structured as follows:

Chapter 2 introduces the state-of the-art approach to understand the complexities of LUCC and ES trade-offs; defines and describes the coupled human-environment systems, and describes the modeling tool applied to understand the complexities.

Chapter 3 deals with the human behavior of the rubber farmers in Indonesia when making land-use choices. Factors affecting their decisions are analyzed and the method to capture the human agents' heterogeneity is applied. Chapter 4 analyzes the factors that affect the adoption of human agents (farm households) in international policy (e.g., REDD schemes) and local policy (e.g. eco-certification of rubber latex) as PES schemes. The importance of rubber agroforest for ES is also described.

Chapter 5 describes and analyses the biophysical conditions of the rubber agroforests and the key biophysical sub-models (species richness, forest-yield dynamics, agronomic yield dynamics, natural succession, and carbon stocks) to demonstrate the ecological processes and complexity of the ecological system. Also, data parameterization and calibration are presented.

Chapter 6 describes the unanticipated core problem in the application of the empirical MAS/AB model that was encountered during the initial simulation runs, and presents ways to resolve the problem. Chapter 7 presents the land-use change analysis and potential ES trade-offs using the new approach in modeling the decision-making process of agents in achieving the core research problem.

Finally, Chapter 8 provides the main conclusions and recommendations based on the study objectives and addresses the insights on the key research questions.

Appendix 1 presents the review of literature on what drives the land-use change in the study site in Jambi Province (Sumatra), Indonesia, and analyses the speed, transition and intensity of land-use change.

2 CHES: MODELING APPROACH TO UNDERSTAND ECOSYSTEM SERVICE TRADE-OFFS

Land-use change is a dynamic and complex process of interactions between human and environmental systems. The complexity of the coupled systems is not well understood due to the traditional separation of ecological and social sciences (Kinzig 2001; Liu et al. 2007; Scholz 2011). The intricate ways in which humans might interact with ecological systems (i.e., responding to ecological change) are rarely considered. The feedback between social processes and ecological dynamics is currently one of the most demanding fields of interdisciplinary research and development. Although several studies have attempted to understand the process, these are based on theoretical work, and very few used empirical data (Nolan et al. 2009; Le et al. 2010); however, the number of social ecological system models applied for real-world cases is increasing (Matthews et al. 2007).

Most ecological theories have been developed in systems where humans are absent or exogenous, or a simple and detrimental perturbing force. Similarly, much of the neoclassical economic theory is asserting on a reliable and uniform biosphere, one with flows of ecosystems services and natural resources that are expected to expand so as to conform to stated political or economic goals (Kinzig 2001).

This chapter presents the state-of-the-art modeling approach for understanding the coupled human-environment system (CHES) and its ecosystem service trade-offs. The LB-LUDAS model as a multi-agent system model for land-use change and analysis of ecosystem service trade-offs is described based on the ODD (Overview, Design concept, and Details) standard protocol.

2.1 Coupled human-environment systems (CHES) models

The interactions between natural and human systems produce complex emergent LUCC dynamics and are best analyzed through CHES models.

CHES (also referred to as social-ecological systems) is a new science that is widely recognized (Cumming 2011; Scholz 2011). Liu et al. (2007) describe the science that CHES builds on. First, it focuses on patterns and processes that link human and natural systems. Second, it emphasizes the reciprocal *interactions* and *feedbacks* – the effects of both humans on the environment and of the environment on humans. Third, understanding within-scale and cross-scale interactions between human and natural components is the major challenge (see Figure 2.1). The unique features of coupled human-environment systems are briefly described below.

Multiple, temporal and spatial scales

Couplings within and among CHES take place across nested multiple spatial scales, ranging from local to global. Villamor et al. (2011) conceptualized the interactions of human agents in a nested hierarchy using sub-system linkages (Figure 2.1).

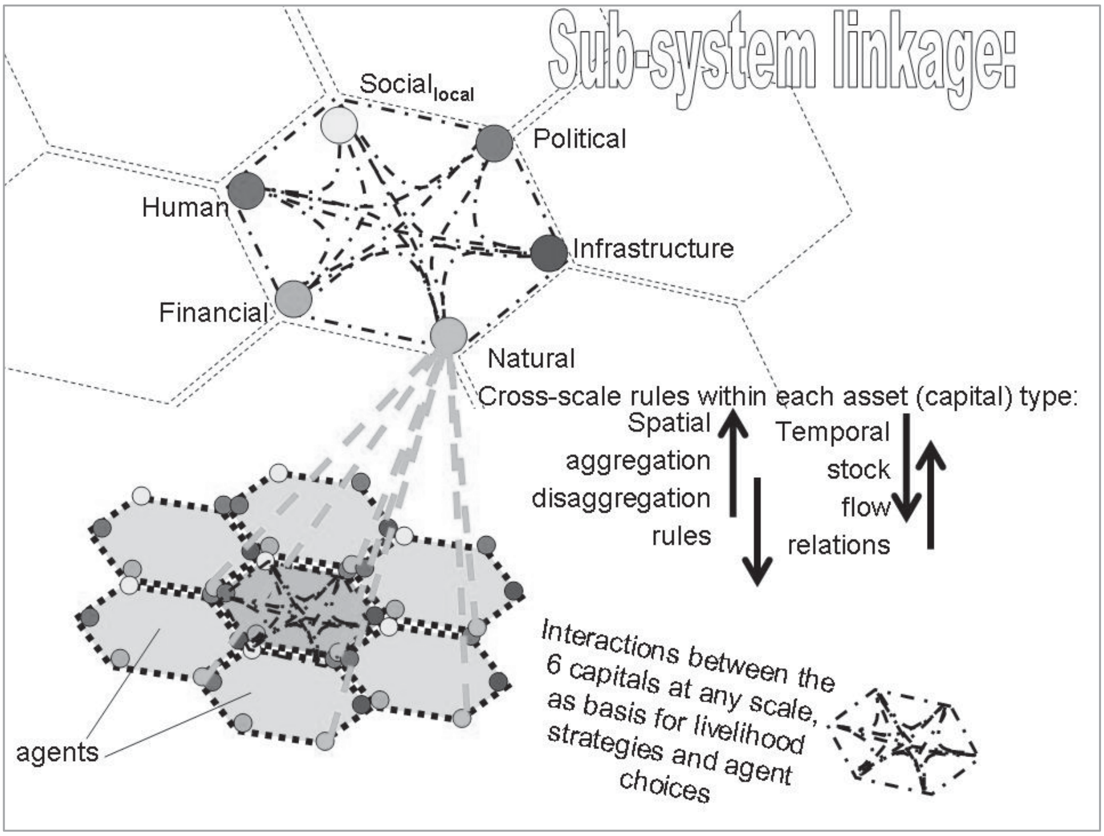

Figure 2.1 Conceptualization of how agents interact at different levels or scales (Villamor et al. 2011).

According to Cumming et al. (2006), scale mismatch happens through changes in the relationships between the spatial, temporal or functional scales at which the environment varies, the scales at which human social organization occurs, and the demands of people and other organisms for resources. For example, scale mismatch is caused by changes within the availability of capital or assets, e.g., population change, physical infrastructure change, food production, land tenure, etc.

Multiple levels of biological and social organizations

Human and environmental systems interact with each other creating feedback between different organizational levels (e.g., gene, cell, individual, community, ecosystem, and biosphere) that also influence the human-environment interactions (Pickett et al. 2005).

Interacting feedbacks and adaptation

Feedback loops in which human influence is affected by natural patterns and processes are a typical characteristic of CHES (Berkes and Folke 1998; Cumming et al. 2006). The loops are either positive or negative, which could lead to either acceleration or deceleration in rates of change of both human and natural components as well as interactions (Liu et al. 2007). In social systems, a form of active adaptation, through decision making and proactive responses to environmental change, may be possible (Cumming 2011). Adaptation claims to be the result of primary and secondary loops in the socio-ecological conditions of the households in the long run (Le et al. 2011).

Non-linear behavior and thresholds

Interactions between humans and the environment reflect non-linear, chaotic or even unpredictable behavior (Cottingham 2002) because the non-linearities in the responses of key system variables to changes in other variables can result in the crossing of a threshold, which is a point at which a system shifts or flips from one state to another (Walker and Meyers 2004; Scheffer 2009).

Legacy effects and time lags

There are varying intervals of time between human-nature interactions and the ecological and socio-economic effects. Thus, the linkages between human and natural systems unfold slowly, and the changes are not detectable (Liu et al. 2007). Also, time lags complicate the process of understanding the interactions between human decisions and their environmental effect and vice versa.

Asymmetries and heterogeneity

Asymmetries could refer to systematic heterogeneity within a complex system. For example, asymmetries in elevation can create a spatial gradient, while asymmetries in biological diversity can structure local food webs in a way that is largely independent of spatial variation (Cumming 2011). In social systems, heterogeneity refers to the agents' preferences or variability in agent characteristics across entire populations and categorization of groups of individuals with similar preferences (Brown and Robinson 2006).

Resilience

Resilience refers to the ability of the system to maintain its identity in the face of internal change and external perturbations (Cumming and Collier 2005; Cumming 2011).

2.2 Multi-agent system (MAS) models

Multi-agent system or agent-based system (MAS/ABM)[1] tools for modeling land-use/cover change (LUCC) have been recognized as being highly appropriate for representing the complex nature of both spatial interactions and decentralized human decision making on land use including ecosystem policy analysis (Ligtenberg et al. 2001; Parker et al. 2003; Bousquet and Le Page 2004; Deadman et al. 2004; Evans and Kelley 2004; Acevedo et al. 2008). Some of the applications examine the shifting cultivation patterns and deforestation in the context of resource use and land markets (Parker et al. 2003), demographic dynamics and tropical deforestation (Huigen 2004; Huigen et al. 2006), and scenario building based on agricultural subsidies and their impact on land-use change (Le 2005; Le et al. 2008; 2010; 2011).

Other agent-based models link geospatial technologies, explicitly considering human-induced drivers and integration of multiple spatial scales (Evans and Kelley

[1] The term ABM originally emerged in a computational context with applications in physics, social sciences and economics. It often describes robotic aggregates responding to a variable environment or simulates complex behavior of humans in social networks. In the ecological perspective, the individual-based model (IBM) uses the same basic concept and is used synonymously with ABM. MAS is also used in a similar concept, however, emphasis is on the interaction of a larger number of autonomously acting software agents and is even more common in technical applications (Reuter et al. 2011).

2004). Only few attempts have been made to investigate the linkages between human behavior and biophysical processes occurring in the landscape such as soil fertility dynamics (Matthews 2006), vegetation succession (An et al. 2005; Manson 2005a; 2005b; Matthews 2006) and crop-yield and forest-yield dynamics (Le 2005; Le et al. 2008). However, these studies are still either at an early stage or on an abstract level (Le pers. com.). Villamor et al. (2011) reviewed existing land-use change models (i.e., ABM) on the basis of agents' decision making, behavior, characteristics, and interactions, and representation of biophysical processes. It was seen that most of the decision making of human agents was based on utility optimization, and integration of non-economic motivation in the decision-making process is a fundamental challenge for the MAS/ABM modelers.

Despite the many strengths and flexibilities of MAS/ABM application, there are also a lot of criticisms of the approach especially with respect to the application for SES. One of the main criticisms is the calibration and validation of the MAS/ABM models. Heckbert et al. (2010) describe this as the "*birthing pains of a new methodology*". The author of this study is very much aware of this challenge. In Chapter 6, a specific example that emerged unexpectedly during the initial simulations of the LB-LUDAS and ways to resolve the issue are presented.

2.3 LB-LUDAS Model

LUDAS (land-use dynamic simulator), a model platform developed by Le (2005), was used and modified in this study. This section follows the ODD (Overview, Design concepts, and Details) protocol as a standard procedure for describing the simulation of LB-LUDAS (Grimm et al. 2006; Grimm et al. 2010).

2.3.1 Purpose

The LUDAS model was primarily designed to support land-use decisions in the forest margins with the following three aims: 1) to explore the magnitude of possible socio-ecological changes over space and time as driven by different land-use policy interventions, 2) to identify the most affected components of the system (*what*), locations (*where*) and periods (*when*) with respect to specific policy intervention, and

3) to highlight sound policy interventions that likely enhance environmental and socio-economic benefits efficiently.

For this study, a fourth objective is added: to explore the potential trade-offs and synergies of the policy intervention on the goods and services temporally and spatially. A conceptual framework of the LB-LUDAS model is illustrated in Figure 2.2.

In LUDAS, the organizations represented through experimental factors that will influence the ecosystem management in the study area are treated externally. The policy factors and management regimes are considered externally with regard to the boundary of modeled system, i.e., limited boundary (Figure 2.2), in order to simplify the modeling task. In this way, different scenarios of policy and management setting will be pre-defined, and the course of future system development will be compared to assess ex-ante impacts of policy interventions or management regimes.

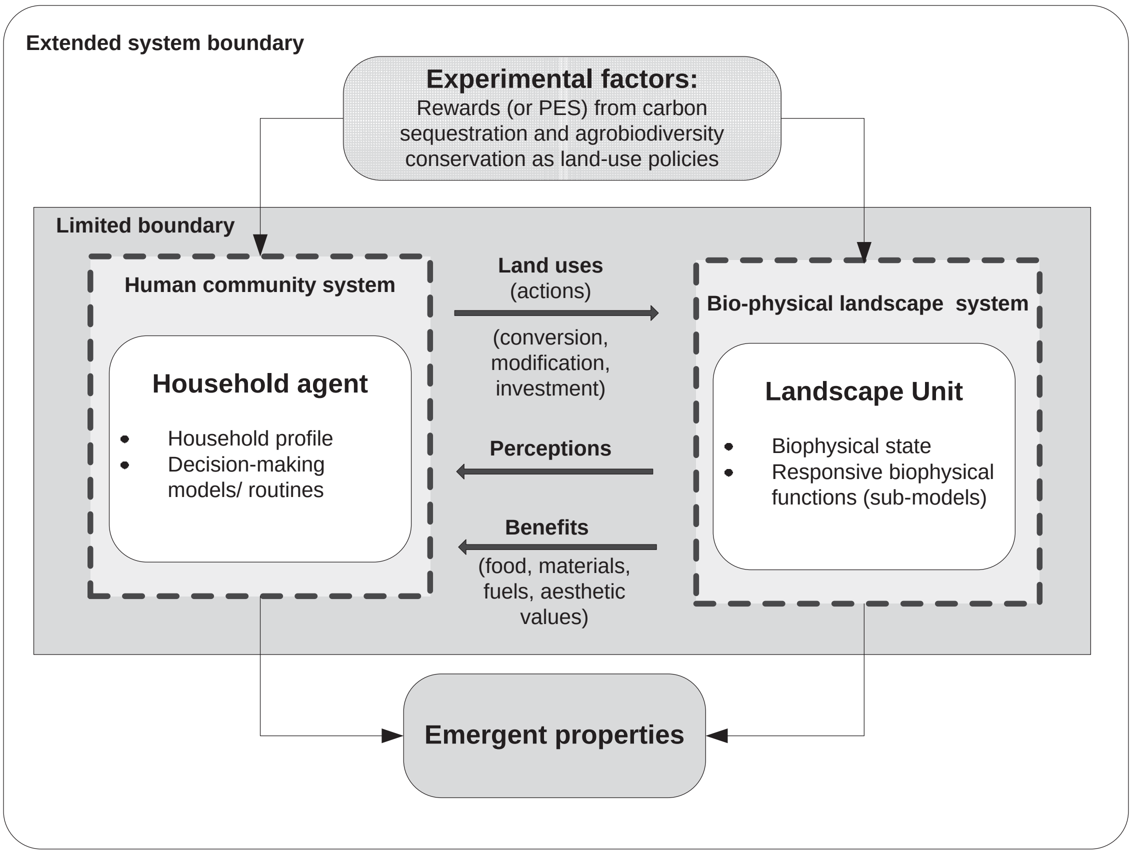

Figure 2.2 Conceptual framework of LB-LUDAS model

2.3.2 Agents and their state variables and scales

Agents

The LB-LUDAS model consists of two types of agents: 1) human agents, and 2) landscape agents, each with several state variables as given below.

1. *Human agents* are representations of individual farming households. The state variables of these agents capture the sustainable livelihood capital of each household. This includes social identity (or simply the identification number), age, group membership, and human resources (e.g., household size, dependency ratio and education), land and natural resources (e.g., land holdings and land structures), financial capital (e.g., gross income and gross income per capita), physical capital (e.g., access to market and distance to town), and policy access (e.g., participation in conservation agreement (CA) and involvement in CA activities).
2. *Landscape agents* are congruent land pixels or patches with state variables corresponding to GIS-raster layers of biophysical spatial variables (e.g., land cover and wetness index), neighborhood spatial characteristics (e.g., enrichment factors of land-use pattern), economical spatial variables (e.g., proximate distance to road and town center or market), institutional spatial variables (e.g., owner and protection zoning), and households' landscape vision (Le et al. 2008).

Spatial and temporal units

One time step represents one year. One grid cell or pixel represents 30 m x 30 m (900 m^2) and the model landscape covers 156 km^2.

Environment

The environment in this context refers to the overall environment or forces that drive the behavior and dynamics of all agents or grid cells (Grimm et al. 2010). In LB-LUDAS, the environmental variables that drive the behavior of the agents in this model are forest protection zoning, market price, policy intervention (e.g., PES schemes) and neighborhood conditions in land use and livelihood. Similar to the general LUDAS framework, the behavior strategy of a household agent changes over time based on its annual evaluation of change in land-use and livelihood structures of the surrounding environment. The parameters specifying the household behavior are treated as state variables, which are stored in the memory of household agents (Le et al. 2010). These variables include the set of preference coefficients reflecting the relative importance of various environmental, socio-economic and policy factors in household decisions about land uses, and the set of ratios determining the amount of labor allocated for each branch of livelihood activities.

2.3.3 Process overview and scheduling

The basic LB-LUDAS model scenario process consists of twelve main steps (Figure 2.3). The main time loop of the simulation program, called annual production cycle, includes sequential steps, which are agent-based and integrated with patch-based processes. In most cases, all household agents and landscape agents are called and perform tasks in parallel (i.e., synchronizing actions). The LB-LUDAS model was coded using the Netlogo version 4.1 (Wilensky 1999).

2.3.4 Design concepts

The LB-LUDAS model is designed to address the concepts of heterogeneity, diversity deficits (Villamor et al. 2011), and the complexity of coupled human-environment systems in land-use decisions resulting in trade-offs. These concepts were taken into account through various variables affecting the agents' decisions and the complex sub-models and processes within agents. So far, there are only few MAS models that build on empirical data (Berger and Schreinemachers 2006) and integrate biophysical and socio-economic model components (Parker et al. 2002).

Emergence

In the original version of the LUDAS model, Le et al. (2010) explains that the livelihood performance of the entire household population or social group emerges from individual land-use decisions that integrate household characteristics, surrounding dynamic environment and policy information. Also, the LUCC at landscape level emerge from two micro-processes, namely 1) land-use conversion or modification caused by household agents, and 2) natural succession of the vegetation cover. With the LB-LUDAS model, the PES-adoption choice is linked with the biodiversity performance (measurement) of a certain land use (see section Sub-model). This linkage would give new insights on the possible impact on the land both spatially and temporally. To the author's knowledge, to date there is no literature available that documents this linkage.

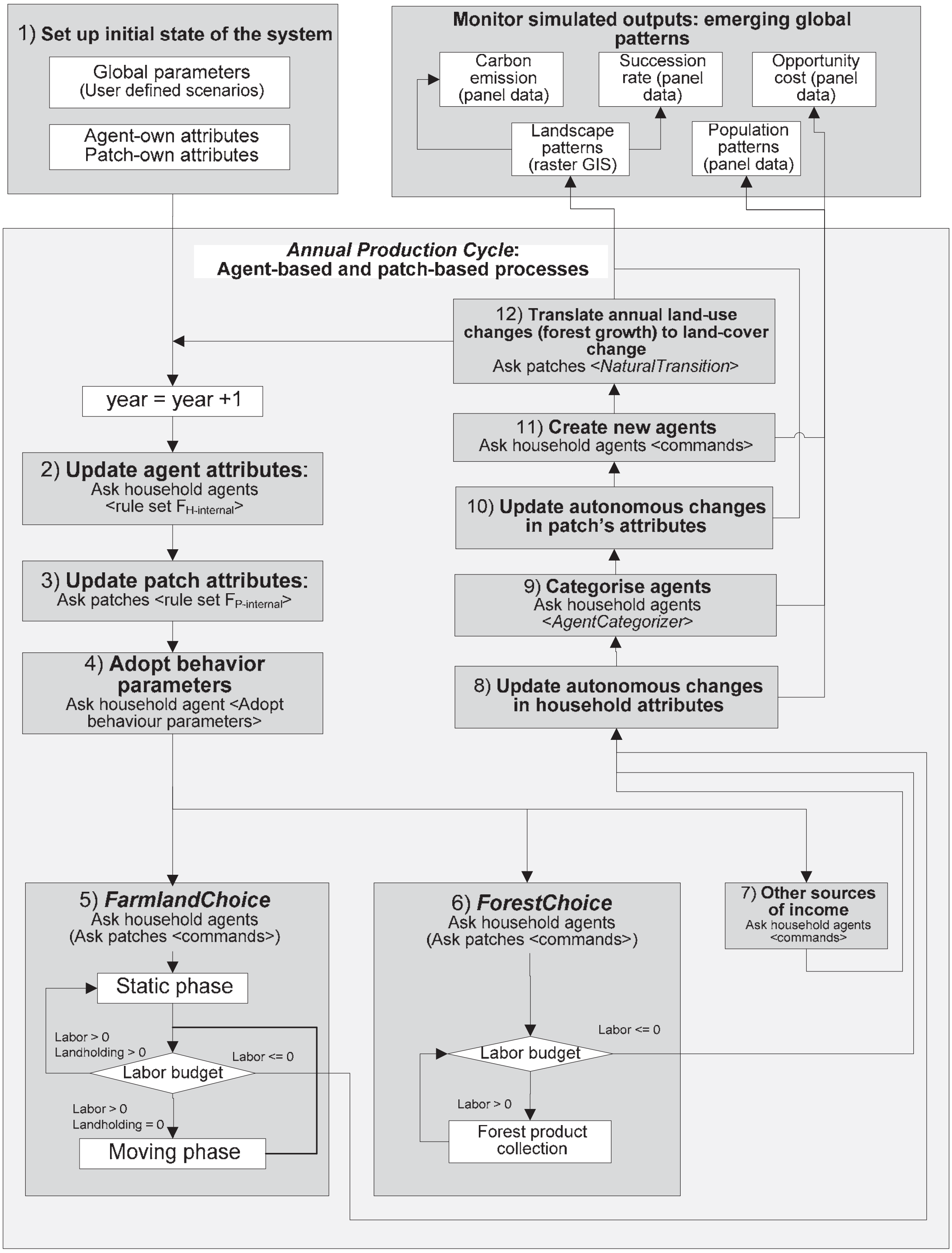

Figure 2.3 Flow chart showing main steps of multi-agent simulation process (modified from Le et al. 2008)

Adaptation/ learning

In reality, when making decisions regarding land use humans employ a variety of strategies beyond maximization of profits or satisfaction or minimization of risks. Current analytical models are also limited in their ability to represent human learning and adaptation (Nolan et al. 2009).

Adaptation of human decision making to environmental change is defined by Le et al. (2011) as the agents' learning with respect to the adjustment of their decision rules, depending on their static internal model of the human-environmental interactions (i.e., fixed behavioral program). In the LB-LUDAS model, adaptive traits of each individual agent are explicitly processed mainly by land-use decisions and the change in behavior strategies (i.e., preference coefficient of land-use choice function and willingness to adopt policies, and structure of labor allocation). At first, agents adapt to current socio-ecological conditions by choosing the best land use in the best location in terms of utility (using heuristic rule-based behavior). Then, a household's behavior model may change by imitating the strategy of that household group most similar to it (Le et al. 2010; 2011). In this way, individual agents' decision model may change over time and context. Also, a household agent generates its landscape knowledge by updating past landscape visions (see section Prediction) to provide the basic landscape space.

Objectives

The LB-LUDAS model applies the bounded-rational approach for the household agents' decision making in which households' access to information is limited. This approach follows an ordered-choice algorithm (Benenson and Torrens 2004; Le et al. 2008). In that algorithm, a household calculates the utilities (expressed in probability terms) for all the land use and locations within his domain and for the scenario of policy adoption. The household can choose the option with the highest utility or take risks by selecting other alternatives (Figure 2.4). This algorithm has two versions, i.e., one- and two-staged. According to Benenson and Torrens (2004), in the one-staged version, an agent does not retract, and in the two-staged, an agent first selects an opportunity for testing and then tries to accept it.

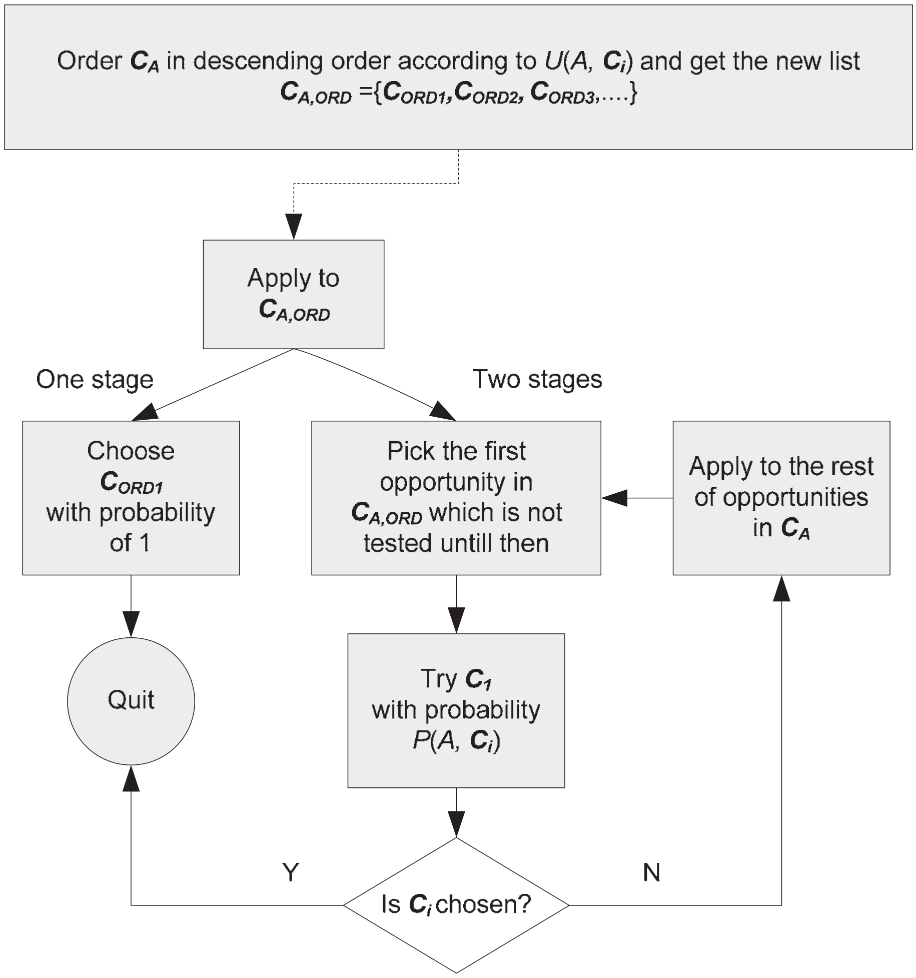

Figure 2.4 Diagram of ordered-choice algorithm where *A* refers to agent and C_A denote the set of opportunities where C_i, $i = 1, \ldots, K$ (Source: Benenson and Torrens 2004).

Prediction

According to Grimm et al. (2010), prediction is fundamental to successful decision making if the agent's adaptive traits or learning procedures are based on estimating future consequences of decisions. The LB-LUDAS model has a landscape vision module, which stores the spatial information that the household agent perceives from the landscape, and a program of instructions for generating the agent's behavior under different circumstances. In this module, household agents recognize spatial information, analyze trade-offs and optimize spatial land-use choices only within their own plots (Le et al. 2008).

Sensing

Related to the abovementioned element, sensing is the way environmental state variables are assumed to be sensed and considered in the decision making of the individual agents. In the LB-LUDAS model, household agents assume to know perfectly the landscape characteristics (i.e., through *landscape vision*) and neighborhood land-use pattern variables (see Chapter 5), which they use for evaluating land-use alternatives.

Interaction

Interactions between agents are assumed in the model both directly and indirectly. Direct interaction occurs when the household agent transfers information (i.e., state variables) to young household agents for their own decision-making process. Another way is when two or more household agents find their best land-use alternative in the same location. In this situation, a random procedure will let the agent(s) leave the location and start another search (Le et al. 2010). Indirect interaction takes place among household agents when land-use conversion caused by households leads to changes in the decision space of other agents in the next time step.

Stochasticity

Stochasticity is applied in the LB-LUDAS model in five different processes, namely 1) initialization of household population, 2) choosing plot locations for the newly created household agents and remaining population generated in the system initialization, 3) preference coefficients in the land-use choice function, 4) ecological sub-models that produce variability in the processes, and 5) some status variables not affected by agent-based processes (all defined by even distribution and pre-defined bounds).

Observation

Data for LB-LUDAS testing, understanding, and analyzing include annual successive land-use/cover map, forest yield, land-holdings and graphs that describe the temporal pattern of crop yield production, economic return, farm income (mean, structure and equality), species richness, carbon stocks and household types (see figure 6.1).

2.3.5 Initialization

Regarding the initial state of the LB-LUDAS at t = 0 of a simulation run, the LB-LUDAS model follows the same initialization steps of the LUDAS model (Le et al. 2010):

Step 1: The data of a household sample (N_s) are imported, and the user can select the size of the total population (N_t). The source of variation depends on the size of N_t that is set by the user. The initial landscape of the model is imported as GIS-raster files of landscape variables that are either from secondary data or produced separately by spatial analyses. Here, the variables of both households and landscape are deterministically set.

Step 2: The land parcels of newly generated households are created using the bounded-random rules.

2.3.6 Input data

Data and parameters were parameterized and calibrated using various external sub-models (Table 2.1). Also, the model used the annual population growth rate of 1.14% from the 2003 Statistics of Rantau Pandan, a sub-district of Bungo.

Table 2.1 External input data and sub-models in LB-LUDAS model

Sub-model	Parameter	Data source
Biodiversity	Plot area (m^2)	Rahayu 2009
Carbon stocks	Time-averaged carbon (Mg ha^{-1})	Tomich et al. 1998; 2004 and ICRAF Kalimantan Project 2005
Forest/ rubber agroforest yield (Le 2005)	Equilibrium basal area	Rahayu 2009; Rasnovi 2006
Oil palm yield	Yield (2009-2010)	ICRAF data
Rubber monoculture yield	Yield (2009-2010)	ICRAF data

2.3.7 Sub-models

In the original LUDAS model, there are 13 key sub-models and calculation routines integrated. For the LB-LUDAS model, 5 additional sub-models and calculation routines were incorporated (Table 2.2), namely 1) *PES-adoption*, 2) *Calculate-species-richness*,

3) *Calculate-carbon-stocks*, 4) *Preferred-land-use*, and 5) *Financial-return*, which are briefly described below. For detailed descriptions (e.g., model parameters, dimension and reference values) and justification of specific sub-models see Chapter 5.

Table 2.2 Main sub-models/ procedures of LB-LUDAS coded in Netlogo (4.1) (modified from Le et al. 2010).

Sub-models/ Calculation routines	**Functions**	**Entities involved**
Initialization[a]	Import GIS data and sampled household data, generate remaining population, create household pixels, generate household coefficients, and calculate initial species richness	Household Pixel
PES-adoption[b]	Calculate the willingness to adopt the PES policy of the household	Household
Preferred land use[b]	Calculate the agent's land-use choice for the new land if financial investments or subsidies are provided	Household
Labor-allocation	Set the labor list of the household annually	Household
FarmlandChoice[a]	Perform the land-use choices (using bounded-rational choice, and nested with rule-based algorithm)	Household Pixel
ForestChoice[a]	Perform forest-use choices, mainly rule-based algorithms	Household Pixel
Financial-return [b]	Calculate the annual economic return of each crop and tree-based production	Household Pixel
Update-household-state	Update the changes in household profiles annually	Household
Agent-Categorizer	Categorize households into similar groups	Household
Generate-household-coefficients	Generate behavior coefficients of household, allow variants within the group but stabilize behavior structure of the group	Household
AgronomicYieldDynamics[c]	Calculate yield production of farmlands in response to production inputs and site conditions	Household Pixel
Forest-Growth-Response	Calculate forest stand basal area in response to human intervention (logging)	Household Pixel
Natural-Transition[c]	Perform natural succession among vegetation types based on accumulated vegetation growth and ecological edge effects	Pixel
Calculate-species richness [b]	Calculate species number per patch (using rule-based species area relationship function)	Pixel
Calculate-carbon-stocks [b]	Calculate carbon stocks for each land use using the time-average carbon stocks	Pixel

Table 2.2 continued

Sub-models/ Calculation routines	**Functions**	**Entities involved**
Create-new-household	Create a young new household controlled by an empirical function of population growth	Household
Plot-Graphs	Draw different graphs of system performance indicators	Household Pixel

[a] Procedures that contain two or more other procedures; [b] newly added procedure for LB-LUDAS;
[c] modified procedures/ routines

PES-adoption

This sub-model calculates stochastically the probability of the household agents whether to adopt or not to adopt the PES schemes based on their preference coefficients. These preference coefficients were derived from binary logistic regression. Detailed descriptions of the sub-model, its parameters and data calibration are presented in Chapter 4. This sub-model is linked to the *Calculate-species-richness* sub-model, creating the interaction between socio-economic state variables and the bio-physical processes in the systems.

Calculate-species-richness

This sub-model deterministically calculates the estimated species richness in each land-use type. The estimated species richness serves as key indicator for scenario analysis. The equation is based on the power function of species-area relationship. For detailed description, parameterization and calibration of the sub-model see Chapter 5; the policy application of the sub-model is discussed in Chapter 7.

Calculate-carbon-stocks

Similar to the species richness sub-model, this sub-model deterministically calculates the carbon stocks of each land-use type by assigning the time-averaged carbon density. The output is used to estimate the possible carbon emissions from land-use changes under different scenarios (see Chapter 5 for detailed description of the sub-model).

Preferred-land-use

Similar to the PES-adoption, this sub-model is integrated in the decision-making routine *FarmlandChoice*. The sub-model calculates the probability of the household agents to choose their preferred land use under the condition of ‘if supported by financial investment’ with the time element of 5 to 10 years. Detailed descriptions of this sub-model and its underlying assumption are presented in Chapter 3 and 5. This sub-model and the PES adoption model are considered confounders for establishing the causal mechanism in the decision-making routines.

Financial-return

The purpose of this sub-model is to estimate the annual financial return from different land uses of household agents. The yields generated from *AgronomicYieldDynamic* sub-model (see Chapter 5) are captured by this sub-model, where all the costs of the crop production (e.g., labor costs and agro-chemical input costs) are deducted from the annual revenues. At the end of the time steps, the results are used to estimate the net present value (or opportunity costs) of the different land uses (see Chapter 7), which serves as a key indicator for the livelihood options of the household agents in each scenario.

2.4 Conclusions

CHES is a new and widely recognized science to understand the complexity and trade-offs of the social-ecological systems. In this chapter, the different characteristics of CHES are discussed, and a multi-agent system model (i.e., LB-LUDAS) is described using the standard ODD protocol for MAS/ABM models. In this way, the LB-LUDAS model could capture the properties inherent in the complex interactions of human-environment systems (i.e., non-linearity, heterogeneity, spatial and temporal scales). Since most of the existing MAS/ABM models are weak on ecology, heterogeneity and scales (Cumming 2011), new features were added and described in the LUDAS model to better represent the ecological processes and feedbacks based on the decision making of the human agent.

3 CAPTURING HETEROGENEITY IN LAND-USE DECISIONS: CASE STUDY OF BUNGO DISTRICT, JAMBI PROVINCE, SUMATRA, INDONESIA

Land-use change is a complex, dynamic process that links together natural and human systems. In MAS modeling, human decision making and interaction are the central elements (Koomen and Stillwell 2007). Human-agent decisions (e.g., farming households) vary and are influenced by a variety of factors and variables such as cultural preferences, resource endowment, and knowledge (Parker et al. 2008; Villamor et al. 2011) that tie behavior to the environment (Parker et al. 2003). Though it is worth including the heterogeneity of human agents in models (Brown and Robinson 2006), most land-use change models tend to aggregate data about them (e.g., Forest, Agroforest, Low-value Lands or Waste? or FALLOW in Suyamto et al. 2003; Integrated Land Use, Transportation, Environment or ILUTE in Miller et al. 2004) or use acceptable values as defined by literature (e.g., Land-Use Change in the Amazon or LUCITA in Deadman et al. 2004).

The challenge of multi-agent system modeling is how to appropriately represent the heterogeneity of agents and their environment as software objects in ways that accurately reflect the actual heterogeneity of the ‘real world’ objects (Brown and Robinson 2006). Villamor et al. (2011) reviewed some of the multi-agent decision-making models and found that most of these models assume that: (1) human agents behave in a uniform mode, formulated in a behavior model, and (2) agents' decision-making models are fixed during the course of a simulation. Only few models have attempted to diversify the agents' decision-making mechanism such as the LUDAS model (Le et al. 2008; 2010; 2011), which specifies different land-use adoption models for different household livelihood typologies. However, most of the agents’ decision-making rules in the MAS/AB models were based on utility optimization, i.e., rational economic assumptions (Villamor et al. 2011).

In this part of this study, evidence is provided that illustrates the ways to:

1. Identify the livelihood typologies of households and endogenous factors based on the socio-economic data of the study site;
2. Identify the factors affecting the land-use choice that have a potential impact on household decision making; and

3. Determine the combinational effects of socio-economic characteristics of farming households and environmental attributes of land for land-use decision making of each typical household group.

The results of the analysis are incorporated in the LB-LUDAS model (see Chapter 6) and provide important insight in the effects that heterogeneity has on the outcomes of the model.

3.1 Socio-economic setting

The study site includes of three villages, namely Lubuk Beringin, Laman Panjang, and Buat, all located in Jambi Province. Together, they have a total population of 2,207 inhabitants belonging to 551 households (Table 3.1) (Rantau Pandan Statistics 2003). Buat is the largest village with 1,080 inhabitants, followed by Laman Panjang and Lubuk Beringin with 731 and 396 inhabitants, respectively. The average family has 4 members. Most of the people belong to the ethnic group Melayu Jambi. Lubuk Beringin and Laman Panjang are considered poor. Access to market roads is insufficient and electric infrastructure is not available since the villages are located far from the nearest town centre (Muara Bungo). The main source of food is the rice paddies, the main source of income is rubber (*Hevea brasiliensis*) and occasionally durian and other local fruits, and medicinal plants are obtained from the rubber agroforests.

Table 3.1 Population and number of households in the study site

Village	Population			No. of persons per km^2	No. of house-holds	Average number of persons per household
	Male	Female	Total			
a. Lubuk Beringin	184	212	396	27.22	102	4.02
b. Laman Panjang	366	365	731	41.17	182	4.04
c. Buat	566	514	1,080	93.28	267	4.25
Total	**1,116**	**1,091**	**2,207**		**551**	

(Source: Statistic of Rantau Pandan 2003)

Jambi Province is the third largest rubber-producing province in Indonesia (after north and south Sumatra). Around 97% of the natural rubber comes from the smallholder farmers in Jambi, who tap rubber gardens (called *kebun karet*) smaller than 5 ha. The majority of the farmers in the province are engaged in rubber-latex production. The high price of rubber latex has led to intensive rubber production through rubber monoculture, which is replacing the traditional rubber agroforests (see Appendix 1 for the historical background). An extensive study on labor requirements for rubber and upland-rice production was conducted by Suyanto et al. (2001) in the nearest town center Muara Buat (Table 3.2). This study revealed that rubber production activities are mostly done by men while women are responsible for the rice production (which is related to land inheritance, see section 3.1.1).

Table 3.2 Labor use in rubber production and activity, gender and dominant age of trees compared to labor use in upland rice production in Sumatra, Indonesia (Source: Suyanto et al. 2001)

Age range	**Land preparation and planting (person-days/yr/ha)**		**Crop care (person-days/yr/ha)**		**Harvesting and hauling (person-days/yr/ha)**		**Total (person-days/yr/ha)**
	Men	**Women**	**Men**	**Women**	**Men**	**Women**	
Rubber:							
1 (forest clearance)	53.3	28.6	6.9	4.1	9.4	25.0	127.4
1 (bush clearance)	19.6	12.2	17.8	7.7	1.0	1.0	59.3
2-3	2.9	0.0	24.2	6.3	0.0	0.0	33.4
4-7	0.0	0.0	9.8	4.2	0.0	0.0	14.0
8-10	0.0	0.0	4.8	4.6	62.2	6.2	77.8
11-15	0.0	0.0	4.8	1.4	90.5	4.5	101.2
16-20	0.0	0.0	3.2	2.6	78.9	3.1	87.8
21-25	0.0	0.0	4.0	11.5	94.3	0.0	109.8
26-30	0.0	0.0	4.2	0.0	109.3	0.0	113.5
30 -	0.0	0.0	4.8	4.2	81.7	0.0	90.7
Upland rice	29.2	53.6	10.1	38.5	11.5	29.8	172.7

Conversion of natural vegetative land cover, e.g., scrubland and natural forest, to highly profitable and intensified farm types such as smallholder oil palm plantations is seen by local farmers as a viable livelihood option. However, as a consequence of conversion and intensification activities, environmental services are at stake, e.g., biodiversity, agronomic sustainability such as soil fertility, and watershed protection. A detailed bio-physical description of the study site and its land uses is presented in Chapter 5.

3.1.1 Land tenure and inheritance

In Jambi province and some parts of Sumatra, people follow the traditional practice of a joint-family or lineage ownership of land wherein a matrilineal inheritance system is applied to rice fields and a patrilineal inheritance system to rubber fields. For example, when a woman dies, land is bequeathed to her sisters, nieces and daughters in accordance with the decision of the lineage head. The basic principle of land allocation in the area is to maintain equity among lineage members.

Suyanto et al. (2001) extensively documented the land tenure system and smallholder rubber production in customary land areas in Sumatra. The study reveals that rice fields are dominated by a communal or lineage type of ownership while rubber fields are under individualized or single-family ownership. Accordingly, the tree planting has promoted the conversion from lineage ownership to joint family ownership (in which usufruct rights are weak) to single-family ownership (in which farmers usually possess rights to rent out and sometimes to pawn without obtaining permission from the head of extended family). In other words, tree planting (i.e., rubber) helps to acquire rights.

3.2 Methodology

3.2.1 Categorization of household agent

Household classification

The household classes in the study site were categorized using the livelihood framework. This is a theoretical framework that includes five core capitals or assets, namely financial, human, natural, physical, and social capitals (Ellis 2000). Siegel (2005) considered household capitals as ‘drivers’ of sustainable growth and poverty reduction. Accordingly, these capitals include the productive, social and locational assets that determine the set of options for livelihood strategies (i.e., the household’s revealed behavior). The advantage of this theoretical framework for generating indicators for livelihood strategies is that it avoids bias when selecting indicators (Campbell et al. 2001; Le 2005).

A total of 30 variables representing the different capitals of the livelihood framework were captured the field study. Among the variables selected for each capital, the following are supported by literature:

1. Human capital: age, education level, labor availability, and dependency ratio (Tomich et al. 1998a; Suyanto et al. 2001; Joshi et al. 2003).
2. Social capital: ethnicity, and group membership (Vosti et al. 1998).
3. Natural capital: managed land area, rubber agroforests, rice fields, total land holdings per capita (Miyamoto 2006).
4. Financial capital: annual gross income, annual gross income per capita, % income from rice, % income from rubber (Tomich et al. 1998).
5. Physical capital: house distance to main road (Miyamoto 2006).

Statistical analyses for household agent groups

Principal Component Analysis (PCA) for statistical description of households

PCA is used to extract the underlying factors from a large set of variables. From the data gathered, a total of 30 variables were identified to describe the household characteristics in the study site. To reduce them to key variables representing the household livelihood pattern in the study area, a PCA was run to condense information from a large number of original variables into new composite components with minimal loss of information. The principal components or factors reflect the common variance of variables, plus unique variance. Each derived principal component interprets the original variables with higher weights or loadings. The first principal component (PC1) gets the greatest variation and has the highest loadings, followed by the next components (i.e., PC2, PC3...etc.) with a decreasing degree of variations or loadings. The PCA was done following the Varimax rotation and Kaiser Normalization methods (i.e., Kaiser Criterion), which drop all components with *eigenvalues* under 1.0.

K-Mean clustering analysis (KCA) using PCA scores

The standardized component scores derived from the PCA were used to run *K*-Mean cluster analyses (KCA) to obtain the typical household agent groups. KCA is a clustering method that aims to partition *n* observations into *k* clusters in which each observation belongs to the cluster with the nearest mean. It works in an iterative process that continues until the sum of squares from points to the assigned cluster centers is minimized. The number of *k* is based on repeated exploratory use of K-means clustering (i.e., *k* = from 2 to 10).

3.2.2 Household agents' behavior estimation regarding land-use choices

Multi-nomial logistic regression for land-use choices

The multi-nomial logistic model (or M-logit regression) is employed to identify determinants of land-use choices by household agent groups (Le 2005). The model is based on the random utility model, and its algebraic manipulation of the equation renders the following functional form:

$$P(y_i = k) = \frac{\exp(X_i \beta_k)}{1 + \sum_{j=1}^{J} \exp(X_i \beta_j)} \tag{3.1}$$

where dependent variable categories k= 1, 2,.. J, to predict the probability (P) of a land use to be chosen (y_i), as the observed outcome for the i-th observation on the dependent variable, X_i is a vector of the i-th observations of all explanatory variables, and (β_j) is a vector of all the regression coefficients in the j-th regression.

The coefficient vectors or parameters were estimated by the maximum likelihood method based on the plot-based dataset of each household agent group using the SPSS package version 16.

Specification of variables

Dependent variable

Land-use choice (P_{use}) by a farming household is the dependent variable of the M-logit model. The categories of choice are: upland rice, rubber agroforest, and other land uses (i.e., monoculture rubber and oil palm plantation). The descriptions of each land use/cover, spatial distribution and intensities of change are presented in Appendix 1.

Explanatory variables

For the land-use choice, farmers have independent variables (Table 3.3) that may influence their choice. These potential independent variables are grouped into three variables: 1) natural attributes, 2) neighborhood characteristics of land-use pattern .(Verburg et al. 2004), and 3) household/plot owner characteristics.

1. Variables of natural attributes

Water availability critically affects agricultural production (Le 2005). The wetness index (P_{wet}) is a terrain variable indicating the approximate spatial pattern of soil moisture content, which is crucial for crop production (ref. cited in Le 2005). Due to the distance of the villages to the town centre and the unpaved access road, the distance of farm plots is hypothesized to reduce their attractiveness for annual crops such as rice. Rubber agroforests are usually located farther from roads as observed in other countries (Fox et al. 1994).

2. Variables of neighborhood characteristics of land-use patterns

Neighborhood interactions between land-use types are one of the main driving factors in a large group of spatially explicit land-use change models (Verburg et al. 2004). These interactions are usually used in land-use change models for urban development through cellular automata (Junfeng 2003), and are now also being used in models for rural land development (White and Engelen 2000; Messina and Walsh 2001). However, this driving factor has never been explored in other land-use change models other than models using cellular automata (Ward et al. 2000; Soares-Filho et al. 2002; Yeh and Li 2002; Dendoncker et al. 2007; Hagoort et al. 2008; Hasbani 2008; van Vliet et al. 2009). In addition, spatial models applied today in agricultural and resource economics often assume that neighborhood conditions are fixed and thus impacts of a particular neighborhood would not alter the spatial environment for a given individual, an assumption that rarely holds in reality (Nolan et al. 2009).

Verburg et al. (2004) describe a method for analyzing neighborhood relations empirically based on land-use change pattern in which results can be incorporated as explanatory variables. Accordingly, neighborhood operations are used to compute a new value for every location as a function of its neighborhood in a raster-based geographic analysis. The enrichment factor (F) is the measure of the neighborhood of a location, which is defined by the occurrence of a land-use type in the neighborhood of a location relative to the occurrence of this land-use type in the study area (see Chapter 5, p.65).

3. Variables of household/plot owner characteristics

Labor shortage and financial capital investments are among the determinants for complex rubber agroforest in the province of Jambi (Suyanto et al. 2005; Wibawa et al. 2005). When labor and capital investments to hire labor are insufficient, household farmers only tap the rubber latex when labor is available e.g., household members have time. The system is thus less disturbed and through time, will become similar to a secondary forest.

The dependency ratio (i.e., number of dependents over number of workers per household) is considered significant in influencing the land-use choice. Households with a high dependency ratio normally have a more urgent need for food, thus preferring short-term crop production such as growing rice. A high dependency ratio favors upland rice rather than tree-based farming practices (Le 2005).

Age, farm income, farm size, and education are all factors that have been found to significantly influence farmers' choices (Fox et al. 1994; Traore et al. 1998; Neupane et al. 2002; Le 2005). Miyamoto (2006) analyzed the effect of the rubber farm size in Sumatra and found that a decrease in the area of rubber fields acquired through inter-generational transfer significantly accelerated the clearing of forest areas. This indicates that households receiving only a few rubber fields had to clear forest soon after marriage in order to acquire their own rubber fields, and this trend significantly correlated to age of household heads.

Table 3.3 Explanatory variables used for M-logit regression model for land use

Variable	Definition	Data source	Direct linked module
***Dependent variable*: Land-use choice by households**			
$P_{\_use}$	1for upland rice, 2 for rubber agroforest, and 3 for other land-use type	Field survey and observation	PATCH LANDSCAPE
Natural attributes of land plots			
$P_{\_wetness}$	Wetness index of plot	GIS-based calculation	PATCH-LANDSCAPE
$P_{\_distanceH}$	Distance from plot to owner's house (m)	GIS-based calculation	PATCH-LANDSCAPE
$P_{\_distanceC}$	Distance from plot to main village centre (m)	GIS-based calculation	PATCH-LANDSCAPE
Neighborhood characteristics of land use			
$P_{\_F2}$	Enrichment factor of rubber agroforest	Calculated using raster-based geographic analysis	PATCH-LANDSCAPE
$P_{\_F45}$	Enrichment factor of other land use	Calculated using raster-based geographic analysis	PATCH-LANDSCAPE

Table 3.3 continued

Variable	Definition	Data source	Direct linked module
$P_{\_F6}$	Enrichment factor of rice field	Calculated using raster-based geographic analysis	PATCH-LANDSCAPE
$P_{\_F8}$	Enrichment factor of settlement	Calculated using raster-based geographic analysis	PATCH-LANDSCAPE
Characteristics of plot owner			
$HH_{\_age}$	Age of household head	Field survey	HOUSEHOLD-POPULATION
$H_{\_depratio}$	Dependency ratio (No. of dependents/ No. of workers)	Calculated based on field survey	HOUSEHOLD-POPULATION
$H_{\_edu}$	Household education status (No. of school year)	Field survey	HOUSEHOLD-POPULATION
$H_{\_labor}$	Availability of household labor (number of workers)	Field survey	HOUSEHOLD-POPULATION
$H_{\_landp}$	Landholding per capita (ha /person)	Calculated based on field survey	HOUSEHOLD-POPULATION
$H_{\_gincpers}$	Annual gross income per capita of household (US$/person/year)	Calculated based on field survey	HOUSEHOLD-POPULATION
$H_{\_size}$	Size of household (person / household)	Field survey	HOUSEHOLD-POPULATION

3.2.3 Data sources

The socio-economic data for this analysis were derived from an extensive household survey conducted in the target villages between December 2009 and March 2010. A survey questionnaire was developed to describe the household characteristics and possessions, farm characteristics (i.e., biophysical, tenure, and temporal dynamics), farm operation and productivity, and access to conservation agreement policy (see Chapter 4). Also, additional questions were asked for each of the two following conditions: 1) for biodiversity conservation, and 2) for the next 5 to 10 years if supported by financial investments. A total of 95 household respondents (90 males and 5 females) were randomly selected and interviewed.

Plot-explicit data were collected through participatory mapping in March 2010. A farm-plot map was developed through images from Google Earth (2003) with a 700-m eye-view processed by PCI Geomatica (9.1) for image geo-referencing. The map gave a good visual representation of actual land cover in the area with roads and houses, which was useful to identify the farm plots of the villagers. A total of 291 farm plots managed by 95 surveyed households were identified and geo-referenced. Plot distances to farmers' houses, major roads and town centre were also derived from this map. The digital elevation map (DEM) with 30-m resolution generated from the World Agroforestry Centre (ICRAF) was processed through GIS software to derive wetness index, aspect and slope. Validated land-cover maps of 1993 and 2005 (30-m resolution) were prepared from Landsat TM, and Landsat ETM images (Ekadinata et al. 2010) in the Landscape Mosaic Project of ICRAF. The land-cover map of 2005 was processed using Netlogo to generate the enrichment factors of different land-use types (Verburg et al. 2004).

3.3 Results and discussion

3.3.1 Typological household agent groups

A total of 6 principal components were extracted by PCA. These components generated 84.8% of the total variance of original independent variables (Table 3.4). Specific components for categorizing the household agents were determined using the rotated component matrix (Table 3.5). Though it makes sense to focus only on the 3 top factors, since loadings and variances of the last 3 factors are not far from each other, all 6 principal components were used for the *Agent-Categorizer* sub-model (see Table 2.2) to better categorize and characterize the household agents.

The principal component 1 (PC1) is strongly related to land variables, thus it is named 'land factor' due to the variables it is composed of. These variables include total managed land $H_{\_manland}$ (loading b = 0.953), total land holdings $H_{\_holding}$ (loading b = 0.966), total land holdings per person $H_{\_holding/per}$ (loading b = 0.870), and total complex rubber agroforest area $H_{\_complex}$ (loading b = 0.765). This factor accounts for 23.2% of the total variance of the original dataset. Because $H_{\_holding/per}$ has a higher economic meaning than the other variables (Le 2005), this variable is the best representative of the land factor.

Table 3.4 Total variance explained by extracted components using Principal Component Analysis

Component	Initial Eigenvalues			Extraction sums of squared loadings			Rotation sums of squared loadings		
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	**3.500**	**25.003**	**25.003**	**3.500**	**25.003**	**25.003**	**3.248**	**23.202**	**23.202**
2	**2.533**	**18.091**	**43.094**	**2.533**	**18.091**	**43.094**	**2.141**	**15.290**	**38.492**
3	**2.443**	**17.449**	**60.543**	**2.443**	**17.449**	**60.543**	**1.990**	**14.217**	**52.709**
4	1.224	8.739	69.283	1.224	8.739	69.283	1.732	12.369	65.079
5	1.095	7.819	77.101	1.095	7.819	77.101	1.477	10.548	75.626
6	1.082	7.731	84.832	1.082	7.731	84.832	1.289	9.206	84.832
7	0.729	5.209	90.041						
8	0.457	3.264	93.305						
9	0.369	2.636	95.941						
10	0.339	2.424	98.364						
11	0.115	0.825	99.189						
12	0.073	0.523	99.712						
13	0.023	0.163	99.875						
14	0.017	0.125	100.00						

Table 3.5 Rotated component matrix (i.e., loadings) using Varimax with Kaiser Normalization method

Variable	Principal component					
	1 *Land factor 23.2%*	2 *Income factor 15.3%*	3 *Labor factor 14.2%*	4 *Dependency ratio 12.4%*	5 *Upland rice factor 10.2%*	6 *Education factor 9.2%*
Age of household head	.188	-.140	.239	**<u>.723</u>**	-.101	-.333
Education of household head	-.152	.148	-.073	-.026	-.018	**<u>.811</u>**
Labor availability	-.004	-.033	**<u>.833</u>**	.513	.031	-.028
Dependency ratio	-.020	-.037	-.036	**<u>-.942</u>**	-.052	-.120
Managed land	**.953**	-.022	.039	.043	.038	-.169
Total landholdings	**.966**	-.025	.038	.052	.018	-.177
Landholding per person	**<u>.870</u>**	-.018	-.304	.135	.075	-.130
Complex rubber area (ha)	**<u>.765</u>**	.018	.210	-.025	-.186	.350
Gross income	-.002	**.942**	.069	-.076	-.107	.054
Gross income per capita	-.043	**<u>.931</u>**	-.197	.003	-.076	.123
% income from rice	-.045	-.283	-.170	-.126	**<u>.651</u>**	.400
% income from rubber	.010	.497	.160	.034	**<u>-.635</u>**	-.081
Size of household	-.016	-.044	**.972**	-.014	-.031	-.099
Rice area	.037	.108	.225	.105	**<u>.758</u>**	-.335

Notes: Numbers in parenthesis are % of total variance of original variable set explained by the principal components. Bold numbers are high loadings indicating most important or original variables representing the principal components. Bold and underlined numbers indicate the variables selected for household categorization.

The PC2 is highly correlated to income variables. It is named ‘income factor’ due to the variables which it is composed of gross annual income of households $H_{\_grossinc}$ (loading b = 0.942) and gross annual income per capita $H_{\_gincpers}$ (loading b = 0.931). This factor accounts for 15.3% of the total variance of the original dataset. However, because the variable $H_{\_gincpers}$ has more economic meaning than the other income variable, this variable is the best representative for the income factor, and is used in the further analysis to characterize the economic status of the agents.

The labor factor represents the PC3. Variables composing of this factor include the size of the household members $H_{\_size}$ (loading b = 0.972) and labor availability $H_{\_labor}$ (loading b = 0.833). This factor accounts for 14.2% of the total variance of the original dataset. Because labor availability $H_{\_labor}$ has more economic meaning than household size, thus it is the best representative for this factor.

The PC4 is labeled as the ‘dependency ratio factor’ due to dependency ratio $H_{\_depratio}$ (loading b = -0.942) variable. This factor accounts for 12.4% of the total variance of the original dataset. The PC5 is labeled as the “upland rice factor” due to the weighted variables that correspond to rice. These variables include total rice area $H_{\_rice}$ (loading b = 0.758) and percent income from rice production $H_{\_RICEinc}$ (loading b = 0.651). This factor accounts for 10.2% of the total variance of the original dataset. The PC6 is strongly explained by the variable education of household $H_{\_edu}$ (loading b = 0.811), thus it is termed as the ‘education factor’ with 9.2% of the total variance of the original dataset. The K-cluster analysis was run using the standardized scores of the six principle components with k = 2 resulting in two household agent groups or types. Household type 1 has 33, and household type 2 has 62 household agents (Table 3.6).

The choice of k > 2 was not suitable due to the small number of surveyed samples. The descriptive statistics and ANOVA confirm the statistical difference in the key livelihood variables between these two household groups (Table 3.6).

Livelihood typologies of household agents

The PCA and K-CA results and the descriptive statistics led to identification of two household agent types or groups.

Household type 1: Rubber-rice farmers

The spider web diagrams (Figure 3.1 and 3.2) show that, based on the livelihood indicators, this household group consists of relatively well-off farmers owning larger areas of upland rice and houses that are near to roads (see also Table 3.6). This group constituted 35% of the sampled population.

Table 3.6 Descriptive statistics for key categorizing variables for each classified agent group

Variable	**Agent group**	**N**	**Mean**	**Std. deviation**	**Std. error**	**95% confidence interval for mean**		X_{min}	X_{max}
						Lower bound	**Upper bound**		
Education of household	1	33	1.1	0.7	0.1	0.8	1.3	0	2
	2	62	1.2	0.6	0.0	1.0	1.2	0	2
	Total	95	1.1	0.6	0.1	0.9	1.2	0	2
Labor availability	1	33	3.4	1.4	0.2	2.9	3.9	1	7
	2	62	3.3	1.6	0.2	2.8	3.7	1	8
	Total	95	3.4	1.6	0.2	3.0	3.6	1	8
Dependency ratio	1	33	0.24	0.31	0.05	0.12	0.35	0	1.0
	2	62	0.65	0.44	0.06	0.54	0.76	0	1.5
	Total	95	0.51	0.44	0.04	0.42	0.60	0	1.5
Landholding per person (ha/person)	1	33	1.74	2.00	0.340	1.02	2.44	0	11.12
	2	62	1.18	1.16	0.148	0.88	1.48	0	5.06
	Total	95	1.38	1.52	0.156	1.06	1.68	0	11.12
Rice area (ha/ household)	1	33	1.12	0.696	0.121	0.87	1.37	0	2
	2	62	0.50	0.449	0.057	0.38	0.61	0	2
	Total	95	0.71	0.621	0.064	0.59	0.84	0	2
Gross income per capita	1	33	1984	3	528.22	908	3060	32	11918
	2	62	628	671	85.21	458	798	0.51	3148
	Total	95	1098	2	201.26	699	1498	0.51	11918
% income from rice	1	33	56	41	7	41	70	0	99
	2	62	65	41	5	54	76	0	100
	Total	95	62	41	4	54	70	0	100

Note: *N = group size (i.e., number of households in each group);* X_{min} *= minimal value of the variable X;* X_{max}*= maximal value of variable X.*

Household type 2: Rubber-based farmers

This household type is composed of low income households (see Table 3.6) who are mainly engaged in tapping rubber farms and have only small areas of upland rice; and their houses are far from road (Figure 3.1 and 3.2). They have limited area for rice production with a high number of dependants. This group constituted 65% of the sampled population.

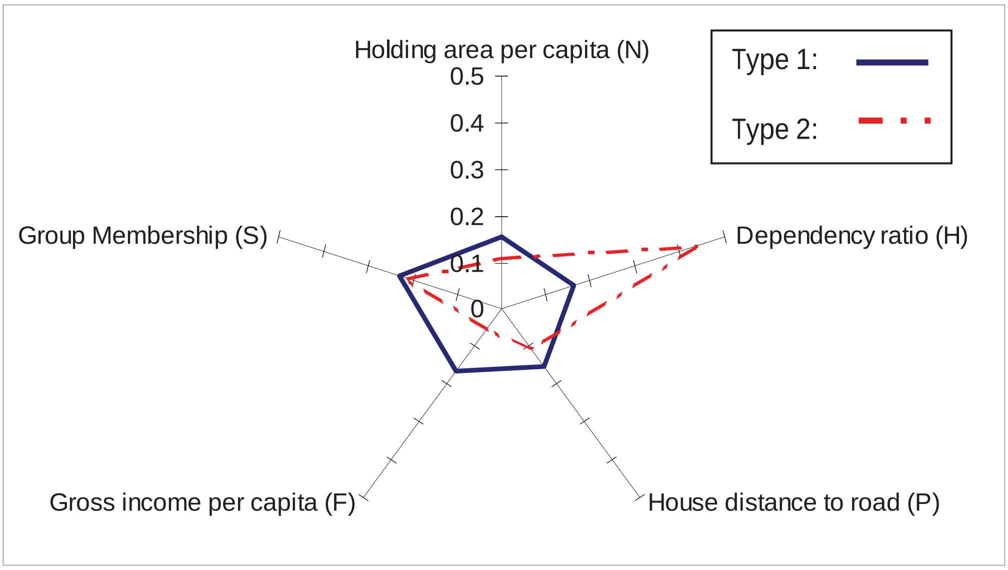

Figure 3.1 Variation between household type 1 and 2 in terms of land holdings per capita, dependency ratio, and gross income per capita. N= natural capital; H= human capital; P = physical capital; F = financial capital; S= social capital.

Note: all variables are normalized within the 0-1 range.

The spider web diagrams distinctly differentiate the groups in terms of income, dependency ratio and land factors. Furthermore, Figure 3.2 clearly presents the difference in terms of rice field area between household type 1 (blue line) and household type 2 (red line). Another difference was identified when the complex rubber agroforest area was plotted (Figure 3.3). The plot shows that household type 2 has less rubber agroforest compared to household type 1. Thus, the results suggest that household type 2 has more diversified livelihood sources.

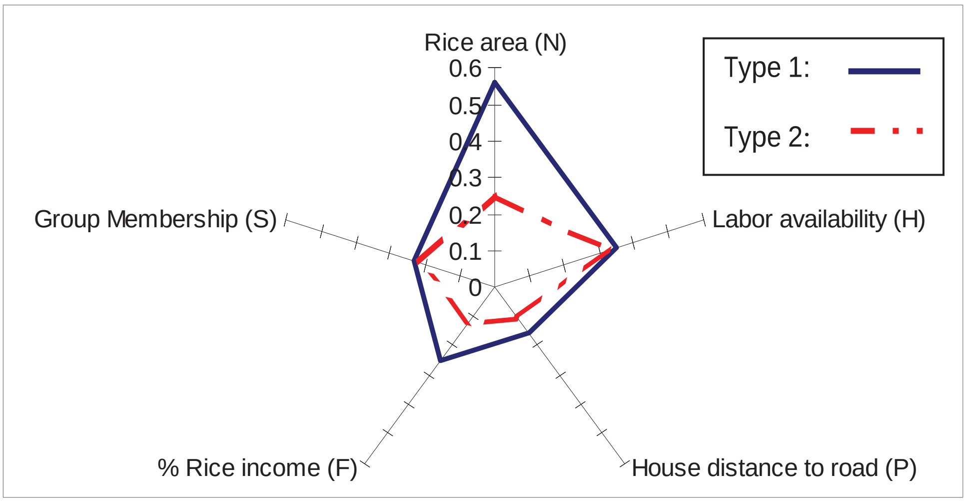

Figure 3.2 Variation between household type 1 and 2 in terms of total rice area, % rice income and road access from house. N= natural capital; H= human capital; P = physical capital; F = financial capital; S= social capital.

Note: all variables are normalized within the 0-1 range.

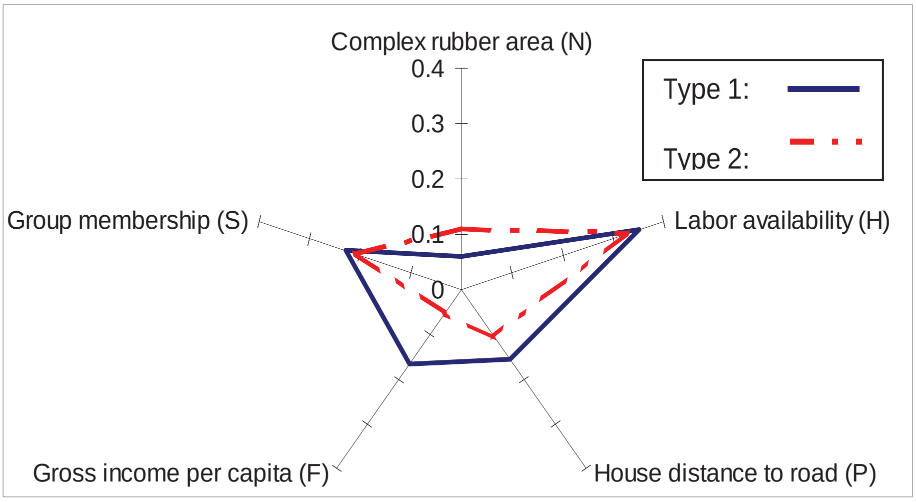

Figure 3.3 Variation between household type 1 and 2 in terms of total complex rubber area, gross income per capital and road access from house. N= natural capital; H= human capital; P = physical capital; F = financial capital; S= social capital.

Note: all variables are normalized within the 0-1 range.

Income composition

A difference in the household agent types was also revealed in income composition (Figure 3.4). Income from upland rice farming of household type 1 is double that of household type 2. On the other hand, income from rubber is 9% higher in household type 2 compared to household type 1; this is attributed to the size of the complex rubber agroforest areas (Figure 3.3).

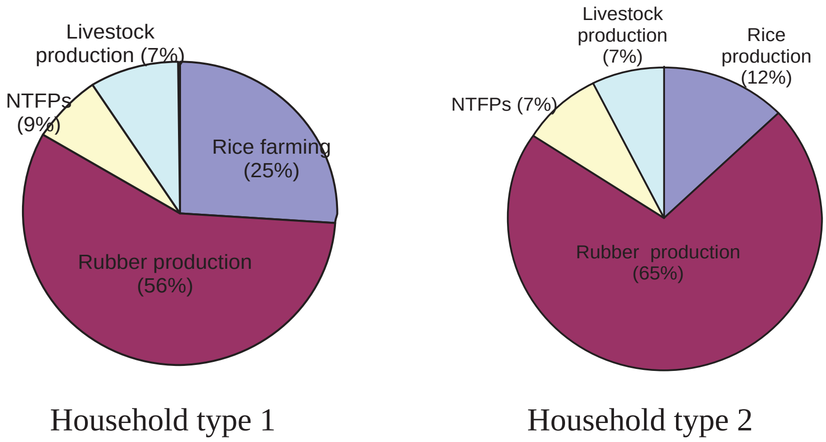

Figure 3.4 Income composition of household types. NTFP = non-timber forest products.

3.3.2 Modeling land-use choices for household agents

Factors affecting land-use choices of "rubber-rice farmers" (household type 1)

Chi-square tests show that the empirical M-logit model is highly significant ($p<0.003$) in explaining the land-use choice of rubber-rice farmers (Table 3.7). The Nagelkerke's pseudo-R^2 is 0.809, which indicate that 81% of the total variation in the probability of land-use choice is explained by the selected explanatory variables. A total of 9 explanatory variables were found to be significant, of which 4 variables correspond to human capital, 2 variables to enrichment factor of land use, and one variable each to policy and environmental attributes. The model has a good overall predictive power of 84.4% and correct predictions for rubber agroforest, upland rice and other land use of 84.6%, 85.6% and 80.0%, respectively.

Regarding the choice of rubber agroforests, only one variable, i.e., $P_{\_F8}$ (-), was found to be significant due to the small sample size of the plots (i.e., 32 plots) of household type 1. This indicates that the probability to choose rubber agroforest decreases as the household head becomes older. The possible effect of the variable $H_{\_ACT}$ is also worth considering as the more a household engages in rubber agroforestry, the less likely it is to support the conservation agreement policy.

With regard to the choice of upland rice, variables significantly influencing the decisions of household agents include $H_{\_age}$ (-), $H_{\_edu}$ (-), $H_{\_depratio}$ (-), $H_{\_gincpers}$ (-), $P_{\_wet}$ (+), $P_{\_F8}$ (-), and $P_{\_F45}$ (-). These indicate that the probability that upland rice is chosen decreases as the farmer gets older.

Table 3.7 M-logit model estimation of land-use choices by rubber-rice farmers who have changed their land use between 1993 and 2005 (n = 32 plots).

Variable	**Definition**	**Rubber agroforest**	**Upland rice**
(constant)		20.576	85.809
		(14.711)	(41.529)**
Human capital			
$H_{\_age}$	Household head age	-0.368	-0.928
		(0.213)*	(0.455)**
$H_{\_edu}$	Household head education	-1.660	-11.436
		(2.786)	(6.675)*
$H_{\_depend}$	Household dependency ratio	-11.169	-16.241
		(8.035)	(9.142)*
$H_{\_size}$	Household size	7.054	9.178
		(5.383)	(5.943)
Financial Capital			
$H_{\_incomep}$	Gross income per capita of household	0.000	-0.002
		(0.001)	(0.001)*
Conservation agreement policy			
$H_{\_ACT}$	Household activities supporting conservation agreement	-0.836	0.781
		(0.716)	(0.714)
Environmental plot attribute			
$P_{\_wetness}$	Plot wetness index	0.813	2.347
		(0.563)	(1.031)**
Neighborhood land use			
$P_{\_F8}$	Enrichment factor of settlement (land use of 2005), neighborhood radius = 270 m	-0.003	-0.006
		(0.003)	(0.004)*
$P_{\_F45}$	Enrichment factor of other land use (land use of 2005), neighborhood radius = 270 m	-0.018	-0.039
		(0.13)	(0.019)**

Fitness and accuracy of the model:
Likelihood ratio test (chi-square statistics): 38.894** $df = 18$ $p = 0.003$
Pseudo-R^2 = 0.809 (Nagelkerke); 0.703 (Cox and Snell); 0.597 (McFadden)

Percentage correct predictions:	Rubber agroforest:	84.6%
	Upland rice:	85.6%
	Others:	80.0%
	Overall percentage:	**84.4%**

Notes: *Numbers in parenthesis are standard errors of estimated preference parameters. ***, **, and * indicate statistical significance at the 0.01, 0.05 and 0.1 level, respectively. Other land uses (e.g., oil palm and rubber monoculture plantation) was selected as the base case for comparison.*

The same trend applies to the number of years of education, which indicates that the higher the number of years of education of the household head, the less likely it is that upland rice will be chosen. The probability of selecting rubber agroforest increases as the dependency ratio of the household decreases. Plots of upland rice are likely located in areas where the wetness index is high and that are relatively far from settlement areas and other land-use type such as oil palm plantations. Also, the probability of selecting upland rice increases when the household gross income per capita decreases. This suggests that rice production is an alternative if the price of rubber latex is not doing well.

Based on these explanatory variables (if all are at their mean value), the probability of the households to choose upland rice is 66% against rubber agroforest, which is 33% (Table 3.8).

Table 3.8 Probabilities of land-use choices of rubber-rice farmers

Land-use type	Probability	95% Confidence interval*	
Rubber agroforest	0.3349	-0.1213	0.7911
Monoculture (rubber or oil palm)	0.0051	-0.0214	0.0316
Upland rice	0.6600	0.1973	1.1226

*Note: * Confidence interval is automatically calculated by STATA software using delta method.*

Factors affecting land-use choices of “rubber-basedfarmers” (household type 2)

Chi-square tests show that the empirical M-logit model is highly significant ($p<0.000$) in explaining the land-use choice by the farmers of this group (Table 3.9). The Nagelkerke’s pseudo-R^2 is 0.779, which indicates that 78% of the total variation in the probability of land-use choice is explained by the selected explanatory variables. Sixteen (16) explanatory variables were found to be significant, of which 4 correspond to human capital and to the enrichment factor of land use, 3 variables to both policy and environmental plot attributes, and one variable each to social and financial capital. The model has a good overall predictive power of 85.1% and correct predictions for rubber agroforest, upland rice and other land use of 93.8%, 84.6% and 53.8%, respectively.

Variables that significantly influence the decision to select rubber agroforest include $H_{\_age}$ (-), $H_{\_depratio}$ (-), $H_{\_edu}$ (-), $P_{\_wet}$ (+), $P_{\_F25}$ (+), $P_{\_F45}$ (+), $P_{\_F6}$ (+), and $P_{\_F8}$ (+). Age of household head of this household type is an important factor influencing this choice. This indicates that younger household heads tend to choose rubber agroforest since it requires more strenuous activities. With regard to dependency ratio and education, the higher the dependency ratio of the household and the higher the number of years the household head was at school, the less likely it is that rubber agroforest is selected. Rubber agroforest is selected in areas where the wetness index is high.

The use of neighborhood interactions in this kind of study is relatively new. Though all the enrichment factors of four land-use types (i.e., rubber agroforest, rice field, settlement and other) as explanatory variables are positively significant, their effect and possible changes are affected by factors such as policy, land-use pressure and temporal stability (Verburg et al. 2004). In this study, the probability of choosing rubber agroforest increases as the enrichment factor of land-use type increases.

Table 3.9 M-logit model estimation of land-use choices by rubber-based farmers who have changed their land use between 1993 and 2005 (n= 74 plots)

Variable	**Definition**	**Rubber agroforest**	**Upland rice**
(constant)		36.568	-271.544
		(19.945)*	(168.928)
Human Capital			
$H_{\_age}$	Age of household head	-0.546	-0.370
		(0.271)**	(0.343)
$H_{\_size}$	Household size	1.960	4.527
		(1.350)	(2.305)**
$H_{\_depend}$	Household dependency ratio	-7.609	8.968
		(3.660)**	(8.992)
$H_{\_edu}$	Education of household head	-4.134	8.498
		(2.354)*	(6.448)
Social Capital			
$H_{\_mem}$	Household number of memberships	2.262	10.771
		(1.666)	(5.098)**
Financial Capital			
$H_{\_incomep}$	Gross income per capita of household	-0.001	-0.003
		(0.001)	(0.002)
Conservation agreement policy			
$H_{\_ACT}$	Household activities in regards to conservation agreement	-0.469	2.029
		(0.331)	(1.182)*
$H_{\_CA}$	Household participation in conservation agreement	-2.592	-12.295
		(2.399)	(7.226)*
$H_{\_ACT\_size}$	Household activities in support to conservation agreement per household size	3.535	-9.539
		(4.356)	(7.150)

Table 3.9 continued

Variable	Definition	Rubber agroforest	Upland rice
Environmental plot attributes			
$P_{\_wetness}$	Plot wetness index	1.009 (0.487)**	4.281 (1.960)**
$P_{\_dtown}$	Plot distance to town centre (m)	-2.884 (1.822)	-1.325 (3.230)*
$P_{\_droad}$	Plot distance to road (m)	2.621 (1.765)	-29.052 (17.427)*
Neighborhood land use			
$P_{\_F2}$	Enrichment factor of rubber agroforest (land use of 2005), neighborhood radius = 270 m	0.017 (0.008)**	0.198 (0.101)**
$P_{\_F45}$	Enrichment factor of others (land use of 2005), neighborhood radius = 270 m	0.025 (0.013)*	0.365 (0.189)*
$P_{\_F6}$	Enrichment factor of rice field (land use of 2005), neighborhood radius = 270 m	0.001 (0.001)*	0.019 (0.010)*
$P_{\_F8}$	Enrichment factor of settlement (land use of 2005), neighborhood radius = 270 m	0.009 (0.004)**	0.096 (0.049)**

Fitness and accuracy of the model:
Likelihood ratio test (chi-square statistics): 77.337*** df = 32 p = 0.000
Pseudo-R^2 = 0.779 (Nagelkerke); 0.648 (Cox and Snell); 0.586 (McFadden)

Percentage correct predictions:		
	Rubber agroforest:	93.8%
	Upland rice:	84.6%
	Others:	53.8%
	Overall percentage:	**85.1%**

Notes: *Numbers in parenthesis are standard errors of estimated preference parameters. ***, **, and * indicate statistical significance at the 0.01, 0.05 and 0.1 level, respectively. Other land uses (e.g., oil palm and rubber monoculture plantation) was selected as the base case for comparison.*

For upland rice, variables that significant affect the decisions of household agents are $H_{\_size}$ (+), $H_{\_mem}$ (+), $H_{\_ACT}$ (+), $H_{\_CA}$ (-), $P_{\_wetness}$ (+), $P_{\_droad}$ (-), $P_{\_dtown}$ (-), $P_{\_F2}$ (+), $P_{\_F45}$ (+), $P_{\_F6}$ (+), and $P_{\_F8}$ (+). Household size is an important factor, since upland rice requires a larger labor (Suyanto et al., 2001), particularly women. The number of group memberships also positively significantly affects the household decision; households that have more group memberships e.g., farmers' cooperatives, show a higher probability to select upland rice. The same trend was observed in terms of household involvement or participation in the conservation agreement policy, where it was observed that the more conservation activities the household is involved in, the more likely it is that upland rice will be selected.

Regarding farm plot distance, the probability to choose upland rice decreases as the distance of the farm plots from the house and town centre increases. Plots of upland rice are also located in areas where the wetness index is high.

In terms of enrichment factor of land-use types, Verburg et al. (2004) pointed out that neighborhood relation is most pronounced for the immediate neighbors. With this, the decision of household agents for a certain land use may be affected by the most pronounced land-use type in the nearest neighborhood. However, the decision of the household will also be affected by the interactions of other variables, e.g., conservation agreement policy.

Based on these explanatory variables (if all are at their mean value), the probability of the households to choose rubber agroforest is 99% (Table 3.10).

Table 3.10 Probabilities of land-use choices of rubber-based farmer

Land-use type	Probability	95% Confidence interval	
Rubber agroforest	0.9938	-0.0000	0.0000
Monoculture (rubber or oil palm)	0.0062	0.9724	1.0153
Upland rice	0.0000	-0.0153	0.0276

3.3.3 Modeling preferred future land use under certain condition (for process-based decison making)[2]

In this section, decisions of household farmers were explored under the condition of "*if supported by financial investment in the next 5 to 10 years*." Only two land-use choices, i.e., rubber agroforest and monoculture rubber or oil palm plantations were frequently mentioned during the survey (see section 3.2.3) since the majority of the interviewed household heads were males. Because of cultural traditions in the study area, mainly one decision maker had to be interviewed. The problem thus arises whether there is a gap between the expressed decision and the implementation of the expressed decision. The expressed intention could be just wishful thinking, anticipated agreement with the other partner or a decision that will be implemented without further consulting. In the given cultural environment, we could assume the latter two cases. The following sub-

[2] This sub-section was added as a result of the initial simulation and to strengthen the prospective element of the process-based decision making sub-model (see Chapter 6).

sections identify the factors affecting the decisions of household agents according to household types.

Factors affecting preferred land uses of household type 1 (rubber-rice farmers)

Chi-square tests show that the empirical Bi-logit model is highly significant ($p < 0.003$) in fitting the preferred land-use of rubber-rice farmers type (Table 3.11). A total of seven explanatory variables were identified. Based on these explanatory variables (if all are at their mean value), the probability of the households to choose rubber agroforest or monoculture plantations is summarized in Table 3.12.

Table 3.11 Explanatory variables used for Bi-logit regression model for land use of (household type 1 - rubber-rice farmers)

Variable	**Definition**	**Rubber agroforest**
(constant)		-41.58 (38.63)
Household characteristics		
$H_{\_age}$	Household head age	-0.71 (0.47)
$H_{\_edu}$	Household head education	-24.96 (15.97)
$H_{\_incomep}$	Household gross income per person	-0.001 (0.0008)
Conservation agreement policy		
$H_{\_ACT}$	Household activities supporting conservation agreement	-1.199 (0.74)
Environmental plot attributes		
$P_{\_dtown}$	Plot distance to town center (m)	15.25 (10.84)
$P_{\_dhouse}$	Plot distance to house (m)	-15.29 (11.07)
Neighborhood land use		
$P_{\_F45}$	Enrichment factor of others (land use of 2005), neighborhood radius = 270 m	-0.014 (0.0089)

Fitness and accuracy of the model:
Likelihood ratio test (chi-square statistics): -8.13*** $df = 7$ $p = 0.0003$
Pseudo-R^2 = 0.78 (Nagelkerke); 0.58 (Cox and Snell); 0.62 (McFadden)

Percentage correct predictions:	Rubber agroforest:	88.9%
(Cut point 50%)	Others:	85.7%
	Overall percentage:	**87.5%**

*Notes: Numbers in parenthesis are standard errors of estimated preference parameters. ***, **, and * indicate statistical significance at the 0.01, 0.05 and 0.1 level, respectively. Other land uses (e.g., oil palm and rubber monoculture plantation) was selected as the base case for comparison.*

Table 3.12 Probabilities of preferred land use of household type 1 (rubber-rice farmers)

Land-use type	Probability	95% Confidence interval*	
Rubber agroforest	0.8665	0.5329	1.2002
Monoculture (rubber or oil palm)	0.1335	-0.2002	0.4671

Note: **Confidence interval is automatically calculated by STATA software using delta method.*

Table 3.13 Explanatory variables used for Bi-logit regression model for land use of rubber –based farmers

Variable	Definition	Rubber agroforest
(constant)		4.14 (1.72)**
Household characteristics		
$H_{\_age}$	Household head age	-0.73 (0.03)*
$H_{\_edu}$	Household head education	-1.12 (0.60)*
$H_{\_landholdings}$	Household landholdings per person	-0.67 (0.28)**
Conservation agreement policy		
$H_{\_ACT}$	Household activities supporting conservation agreement	0.17 (0.066)**
Neighborhood land use		
$P_{\_F45}$	Enrichment factor of others (land use of 2005), neighborhood radius = 270 m	-0.002 (0.001)**

Fitness and accuracy of the model:
Likelihood ratio test (chi-square statistics): -38.0447** $df = 5$ $p = 0.003$
Pseudo-R^2 = 0.29 (Nagelkerke); 0.26 (Cox and Snell); 0.18(McFadden)

Percentage correct predictions:	Rubber agroforest:	60.0%
(Cut point 50%)	Others:	82.1%
	Overall percentage:	**71.6%**

Notes: *Numbers in parenthesis are standard errors of estimated preference parameters. ***, **, and * indicate statistical significance at the 0.01, 0.05 and 0.1 level, respectively. Other land uses (e.g., oil palm and rubber monoculture plantation) was selected as the base case for comparison.*

Table 3.14 Probabilities of preferred land use of rubber –based farmers

Land-use type	Probability	95% Confidence interval*	
Rubber agroforest	0.4748	0.3382	0.6114
Monoculture (rubber or oil palm)	0.5252	0.3886	0.6618

Note: **Confidence interval is automatically calculated by STATA software using delta method.*

Factors affecting preferred land uses of household type 2 (rubber-based farmers)

Chi-square tests show that the empirical Bi-logit model is highly significant ($p < 0.003$) in fitting the preferred land-use of rubber-based farmers (Table 3.13). A total of five significant explanatory variables was identified.

The probability of the type 2 households to choose rubber agroforest or monoculture plantations is summarized in Table 3.14. The results of the probabilities of the two household types under the condition of financial investments suggests that type 1 agents, which are described as better-off households compared to type 2 households (see Section 3.3.1) are 87% (Table 3.12) likely to stay with rubber agroforest. On the other hand, type 2 households take slightly more risks regarding more profitable land-use practices (e.g., monoculture plantations with 52% probability) (Table 3.14). In both cases, rice paddies were not preferred. The probable reason is that the survey was mainly done with male household heads. These are largely responsible for rubber and oil palm productions, whereas females are solely responsible for rice production. This mainly gender-specific aspect is a known confounder in this modeling that one could adjust.

3.4 Conclusions

The heterogeneity through categorization (Brown and Robinson 2006) is presented in this part of the study. The results of the PCA and KCA reveal the household typologies in the study area, namely (1) rubber-rice farmers (household type 1) and (2) rubber-based farmers (household type 2). In other research in land-use decision making, the conventional way has been to aggregate the household agents. However, in this study, the disaggregation (or heterogeneity) of the household agents is justified due to the differences in the factors such as land (i.e., rubber agroforest area vs. rice field area), income composition, labor pool, etc., which were generated by PCA.

Most of the factors affecting land-use choice are combinations of human, financial, social and natural capital and the impact of policy that affects the households' activities, i.e., conservation agreement. Highly significant new variables were found to influence the household agents' decision making that had not yet been considered in other MAS models, i.e., enrichment factor of land-use types. The coefficients generated for each household agent are incorporated in the LB-LUDAS model for the land-use decision making under the baseline scenario. However, the preferred land use of household agents if supported by financial investment was modeled for the agents' process-based decision making. The application of this as a new layer of the agents' decision making is an adjustment to address the cause-effect relationship mechanism and unknown confounder (in this case is the decision-making process, see Chapter 6). Also, it is noteworthy to consider this aspect, since the probability of choosing certain land uses changes significantly according to a given situation or condition.

4 NATIONAL AND LOCAL PAYMENTS/ REWARDS FOR ENVIRONMENTAL SERVICES (P/RES) SCHEMES IN RUBBER AGROFORESTS CONSERVATION

Land-use and land-cover change is one of the most important anthropogenic causes of agro-biodiversity loss (MA 2005b). Agro-biodiversity by definition is essentially the biodiversity present in and supported by agricultural landscapes (Kuncoro et al. 2006), and has been selected and modified by thousands of years of human utilization to better serve human needs (Wood 1993). Agro-biodiversity is crucial, since it is the source of many agro-ecosystem benefits and services that are of local and global value (e.g., food production and security, non-timber forest products and medicinal plant sources). However, it is threatened because most commercial production focuses on a few major crops (e.g., oil palm and other monoculture plantations) to meet the demand of the increasing market (Thies 2000). The use of economic incentives such as Payments/rewards for Environmental Services (P/RES)[3] is becoming increasingly accepted for conserving agro-biodiversity (Bennett and Balvanera 2007). In Indonesia, where rubber agroforest areas are considered to support agro-biodiversity (Kuncoro et al. 2006), it is threatened by expansion of monoculture tree plantations, e.g., oil palm, and incentives to prevent the conversion are seen as an urgent need (Ekadinata et al. 2010). Pascual and Perrings (2007) perceive the agro-biodiversity change in the landscape as an investment/disinvestment decision made in the context of a certain set of preferences, value systems, moral structures, endowments, information technological possibilities, and social, cultural and institutional conditions.

In this part of the study, the aim is to 1) identify different factors influencing the adoption of the households to two P/RES schemes for conserving rubber agroforests in Jambi province, and 2) determine the possible effect of the identified factors which will be incorporated in the decision-making sub-model of LB-LUDAS model for the possible land-use change and ecosystem trade-offs. For qualitative analysis of the households' behavior and perceptions under these schemes (using a role playing game), see Villamor and van Noorwijk (2011).

[3] In this chapter, P/RES refers to the ICRAF project on rewarding environmental services. Here, environmental services and ecosystem services are synonyms, though some literature differentiates the two based on the inclusion or exclusion of provisioning services (Swallow et al. 2009; Leimona 2011).

4.1 Ecosystem services provided by rubber agroforests

Rubber agroforest, also known as 'jungle rubber' (Gouyon et al. 1993, Williams et al. 2001), is the dominant land use in Bungo District, Jambi Province, Indonesia (see Chapter 3). It is a traditional multi-strata agroforestry system in Indonesia that extends over an area of more than 2.6 million ha mostly in the forest margins of Sumatra and Kalimantan (Williams et al. 2001). This land use is the major rural livelihood of the people living there. The farming system practiced since 1904 allows natural vegetation to grow amongst the rubber trees. Farmers selectively nurture some economically valuable plants to create a mix of food, medicine, timber and fiber producing trees (Leimona and Joshi 2010).

Laumonier (1997) recognized rubber agroforest as an important agro-ecosystem type in the island of Sumatra. With about 60-80% of the total plant species found in neighboring primary forests (Beukema et al. 2007), this rubber agroforest is the most forest-like form of agroforestry (Long and Nair 1999). Thus, rubber agroforest is an important refuge for forest biodiversity in the lowland (Tata et al. 2008) and has a high biodiversity value including Red List and threatened species (Griffith 2000; Schroth et al. 2004; Rasnovi 2006; Beukema et al. 2007). Moreover, rubber agroforest provides ecosystem services such as soil conservation, protection of water quality, carbon sequestration and landscape beauty (Joshi et al. 2003; Suyanto et al. 2005). For example, the woody biomass in a typical old rubber agroforests could hold carbon stocks of more than 20 Mg C ha^{-1} above the time averaged value of rotational agroforests (Tomich et al. 2004).

In contrast to the positive ecological benefits, the latex productivity of rubber agroforest is very low. Joshi et al. (2006) compared the yield productivity of complex rubber agroforest to rubber monoculture, which is 400 to 600kg of dry rubber ha^{-1} $year^{-1}$ and 1000 to 1800kg $ha^{-1}year^{-1}$, respectively. However, farmers benefit annually from other resources in the rubber agroforest such as food, fruits (e.g., durian, mangosteen, coffee, etc.), fodder, fuel wood and timber (Gouyon et al. 1993; Michon 2005).

4.1.1 Conservation agreements (CAs): initial effort to establish reward schemes

The development of a reward scheme for biodiversity conservation was conducted through an action research under Phase 1 project of the Rewarding Upland Poor for

Environmental Services (RUPES) operating since 2002. The target of the action research was to identify the environmental services, to determine how they can be measured, who the rewards should go to, who is to pay the rewards, how and in what form could they be collected, and what amount or form would be appropriate.

The conservation agreements were the result of a long process of discussion and exploration with the villagers in four villages in Jambi province, namely: Lubuk Beringin, Sungai Mengkuang sub-village, Sangi sub-village, and Letung sub-village. The aim was to develop and test schemes for agro-biodiversity conservation appropriate for rubber agroforests. As a village-level policy, the conservation agreements were created and signed in 2007 by the villagers, with the following foreseen activities:

1. Provision of high yielding (cloned) rubber seedlings to be integrated in the farms;
2. Establishment of communal jungle rubber;
3. Support of *Hutan desa* (or village forest):
4. Installation of improvised mini-hydro power generators that provide electricity to the villagers; and
5. Establishment of mini-reservoirs in the river that produce fish stocks for food consumption.

Support funding was provided by the RUPES Program to the communities as fulfillment of the RUPES goals to preserve the biodiversity-rich jungle rubber ecosystem taking into consideration the economic needs of the community. The agreements include the farmers' biodiversity-conserving rubber agroforest practices, the way in which the communities will manage their rewards and how they will monitor the agreements.

Through the technical assistance of RUPES and based on the performance of the households in meeting the above-mentioned agreements, the villages will negotiate and build their case for rubber latex eco-certification and reduce emissions from deforestation and degradation (REDD) schemes as presented in the following sub-section. These market-based incentive schemes seem to be the only way to save the remnants of jungle forest and prevent it from being converted to rubber monoculture and oil palm plantations (Feintrenie and Levang 2009).

4.1.2 REDD as a national P/RES scheme

Indonesia is not only the leader in terrestrial carbon emissions (Ekadinata et al. 2010), it is also a leader in its commitment to Nationally Appropriate Mitigation Action (NAMA) as a basis for building global trust and achieving global cooperation to manage climate change. The *Hutan desa* (village forest) agreement in Indonesia was facilitated by expectations of REDD benefits flowing to government agencies (Akiefnawati et al. 2010). The first village forest in Indonesia was Lubuk Beringin village with an area of 2,300 ha, which consists of watershed protection forest and production forest where no concession rights exist. Under the Ministry of Forestry regulation #P.49/Menhut-II/2008, management of the village forest will be given to the local village organization. It entails the development of village forest plans, and management and allocation of benefits derived from the forests. A village rule guides the villagers on how to manage the water and utilize both timber and non-timber products. Under the rule, villagers are not allowed to clear cut the forests. The designated village forest has to be administratively part of the village; the right to manage is valid for 35 years and is renewable for another 35 years subject to approval of the work plans.

Hutan desa is one of the areas identified by the Indonesian government that qualifies for REDD+ schemes (for further relevance of *Hutan desa* to the international REDD debate see Akiefnawati et al. 2010). Indonesian REDD policy intervention strategies that could be applied to *Hutan desa* are (1) development of more effective protected conservation and management areas, and (2) development of more effective management of production forests. The Ministry of Forest regulation on REDD (PERMENHUT No. P30/2009) provides the guidelines for qualified areas that include establishment of reference emission levels (REL), monitoring and reporting to national and sub-national designating authorities, verification and certification, among others. It is expected that the REDD schemes will be implemented in 2012. External agents such as ICRAF and NGOs (e.g., WARSI) are helping the Lubuk Beringin village forest organization to meet the requirements. Once compliance with all requirements has been achieved, the proposed revenue-sharing appropriate for *Hutan desa* is 20% for the government, 50% for the community and 30% for the developer (www.dephut.go.id). A discussion about the forest definition in Indonesia is now on-going to allow the rubber agroforest to be included as a land use in the REDD+ scheme.

4.1.3 Rubber eco-certification/labeling as local P/RES scheme

Studies on rubber agroforests in Jambi Province have claimed that the physiognomy and functioning of the rubber agroforests are close to those of the natural forest ecosystems (Michon and de Foresta 1994; van Noordwijk 2002a). Although most of the complex rubber agroforests have disappeared in Malaysia and Thailand, around 2 million ha of rubber agroforests are still thriving in Indonesia (Gouyon 2003; Akiefnawati et al. 2011). If left neglected, they will soon be converted to agriculture and industrial plantations. And since very little primary forest is left in the country, maintaining these forests is the only option to support the high forest diversity in the area. In the absence of specific incentives, there is no reason why smallholders should agree to forego the benefits of more profitable land uses for the sake of biodiversity conservation.

Eco-certification or eco-labeling of rubber agroforest has been explored by ICRAF for the past decade as a mechanism for conserving biodiversity habitats and furthering economic development in rubber-growing areas. This kind of scheme guarantees that the production practices used to generate a product meet a set of eco-standards or that the raw materials of the product are produced in bio-diverse systems, and verifies that producers have used management practices that conserve environmental services (Bennett 2008). Thus, selling eco-labeled rubber latex at a price higher (price premium) than the average (farm gate) price would increase the farmers' economic returns from rubber agroforests.

Though there is no market yet for certified rubber products, interest has been shown by a tire manufacturing company to develop a "green rubber tire", and negotiations are currently underway. Research has been conducted to establish indicators (Tata et al. 2006) that would be required by certification agencies such as the Forestry Stewardship Council (FSC) (see Chapter 7, p.117). About 30% of the natural rubber latex is used for tire making, and the production of natural rubber is mainly in Asia. Hence, there is a great potential to develop the market, as a great number of natural rubber consumers are still untapped (Gouyon, 2003). Based on the current negotiations with the tire manufacturer, clean and dry green rubber costs US$[4] 3kg^{-1} (Akiefnawati, pers.com.), which is twice the farm-gate price. A lot of research is currently being done, since the eco-certification of natural rubber latex is very promising (Akiefnawati et al. 2011). However, there are still constraints and bottlenecks that would affect the decisions of farmers to adopt the scheme. These are:

1. Compliance with the set certification standards could be difficult for the farmers;
2. To date, no factories are willing to receive eco-certified rubber;
3. Conflict with government policy that promotes oil palm companies (no government policy supports rubber agroforests conservation); and
4. The market for certified-rubber is still underdeveloped.

4.2 Methodology

4.2.1 Binary logistic regression model for P/RES adoption

Though there is limited literature on the adoption of P/RES schemes, the methodology for this research can be drawn from and supported by the previous literature on the economics of technology adoption and farm and forestry program participation (Neupane et al. 2002; Zbinden and Lee 2005; Knowler and Bradshaw 2007). The binary logistic (Bi-logit) regression analysis was used to model the decision of household agents to adopt or not to adopt P/RES schemes. The model is based on maximization of an underlying utility function, which is assumed to be consistent with individual household behavior (Zbinden and Lee 2005). The model characterizing P/RES adoption is specified as:

$$\log(\frac{P_i}{1-P_i}) = \beta_0 + \beta_1 x_i + \beta_2 X_2 + ... + \beta_k X_{ki} \quad (4.1)$$

where i denotes the i-th observation in the sample, P_i is the predicted probability of adoption, which is coded with 1 (willingness to adopt) or with 0 (not to adopt), $ß_ï$ is the intercept term, and $ß_1$, $ß_2$, ..., $ß_k$ are the coefficients associated with each explanatory variable X_1, X_2, ...X_k.

The coefficients in the logistic regression were estimated using the maximum likelihood estimation method using SPSS package version 16.

[4] 1 USD = 9,000.00 Rupiah (at the time of writing)

Specification of variables

Dependent variable

Willingness to adopt or not to adopt the P/RES scheme ($H_{\_policy}$) is the dependent variable for this Bi-logit model. The P/RES schemes in this study are the conservation agreements as pilot schemes for eco-certification and REDD. Based on the above theoretical framework, the farmer may choose options (i.e., to participate or not to participate) in the P/RES scheme if the highest utility is generated according to the available resources and the natural and institutional constraints.

Explanatory variables

The independent variables hypothesized to influence households' decisions are presented in Table 4.1 These variables can be grouped into farmers' and farm characteristics, farm operational income and information on or participation in conservation schemes. Farmers' characteristics such as age and educational status are often used, although the influence on the decision making of these variables differs from farmer to farmer. Younger farmers tend to be more explorative, while older ones tend to keep to their old ways (Wossink and van Wenum 2003). Other studies showed different effects (Vanslembrouck et al. 2002). Age and education were found to be positively significant in the willingness to engage in P/RES both in the upstream and downstream areas in Thailand (Neef 2010). Labor demand, availability and allocation are often found to be central in determining adoption and program participation decisions (Neupane et al. 2002). For example, agroforestry may be an attractive option in the long run when family labor is scarce (Zbinden and Lee 2005).

In other studies, farm-biophysical characteristics such as distance to road, area planted for rice or rubber or left fallow (often related to farm size) have been found to be important factors explaining farmers' environmental behavior (Kristensen et al. 2001; Knowler and Bradshaw 2007; Neef 2010). Farmers with large farms are more likely to be able to sacrifice a portion of land for conservation without jeopardizing their household food security or short-term income-generating potential (Zbinden and Lee 2005). Neef (2010) found that upland rice as the main crop of a household is a highly significant factor in its decision to engage in the P/RES scheme.

The financial characteristics such as percentage of income from different sources may influence the decision of a farmer to adopt a new scheme. Studies have shown that the impact of income, gross income and farm profitability on adoption was positively correlated (Gould et al. 1989; Saltiel et al. 1994; Somda et al. 2002). However, adoption of conservation practices with high up-front costs would reduce attractiveness to the farmers (Pannell et al. 2006). For this research, farmers with lower income are hypothesized to adopt the P/RES schemes.

Information on or participation in conservation schemes such as conservation farming (Knowler and Bradshaw 2007; Neef 2010) is frequently found to positively correlate with the adoption of the schemes. It is also positively correlated with the education of a farmer's household, which is often assumed to influence the adoption decision because of the link between education and knowledge or awareness. A lack of knowledge about the conservation agreements and incentive programs would hamper the farmers' participation or adoption (Wossink and van Wenum 2003).

Table 4.1 Potential and explanatory variables influencing household decisions

Variable	Definition	Possible effect
HH_{age}	Age of household head	-
$H\_{education}$	Household head education status	+
$H\_{rdistance}$	Household house distance to road (m)	-
H_{motor}	Number of household motorcycle vehicle	+
H_{labor}	Availability of household labor (number of workers)	-
$H\_{landhold\ per}$	Landholding per capita (ha/person)	+
H_{rice}	Total land area of rice (hectare)	-
H_{ladang}	Total land area of fallowed farm (hectare)	+
$H\_{complex}$	Total land area of complex rubber agroforest farm (hectare)	+
$H\_{gincpers}$	Gross income per capita of household (US $/person/year)	-
$H_{RICEinc}$	Percentage income from upland rice (%)	-
H_{RUBinc}	Percentage income from rubber agroforest (%)	-
H_{LIVinc}	Percentage income from livestock (%)	-
H_{ACT}	Household activities based on conservation agreement	+

4.2.2 Data sources

The socio-economic data for this analysis were derived from an extensive household survey conducted in the target villages (see section 3.2.3). The survey covered the access to conservation agreements (see section 4.1.2), motivation to participate and continue, and perspective on the agreements regarding their potential to conserve biodiversity in the area. A total of 95 household respondents (90 males and 5 females) were randomly selected and interviewed. Of these 95 households, 73% had already joined the conservation schemes.

4.3 Results and discussion

The two household types, namely (1) rubber-rice farmers, and (2) rubber-based farmers that were generated by PCA and K-CA (see section 3.2.1) were analyzed using the Bi-logit model.

4.3.1 Factors affecting P/RES adoption of "rubber-rice farmers"

The results of the Bi-logit model are summarized in Table 4.2 for household type 1 together with the maximum likelihood estimation that was used to estimate the coefficients. Chi-square tests show that the empirical Bi-logit model is significant ($p<0.093$) in explaining P/RES scheme adoption by farmers of the group. The Nagelkerke's pseudo-R^2 is 0.589, which indicates 59% of the total variation in the probability of P/RES adoption is explained by the selected explanatory variables. Out of 14 explanatory variables (see Table 4.1), a total of 8 variables were used for the model, of which 6 variables correspond to household and farm characteristics, and 2 variables are related to farm operation income. The combination of all variables was not possible due to the very small samples of household type 1 (n=32), thus the Bi-logit regression was conducted several times until the best pseudo-R^2 result was reached. The model has a good overall predictive power of 87.9%, and predicted the willingness to adopt P/RES with 92.9% and not to adopt it with 60.0%.

Among the variables that are affecting the decisions of the household agents are $H_{\_edu}$ (+), $H_{\_mem}$ (+), $H_{\_size}$ (+), $H_{\_depratio}$ (+), $H_{\_rice}$ (-), $H_{\_rdistance}$ (+), $H_{\_RUBinc}$ (-), and $H_{\_RICEinc}$ (-). However, only percentage income from rubber agroforest was found to be significant ($p<0.10$). The probability of a household to adopt P/RES increases with increasing education, group memberships and household members with a high dependency ratio, and a greater distance to a road. On the other hand, the probability to adopt P/RES increases when the household has small rice fields and low income from rice and rubber production. This corresponds to findings on farm size and number of years of education in a study by Zbinden and Lee (2005).

Table 4.2 Bi-logit model estimation of P/RES adoption by rubber-rice farmers (n= 32 households)

Variable	Definition	Coefficient (β)	Sig.
(constant)		3.516	0.489
Household characteristics			
$H_{\_edu}$	Education of household head (level)	2.683	0.105
$H_{\_mem}$	Household number of group memberships	2.759	0.119
$H_{\_size}$	Household size	0.890	0.200
$H_{\_depratio}$	Dependency ratio of household	3.104	0.211
Farm characteristics			
$H_{\_rice}$	Size of rice field (ha)	-2.353	0.186
$H_{\_rdistance}$	House distance to road (m)	0.000	0.485
Farm operation income			
$H_{\_RUBinc}$	% income from rubber agroforest	-0.089	0.086
$H_{\_RICEinc}$	% income from rice	-0.048	0.359

Fitness and accuracy of the model:
Likelihood ratio test (chi-square statistics): 13.589 $df = 8$ $p = 0.093$
Pseudo R^2= 0.589 (Nagelkerke); 0.338 (Cox & Snell)
Percentage correct predictions:

Household willingness not to adopt:	60.0%
Household willingness to adopt:	92.9%
Overall percentage**:**	**87.9%**

4.3.2 Factors affecting P/RES adoption of "rubber-based farmers"

In Table 4.3, the results of Bi-logit are summarized together with the maximum likelihood estimation that was used to estimate the coefficients for household type 2 (rubber-based farmers). Chi-square tests show that the empirical Bi-logit model is highly significant (p<0.000) in explaining P/RES adoption by farmers of the group. The Nagelkerke's pseudo-R^2 is 0.709, which indicates that 71% of the total variation in the probability of P/RES adoption is explained by the selected explanatory variables. A total of 12 explanatory variables included in the model were found to be important, of which 8 variables are related to farmers' and farm characteristics, 3 variables are related to farm operation income, and one variable corresponds to conservation agreement policy participation. The model has a very good overall predictive power of 91.9%, and predicted the willingness to adopt P/RES with 95.9% and not to adopt it with 76.9%.

For household type 2, variables that significantly influence the decisions are $H_{\_age}$ (-), $H_{\_size}$ (+), $H_{\_rice}$ (-), $H_{\_complex}$ (-), $H_{\_RICEinc}$ (-),$H_{\_gincpers}$ (-), and $H_{\_ACT}$ (+). The probability to adopt P/RES scheme is higher with younger household heads, which agrees with the findings of Wossink and van Wenum (2003), who observed that younger farmers are more explorative. With respect to farm size, it has been regularly hypothesized that owners of large farms are more willing to adopt a new technology or scheme (Knowler and Bradshaw 2007), and this was also observed for this household type. Households with larger areas with rice fields and (complex) rubber agroforests have a low probability of adopting P/RES schemes. The same trend can be observed for rice income and annual gross income per capita of the household. Participation in conservation activities such as planting clonal rubber seedlings significantly influences the probability of adopting the P/RES scheme.

Table 4.3 Bi-logit model estimation of P/RES adoption by rubber-based farmers (n= 63 households)

Variable	Definition	Coefficient *(β)*	Sig.
(constant)		3.599	0.551
Household characteristics			
$H_{\_age}$	Age of household head	-0.192	0.096
$H_{\_edu}$	Education of household head (level)	1.471	0.474
$H_{\_mem}$	Household number of memberships	-0.437	0.742
$H_{\_size}$	Household size	1.247	0.085
$H_{\_depratio}$	Dependency ratio of household	1.920	0.513
Farm characteristics			
$H_{\_rice}$	Size of rice field (ha)	-2.285	0.097
$H_{\_complex}$	Size of complex rubber agroforest (ha)	-0.392	0.067
$H_{\_rdistance}$	House distance to road (m)	0.003	0.216
Farm operation income			
$H_{\_RUBinc}$	% income from rubber agroforest	-0.046	0.231
$H_{\_RICEinc}$	% income from rice	-0.167	0.081
$H_{\_gincpers}$	Gross income per capita of household (US $/person/year)	-0.001	0.405
Conservation agreement policy participation			
$H_{\_ACT}$	Household activities based on conservation agreement (weighted value)	0.847	0.026

Table 4.3 continued

Variable	Definition	Coefficient *(β)*	Sig.
Fitness and accuracy of the model:			
Likelihood ratio test (chi-square statistics): 37.676 *df* = 12 *p* = 0.000			
Pseudo R^2= 0.709 (Nagelkerke); 0.455 (Cox & Snell)			
Percentage correct predictions:			
	Household willingness not to adopt:	76.9%	
	Household willingness to adopt:	95.9%	
	Overall percentage:	91.9%	

4.4 Conclusions and policy implications

The results of the Bi-logit regression models show the different variables that influence the decision making process of the households in the rubber agroforests landscape while household agents heterogeneity was considered. For instance, number of education is significantly affecting the decision of relatively well-off households in participating PES schemes. These range from factors associated with households' and farm characteristics, farm income operation, and participation in the conservation agreement policy. Agro-biodiversity conservation through P/RES schemes in the rubber agroforest landscape of the Bungo District is greatly affected by these factors, and they influence the decision-making process.

From the results, we could identify useful variables, which could help programs like RUPES and government agencies to create or establish criteria and indicators for households' eligibility to accept rewards or payments from programs such as REDD and eco-certification schemes. Thus, they would help to reduce free-riders and to target households who are very much involved in the process. Also, policy makers could better target households that need follow-up activities or support to ensure the success of P/RES schemes. Ekadinata et al. (2010) recommend a priority setting for eco-certification of rubber agroforest by identifying the areas where there is a high percentage of rubber agroforests. Thus, the results of this research provide significant insights on the type of household that would possibly adopt the P/RES scheme.

The parameterized coefficients of the above analysis will be used in the simulation of the LB-LUDAS model (Chapter 6).

5 ECOLOGICAL DYNAMICS IN RUBBER AGROFOREST LANDSCAPE: CASE STUDY OF BUNGO DISTRICT, JAMBI PROVINCE (SUMATRA)

Ecological systems are complexes of biotic and abiotic elements that are interrelated by flows of energy, matter and information (Breckling and Mueller 1997). These interactions build up comprehensive and complicated networks of heterogeneous direct and indirect effects (Fath and Patten 2000). Unintended domestication of ecosystems, e.g., for food and timber, can result in the decline of other services such carbon emission reduction, pollination, flood control, etc. Bennett et al. (2009) point at the need to understand the relationships among multiple ES and the mechanisms behind the relationships to improve man’s ability to sustainably manage landscapes. However, the multi-agent simulation/ agent-based (MAS/AB) models for understanding social-ecological systems (SES) are criticized as weak in ecology (Cumming 2011).

In this chapter, the rubber agroforest landscape in Jambi province is investigated. Studies show that this agroforest type is an important agro-ecosystem worth conserving (see Chapter 4). Yet the rubber agroforest is currently endangered by various social-economic and political factors leading to possible conversion into more profitable land uses (see Appendix 1).

The starting point for quantifying trade-offs involved in land-use change is the measurement of field-level differences in economic, agronomic and other ecological consequences of the various land uses. Thus, the following objectives are addressed:

1. Characterize the heterogeneity and biophysical characteristics of landscape agents,
2. Identify the variables that are ecologically and economically relevant to the productivity and land-use decision-making process, and
3. Formulate and calibrate ecological sub-models (i.e., biodiversity, forest yield, agronomic, and natural transition[5]) of landscape agents.

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[5] Only modifications and calibration of the sub-models (i.e., forest yield, agronomic and natural transitions) are presented in this chapter. For detailed explanation of the sub-model development, see Le 2005.

5.1 Bio-physical characteristics

5.1.1 Climate

The climate in Bungo district belongs to the Type-A (Schmidt and Ferguson 1951), which is based on the seasonal rainfall variation (Hamada et al. 2002). During the last 10 years (1998-2002), the mean annual rainfall was 2,330 mm year^{-1}, and the mean number of rainy days year^{-1} was 124 (recorded at the climate station of Muara Bungo; Tata et al. 2008). In 2007, according to the rainfall data recorded by the Bungo district's Agricultural Extension Service, the mean rainfall was 225 mm and the mean number of rainy days was 10 (Figure 5.1).

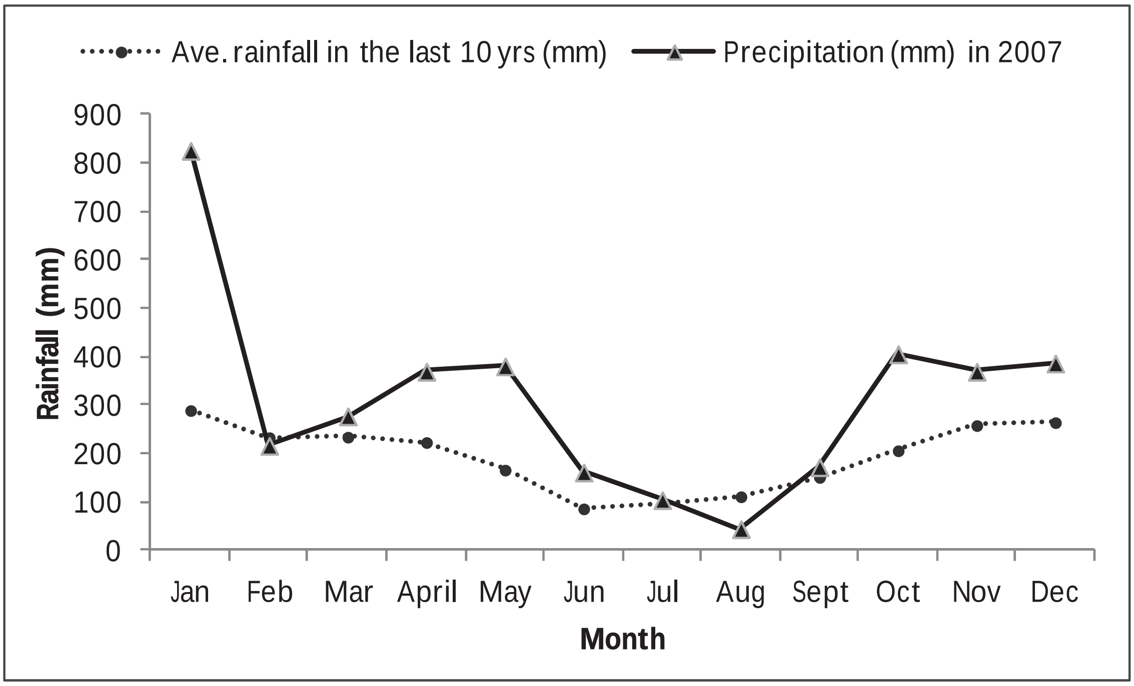

Figure 5.1 Average rainfall data, 1997-2006. Source: Agricultural Extension Service of Bungo Regency, 2007

5.1.2 Soils

Jambi province crosses the five ecological zones of Sumatra, namely coast, mountain, piedmont, peneplain, and swamp. The study site is comprised of three villages (Lubuk Beringin, Laman Panjang, and Buat; see Chapter 4) and is located in the piedmont zone, which is formed mainly of granite and andesitic lava (Murdiyarso et al. 2002) with elevations ranging from 100 to 500 masl. According to the US Soil Taxonomy, the soils in this region of Sumatra are classified as Hapludox and Kandiudox (Soil Survey Staff,

1999) and as Orthic Ferrasols according to the FAO classification (Ketterings et al., 2002). In Rantau Pandan area (where the villages belong), the soils are more varied and complex—ranging from shallow to very deep, moderate to fine texture, and well to moderately excessive drained, but they are also very acid and have low soil fertility (van Noordwijk et al. 1995).

5.1.3 Vegetation cover

Sumatra lies in the lowland humid tropical forest zone in insular Asia. This forest type is characterized by high diversity and species richness. However, over the last decades, large tracts of forest have been converted to various land uses, e.g., rubber, and oil palm plantations and other agricultural land uses. Ekadinata and Vincent (2011) recently describe the three major land-cover changes in Bungo district, in an area of 4550 km^2, in Jambi province, for the period between 1973 and 2005, namely (1) natural forest loss was lost with cover going from 70% to 30%, (2) an increase in the area of intensive tree crops from 3% to over 40% monoculture plantations, and (3) decrease in the area of rubber agroforests from 15% to 11%.

Tata et al. (2008) described the top five dominant tree species in the forest of Jambi. These are *Alanguim javanicum*, *Alseodaphne sp*., *Alstonia angustifolia*, *Antidesma montanum* and *Aporosa nervosa*, the majority of which belong to the family Euphorbiaceae. Though dipterocarp species usually dominate in this forest, this was not the case in the above study. In rubber agroforest, the five dominant trees species are *Hevea brasilienis* (rubber tree), *Artocarpus integer* (jackfruit), *Macaranga trichocarpa*, *Parkia sumatrana* and *Parkia speciosa* (stinky bean). Most of the dominant tree species belong to the Euphorbiaceae and Burseraceae families. In terms of shadow species (tree species observed at least once), the same study estimated the number of shadow species at 34.4% only for forest and 33.5% only for rubber agroforests, and 2.7% for species observed in both land-cover types.

5.1.4 Carbon stocks

Lowland tropical rain forests have the highest standing biomass and aboveground carbon stocks (C-stocks) in the world (Murdiyarso et al. 2002). Hairiah et al. (2000) indicated that the total carbon stocks of natural forest in Jambi on the peneplains can reach up to 500Mg ha^{-1}. The time-average aboveground carbon stocks of the main land-use systems in Sumatra (particularly in Bungo district) were estimated in the Alternative-Slash and Burn (ASB) project (Tomich et al. 1998). Of all the land uses quantified, the natural forest remains the highest source of carbon (Table 5.1).

Table 5.1 Time-averaged mean annual aboveground carbon stocks of land-use systems in Sumatra

Land-use type	**Maximum years (life-span)**	**Time-averaged annual carbon stocks (Mg ha^{-1})**
Natural forest	120	254
Secondary forest	60	176
Rubber agroforest	40	116
Rubber monoculture	25	97
Oil palm plantation	20	91
Rotation crop (upland rice)	7	74
Rotation crop (yam)	3	36

Source: Tomich et al. 1998

5.2 Methodology

5.2.1 Calculation of bio-physical landscape variables

Wetness index, soil properties and other terrain parameters are among the widely used bio-physical variables for explaining the causal relationships between topography and landscape patterns of soil and water. The following are the bio-physical variables available for the study site:

Wetness index and proximities to roads and town

The topographic wetness index ($p_{\_wetness}$) used in the selected land-use choice model (see Chapter 3) is a compound terrain index applied for delineating the spatial pattern of soil moisture content. It has been used extensively to approximately delineate the spatial pattern of soil moisture content, which is important for agricultural production (Le 2005). The index was calculated from a digital elevation model (DEM) using the grid-based algorithm developed by Zevenbergen and Thorne (1987).

For spatial accessibility analyses two variables, namely distance to road ($p_{\_droad}$) and distance to town center ($p_{\_dtown}$) are used for accessibility purposes in the land-use choice model (see Chapter 3). A study conducted by Miyamoto (2006) shows that roads in the study area are an important factor for forest clearing or land-use change. These variables were calculated based on the road and town networks digitized from a base map of 1:50000 developed by ICRAF. The computational method for LUDAS models is described by Le (2005).

Neighborhood interactions (enrichment factor)

Neighborhood characterization of land-use patterns ($p_{\_f2}$, $p_{\_f45}$, $p_{\_f6}$, and $p_{\_f8}$) is a new way to unravel the processes of land-use change allocation (Verburg et al. 2004). In the context of cellular automata, the neighborhood terminology is called Neumann neighborhood, in which neighborhood cells are those that can influence the state of a particular focal cell. The neighborhood of a location in a land-use map is measured by the enrichment factor. This measure is defined by the occurrence of a land-use type in the neighborhood of a location relative to the occurrence of this land-use type, and is expressed as:

$$F_{i,k,d} = \frac{n_{k,d,i} / n_{d,i}}{N_k / N} \tag{5.1}$$

where $F_{i,k,d}$ characterizes the enrichment of neighborhood d of location i with land-use type k. The shape of the neighborhood and the distance of the neighborhood from the central grid-cell i is identified by d (see Verburg et al. 2004, p.671).

Verburg et al. (2004) suggest that the enrichment factor can assist the modeler in formulating the transition rules for cellular automata. Though it is commonly applied in modeling urban development, the neighborhood characteristics of land-use patterns was applied in this study by integrating in the land-use choice model as an independent variable (see Chapter 3). To the author’s knowledge, this has not been applied before. The enrichment factor of the neighboring patch is calculated using ArcVIEW software (Figure 5.6).

Land-cover data and change detection

The land-cover map of 2005 for the study site was prepared using the Jambi province land-cover map of 2005 generated from Landsat ETM images and processed by ICRAF under the Landscape Mosaic Project. The boundary of the study site (i.e., basin boundaries were used since administrative boundaries of the villages were not available) was determined using DEM images as a basis. The map was processed using the spatial analyst extension of ArcGIS. Land-cover change assessment was also done using the land-cover map of 1993. The 2005 map was overlaid on the 1993 map resulting in a land-cover transition matrix (see Appendix 1 for detailed methodology). This was used to generate the net-carbon release, and sequestration (see Section 5.3.6).

5.2.2 Modeling species richness

Species-area relationship (SAR)

Species richness is a natural measure of biodiversity, and the species-area relationship (SAR) is one of the most important and oldest tools available in the study of species diversity, conservation biology, and landscape ecology (Tjorve 2003). The SAR is a well-proven pattern in ecology (Schoener 1976; Lawton 1999; Lomolino 2000) and provides a classic example of scale dependence, i.e., species richness depends on the size of the area sampled (Cumming 2011). It has been also used to estimate how fast the biodiversity is lost in a region as caused by habitat changes (Perreira and Daily 2006).

Arrhenius (1921) set the basic equation of SAR and made popular by Preston (1960) as power function, which is formally expressed as:

$$S = kA^z \tag{5.2}$$

where S is number of species, A is the area of the sample, k and z are fitted coefficients.

The log form (to the base 10) is expressed as:

$$\log S = \log k + z \log A \tag{5.3}$$

Desmet and Cowling (2004) applied the power function to set baseline targets for conservation. Their study demonstrated how the z-value (as the exponent) of the power function model estimates the proportion of an area necessary to represent the given proportion of species present in any land class. The SAR has been applied to estimate how many species might be threatened with extinction following habitat destruction (Wilson 1983; Simberloff 1984; Wilson 1992). Tilman and Lehman (1997) further developed the equation using the power function to determine the proportion of original species that survived after destruction, which is formally expressed as:

$$\frac{S_D}{S_v} = (1 - D)^z \tag{5.4}$$

$$S_D = k[(1 - D)A_v]^z \tag{5.5}$$

where SD is number of species remaining after habitat destruction, S_v is number of species in the area of virgin habitat, D is the proportion of area destroyed, and A_v is the area of virgin habitat. These equations were later applied in Chapter 7.

Modeling approach

Empirical model selection

There are various SAR models available and their advantages are reviewed by Tjorve (2003). Among these models, the two oldest are most frequently applied namely, the power function (see Eq. 5.2, Arrhenius 1921; Preston 1962) and the logarithmic function (see Eq. 5.3, Gleason 1922; Tjorve 2003). However, the best fit is most often reported for the power function (Williamson 1988; Drakare et al. 2006; Dengler and Boch 2008).

Dengler (2009) conducted a more comprehensive review of 21 SAR models to assess the goodness-of-fit metrics theoretically and empirically. Results suggest that the choice of model depends on the number of parameters and their goodness-of-fit, its stability, source of data sets (i.e., from islands, nested plots or homogenous areas) and its extrapolation capability. Accordingly, the normal power function (*S* as compared to log *S*) "performed very well for extrapolating richness data far beyond the largest plot throughout the wide range of vegetation types" (Dengler 2009, p.737). The same study rated the normal power function as best for the Akaike information criterion (AIC) and its correction for small sample bias.

Scaling from plot to landscape level

The biodiversity sub-model of the FALLOW[6] Model (van Noordwijk 2002b) scales the total species richness (S_{total}) from plot level to landscape level. The sub-model follows the SAR model based on the power function (see Eq. 5.2 of Arrhenius, 1921). For this study, the sub-model was modified for the LB-LUDAS model for extrapolation. The following are the main steps of the sub-model (also part of calibration):

1. Plot-level species richness (S_{obs})

First, the sub-model assumes that species richness of a plot is a function of the time since the last field-clearing event or major disturbance (i.e., slash and burn) (Figure 5.2).

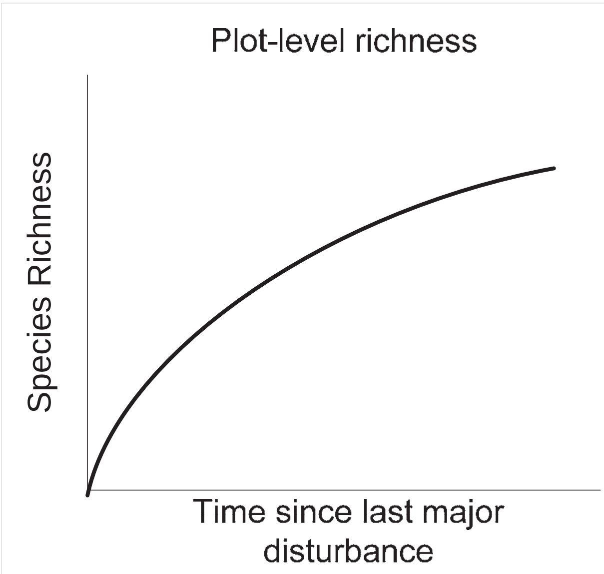

Figure 5.2 Plot-level richness after major disturbance (i.e., clearing).

Gillison's (1999) data on higher plant richness for a range of land-cover types were indeed found to relate to time since disturbance in a similar way (van Noordwijk, 2002b). There is a growing literature on space (area) and time relationship to support this assumption (Rosenzweig 1995; Hadley and Maurer 2001; Adler and Lauenroth 2003; White 2004; Adler et al. 2005). For this study, time refers to the event after logging or major land clearing.

[6] Forest, Agroforest, Low-value Lands Or Waste

2. Vegetation (age) classes

The vegetation was classified into age classes, e.g., pioneer (0-5 years), young secondary (5-20 years), late secondary (20-50 years), and forest (>50 years). For each class, an allometric relation between class-level richness and the number of fields was derived as driven by the parameters z. Simple species estimators (S_{obs}) at each plot-level are calculated using EstimateS software version 7.5 (Colwell 2009). This software computes expected species accumulation curves based on sample-based rarefaction curves (Gottelli and Colwell 2001) with 95% confidence intervals. The observed species number estimators of Mao Tau, Chao 1 (based on the number of rare species in the sample) and Jack 1 (based on the number of species that occur in only one sample) are used to derive species accumulation curves for each vegetation-age class (see Appendix 2 for equations of each estimator).

Results from the plot data were fitted to species-area curve using the log form equation (Eq. 5.3). The k and z constants were estimated using regression analysis where the species richness (S_{obs}) at the plot level was the dependent variable, while the area (A) was the independent variable (Table 5.2).

Table 5.2 Variables used for estimating species richness (biodiversity sub-model)

Variable	**Definition**	**Data source**	**Direct linked module**
Species richness (dependent variable)			
S_{obs}	Observed species number (using EstimateS) per each vegetation class	Field survey from Rahayu (2009) (n=15 plots)	PATCH LANDSCAPE
Area (independent variable)			
A	Area (m^2) of the sampled plots	Field survey from Rahayu (2009) (n=15 plots)	PATCH LANDSCAPE

3. Species richness at landscape level

The species richness in each land-cover type (S_i) can be expressed as:

$$\log S_i = \log k + z \log A \qquad (5.6)$$

while the total landscape level richness (S_T) is finally derived by summation over the various vegetation classes while deducting the species number due to overlap of two vegetation classes. This is expressed as (van Noordwijk 2002b):

$$S_T = \sum_t \left\lfloor S_t - \left(\sum_j p_{ij} S_j \right) \right\rfloor \tag{5.7}$$

where S_T is total species richness at landscape level, p_{ij} S_j is probability of species overlap in species composition between two vegetation types, and S_i is species richness of land-cover type.

However, only one land-cover type (rubber agroforest) was considered for the study due to the limited number of samples of other land-cover types.

In the biodiversity sub-module of the FALLOW model, the probability of occurrence of various vegetation classes in an open plot is a function of the ecological distance or forest neighborhood effect. In LB-LUDAS, the concept is addressed in the *NaturalTransition* sub-model (see section 5.3.5).

Decision rules

For LUDAS model, only the species richness in the rubber agroforests was estimated. The plot age (or time of major disturbance) was the determining factor for selecting the calibrated power model equation (see above for scaling process), which is translated as the decision rule of the LUDAS biodiversity sub-model (i.e., *Calculate-species-richness*). For example, if a rice field or a rubber monoculture plot is abandoned, the vegetation class (e.g., pioneer, young or late secondary) is determined by the plot age and the ecological distance from the forest that is covered in the *NaturalTransition sub-model* (see section 5.3.5).

Data source

The data of vegetation (i.e., higher vascular plants) survey conducted by Rahayu (2009) in Lubuk Beringin were used in this study. The data represented samples of land-cover types e.g., rubber agroforests, monoculture rubber, shrub and forest. Because the data were sampled according to the estimated age of the plots, grouping according to each vegetation-age class was made possible. Five sample plots with plot dimensions of 40m x 5m were used for the vegetation-age class of 5 – 20 years. For the vegetation-age class of 20-50 years and >50 years, each class has 5 sample plots measured 200 m x 50 m.

5.2.3 Modeling crop yields

This study follows the simple production function of Cobb-Douglas approach (Cobb and Douglas 1928) in which the yields are explained by predictors of labor and capital employed by the farmer agents. This function is widely used to represent the relationship of an output to inputs and is formally expressed as follows:

$$P(L, K) = bL^{\alpha}K^{\beta} \tag{5.8}$$

where *P* is total production (monetary value of all goods produced in a year)
L is labor input (total number of man-days employed in a year)
K is capital input (e.g., agrochemical, seedlings, etc.)
b is total factor productivity
a and β are output elasticities of labor and capital, respectively; they are constant values as determined by the available technology.

The output elasticity measures the responsiveness of output to a change in levels of either labor or capital used in production, all other things being equal (Tan 2008). For instance, if *a* = 0.15, a 1% increase in labor would lead to an increase in output of approximately 0.15%.

Table 5.3 and 5.4 list the variables (i.e., natural and management predictors) of the production functions for rice and rubber agroforest. From these variables, production yield equations are expressed as:

$$P_{\_yieldrice} = f(I_{\_rain}, P_{\_wetness}, I_{\_RICEsize}, I_{\_ricelab}, I_{\_fert}) \tag{5.9}$$

$$P_{\_yieldRAF} = f(P_{\_areaRUB}, P_{\_wetness}, I_{\_rublab}, I_{\_tree}, I_{\_seedling}, T_{\_age}) \tag{5.10}$$

Table 5.3 Variables used for the agronomic-yield dynamics sub-model (rice)

Variable	Definition	Data source	Direct linked module
Yield response (dependent variable)			
$P_{\_yieldrice}$	Yield of upland rice plot (kg ha^{-1} year^{-1})	Field survey (n=34 plots)	PATCH LANDSCAPE
Natural predictor (independent variable)			
$I_{\_rain}$	Amount of rainfall during the whole planting season (mm)	2006 Rainfall data (2007 Bungo Statistics)	PATCH LANDSCAPE
$P_{\_wetness}$	Plot wetness index	GIS-based calculation	PATCH LANDSCAPE
$I_{\_RICEsize}$	Rice plot area (m^2)	Field survey	PATCH LANDSCAPE
Management predictor			
$I_{\_ricelab}$	Man-days employed for the rice production activities (day ha^{-1} year^{-1})	Field survey	PATCH LANDSCAPE
$I_{\_fert}$	Fertilizer input (i.e., NPK, urea, etc.) (g ha^{-1} year^{-1})	Field survey	PATCH LANDSCAPE

Table 5.4 Variables used for the agronomic-yield dynamics sub-model (rubber agroforest)

Variable	Definition	Data source	Direct linked module
Yield response (dependent variable)			
$P_{\_yieldRAF}$	Latex yield from rubber agroforest plot (kg ha^{-1} year^{-1})	Field survey (n=51 plots)	PATCH LANDSCAPE
Natural predictor (independent variable)			
$P_{\_wetness}$	Plot wetness index	GIS-based calculation	PATCH LANDSCAPE
$P_{\_areaRUB}$	Rubber farm plot area (m^2)	Field survey	PATCH LANDSCAPE
Management predictor			
$I_{\_rublab}$	Man-days employed for the rubber latex production (day ha^{-1} year^{-1})	Field survey	PATCH LANDSCAPE
$I_{\_tree}$	Number of rubber trees per plot (ha^{-1})	Field survey	PATCH LANDSCAPE
$I_{\_seedling}$	Number of rubber seedling per plot (ha^{-1})	Field survey	PATCH LANDSCAPE
Temporal factor			
$T_{\_age}$	Rubber tree age	Field survey	PATCH LANDSCAPE

Data sources

The crop production yield data were collected together with the socio-economic survey between December 2009 and March 2010 (see Chapter 3). A total of 35 respondents provided data on agricultural inputs (e.g., NPK and urea fertilizer, labor needed, etc.) for rice production while 51 respondents shared data (e.g., number of trees planted, age of trees, labor needed, etc.) on rubber latex production. Secondary yield data (i.e., oil palm and rubber monoculture) were also provided by ICRAF. Topographical data, e.g., wetness index, were calculated from the DEM (see section 5.3.1).

5.2.4 Modeling forest-yield dynamics

Forest growth model

Le (2005) developed a forest-yield dynamics model using the basal area of forest stands specific for LUDAS that is described in this section. The forest yield response function is formulated based on the basic concepts of forest growth and succession and on the principles of biological system and theory, which is formally expressed as:

$$ {}^{t}P_{Gr} = \left({}^{t-1}P_{Gr} + {}^{t-1}Z_{G} \right) - G_{removals} \tag{5.11} $$

where ${}^{t}P_{Gr}$ is the sum of basal area (G_i) at time t, ${}^{t-1}P_{Gr}$ is the previous residual stock,
${}^{t-1}Z_G$ is the instant growth rate; and $G_{removals}$ is the harvested basal area that includes the logging damage and logging-driven mortality.

According to Vanclay (1994), Z_G expresses the theoretical basal area growth of a forest stand as a whole and can be calculated as:

$$ Z_G = a(P_G)^{\varepsilon} - b(P_G) \tag{5.12} $$

where P_G is stand basal area, α and b are the constants, and ε is a coefficient of very small value ($\varepsilon \rightarrow 0$).

To determine the parameters α and b of Eq. 5.12, the following is assumed:

1. The stand growth rate Z_G is asymptotically zero in the equilibrium state (${}^{eq}P_G$).
2. The derivative of the growth function Z_G is zero when it reaches the maximum (${}^{max}Z_G$).

3. ${}^{eq}P_G$ is constant over space since there is no evidence to correlate this parameter with location variables.

Accordingly, the ${}^{eq}P_G$ and ${}^{max}Z_G$ are settable either by forestry experts or review of literature on tropical forests (Havel 1980; Leigh 1999; Vanclay 1994). Assuming that the parameters ε, ${}^{eq}P_G$ and ${}^{max}Z_G$ are known, the following equations will determine the parameters α and b:

$$a = {}^{\max}Z_G / [\left({}^{eq}P_G\right)^{\varepsilon}\left(\varepsilon^{\varepsilon/(1-\varepsilon)} - \varepsilon^{1/(1-\varepsilon)}\right)] \tag{5.13}$$

$$b = {}^{\max}Z_G / \left[{}^{eq}P_G\left(\varepsilon^{\varepsilon/(1-\varepsilon)} - \varepsilon^{1/(1-\varepsilon)}\right)\right] \tag{5.14}$$

where ${}^{max}Z_G$ is the value that can be approximated from the projected outputs of empirical growth models, ${}^{eq}P_G$ is the upper confidence limit of the mean basal area of the surveyed dense/rich natural forest plots, and ε is fixed by setting a very small value (i.e., $\varepsilon = 10^{-6}$).

The removed basal area ($G_{removals}$) as mentioned above includes harvested amount (G_{logged}), logging area (G_{damage}) and logging-driven mortality ($G_{mortality}$) which can be calculated as (Alder 2000):

$$G_{removals} = G_{logged} + G_{damage} + G_{mortality} / T \tag{5.15}$$

where Glogged is the basal area logged by human agents, Gdamage is the standing basal area damaged immediately by logging operation, and Gmortality is the basal area lost through tree mortality occurring over some years (T) after the logging event.

Alder and Silva (2000) empirically approximated G_{damage} and $G_{mortality}$ based on the logging impact model developed for the Amazons and converted by Le (2005) using the mean basal area of logged trees (g_{logged}) which are expressed as follows:

$$G_{damage} = {}^{t-1}P_{Gr}\,(0.0052 G_{logged} / g_{logged} + 0.0536) \quad (R^2 = 0.8987) \tag{5.16}$$

$$G_{mortality} = {}^{t-1}P_{Gr}\,(0.0058\, G_{logged} / g_{logged} + 0.0412) \quad (R^2 = 0.9044) \tag{5.17}$$

The parameters and variables of the *ForestYieldDynamics* sub-model are presented in Table 5.5.

Table 5.5 Summary of parameters and variables of *ForestYieldDynamics* sub-model

Parameter and variable	Definition	Source	Direct link module
Parameter			
$^{Eq}P_{Gr}$	Stand basal area at the equilibrium state ($m^2 ha^{-1}$) (a) Natural forest: 44.8 (b) Rubber agroforest: 27.0	Le (2005); Alder (1998, 1996a, 1996b); + the descriptive statistics of the plot	Patch-landscape
$^{Max}Z_g$	Potential maximum growth rate of stand basal area (m^2ha^{-1}) (a) Natural forest: 0.61 (b) Rubber agroforest: 0.92	Yarwudhi et al (1997) Approximated from Schroth et al. (2004)	Patch-landscape
G_{logged}	No logging is done in natural forest under village forest policy Average basal area of logged trees in rubber agroforest and rubber monoculture plantation (m^2 ha), range: 0.511 – 0.621 (m^2 ha)	Akiefnawati (2010) Approximated based on the interviews with key informants	Experimental factor module
T	Post logging period with severe mortality due to logging operation (yr).		Patch-landscape
Variable			
$^{2009}P_G$	Forest basal area calculated based on 2009 biodiversity survey as initial forest yield	Spatially random-bounded extrapolation (Le 2005) of plot data 2009	Patch-landscape (as initial forest condition)
G_{logged}	Basal area logged by households (m^2)	Defined by human agents in simulation runs	Decision module (logging action)
Pt	Years after logged (temporary variable)	Elapsed year since logging (initiated by human agent simulation runs)	Decision module (fallow action)

Data sources

The plot-based vegetation inventories by Rahayu (2009) and Rasnovi (2006) were used in this study. The data include species name, species individual number, and DBH (diameter breast height measured at 1.3 m height). A total of 32 plots ranging from 20m x 100m to 40m x 5m were available for the main land-use covers of Jambi province. The basal area was calculated using the formula:

$$\text{Basal area } (m^2\ ha^{-1}) = 0.00007854 \times DBH^2 \qquad (5.18)$$

Only trees with DBH ≥ 10cm were considered.

5.2.5 Modeling natural transition (succession)

Transition or conversion from one land use or cover to another can be in two forms: 1) through a natural process (transition Nx) with no human intervention, or 2) through human activities (transition H) resulting from farming practice or land-use decisions. The conversion of one land-cover type to another in the study site is depicted in Figure 5.3.

The *NaturalTransition* sub-model is a set of transition rules that governs the natural transitions among vegetative covers (Le 2005; Le et al. 2008). It follows the ecological principles of natural succession process, which is more or less predictable and is characterized by orderly changes in composition or structure of an ecological community, e.g., pioneer → intermediate → climax. Its rules are based on the evaluation of four patch variables, namely 1) previous cover type (${}^{t-1}P_{cover}$), 2) life span of existing cover type ($P_{\_t}$), 3) existing basal area (P_{Gr}), and 4) distance to nearest forest ($P_{d\text{-}forest}$).

Two natural transitions are depicted in Figure 5.3 and the following are the transition rules for the modeling:

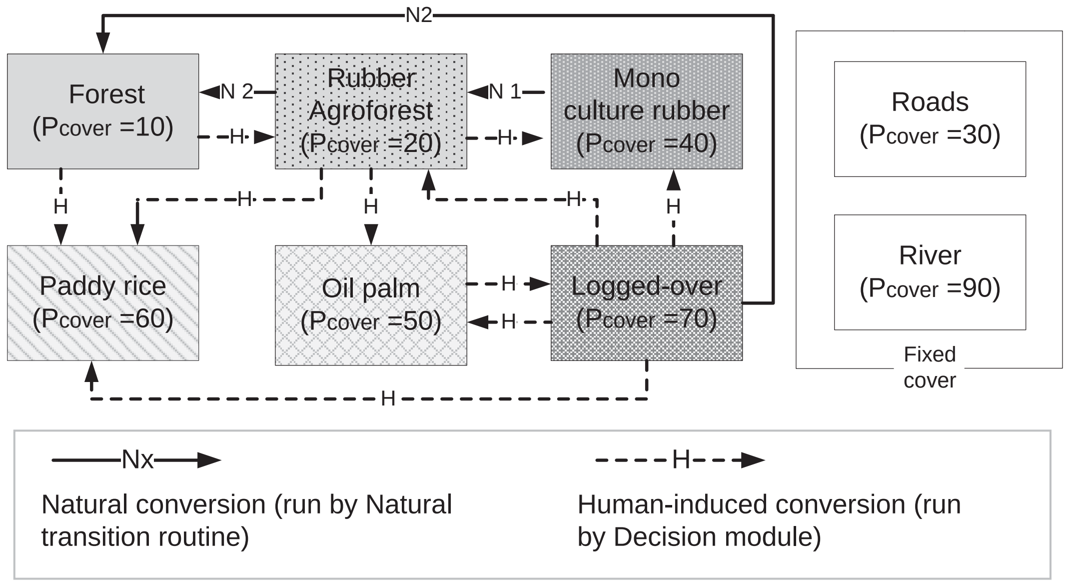

Figure 5.3 Schematic diagram of land-cover transitions in LB-LUDAS model showing a combination of human-induced and natural transition

1) **N1 transition rule**: from one non-forest to another non-forest cover type

The specific example depicted in Figure 5.3 is the transition from rubber monoculture to rubber agroforest. In reality, this kind of transition only happens when a farmer abandons his rubber plot due to factors such as lack of labor force, weed competition, and/or lack of financial capital (Gouyon 1993; Joshi et al. 2003). The same applies to the transition from rubber agroforest to secondary forest. The transition rule for this type is based on the following conditions:

1. Patch belongs to the non-forested category,
2. Life-span of the existing cover type,
3. Present stand basal area (P_{Gr}) against the thresholds for each land-cover type, and
4. No human disturbance (e.g., burning, harvesting, etc.) for a long period of time.

Thus, the logical expression for the rule N1 is expressed as:

$$ {}^{t}P_{cover} = \begin{cases} 20 & if \quad {}^{t-1}P_{cover} \in \{20,40\} \quad and \quad {}^{t}P_{Gr} \geq \theta_{tb-AF} \\ 40 & if \quad {}^{t-1}P_{cover} \in \{20,40\} \quad and \quad {}^{t}P_{Gr} \leq \theta_{tb-RubMN} \end{cases} \tag{5.19} $$

where 20 and 40 are the cover codes for rubber agroforest and rubber monoculture, respectively; θ_{tb-AF} is the threshold of stand basal area for rubber agroforest (AF), and $\theta_{tb-RubMN}$ is the threshold of stand basal area for rubber monoculture (RubMN).

2) **N2 transition rules**: from non-forest to forest cover type

The transition from a logged-over area to forest is a common natural transition (Figure 5.3). However, patches at forest edges or in forest gaps have a better chance to convert to secondary forest. Patches far from natural forests have less or no capacity to regenerate because they lack a source of seeds or are prone to soil degradation (Le 2005, Le et al. 2008). Transition rules are defined based on the same conditions as in N1 (see above) plus the effect of the distance from the natural forest.

Thus, if a patch has a logged-over cover status (relatively similar to the shrub class in the study site), the life-span of the existing land cover would be too long to reach the threshold, but if the patch is located next to a natural forest, the cover state of the patch will change to secondary forest[7] otherwise it remains a logged-over area. The expression of the N2 rule is as follows:

$$ {}^{t}P_{cover} = \begin{cases} 10 & if \quad {}^{t-1}P_{cover} = 70 \quad and \quad {}^{t}P_{cover-age} > \theta_{t-forest} \quad and \quad {}^{t}P_{d-forest} < \theta_{d-forest} \\ 70 & if \quad otherwise \end{cases} \tag{5.20} $$

where 10 and 70 are land-cover codes of forest and logged-over patch, respectively, $\theta_{t\text{-}forest}$ is the threshold of the life-span of the forest, and $\theta_{d\text{-}forest}$ is the threshold distance from the patch to the nearest natural forest, which is used for determining if the logged-area patch can change to (secondary) forest.

Whereas,

$$ {}^{t}P_{cover} = \begin{cases} 10 & if \quad {}^{t-1}P_{cover} = 20 \quad and \quad {}^{t}P_{cover-age} > \theta_{t-forest} \quad and \quad {}^{t}P_{Gr} \geq \theta_{tb-forest} \\ 20 & if \quad otherwise \end{cases} \tag{5.21} $$

where 10 and 20 are land-cover codes of forest and rubber-agroforest, respectively, $\theta_{t\text{-}forest}$ is the threshold of the life-span of the forest, and $\theta_{tb\text{-}forest}$ is the threshold of stand basal area for forest.

All threshold values in the transition rules in equations 5.19, 5.20, and 5.21 were calibrated based on the field inventory data from Rahayu (2009) and Saida (2006) (see Table 5.14).

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[7] The forest in this context mostly refers to a secondary forest type. Gouyon (1993) studied the structure of rubber agroforest (i.e., the jungle rubber in Jambi province) and found that its structure is similar to that of old secondary forest.

5.2.6 Carbon stocks and emissions

Landscape carbon-stock estimation

There are several models for estimating carbon stocks from the land-use changes. These include normalized difference vegetation index or NDVI-derived carbon stocks and land-cover-derived carbon stocks. The first model uses the relationship between the pixel level carbon stock and pixel-level NDVI as a basis for extrapolation. The latter uses the land-cover information (e.g., from land-cover change matrix) and multiplies the area by class with the typical aboveground C-stock density. Widayati et al. (2005) applied and compared the two methods in East Kalimantan, Indonesia. They found NDVI-derived estimations frequently underrated due to the low correlation between NDVI and measured carbon density in tropical forests. Accordingly, the non-linear aspect of the NDVI C-stock regression line leads to a bias in the C-stock results. For land-cover-derived carbon stocks, ground-truth checks of the land-cover maps are needed for accuracy. The study suggested that verification of carbon density results could be done using independent C-stock measurements.

In this study, the land-cover-derived C-stocks method is applied by assigning the time-averaged C-stocks (Table 5.1) and is estimated in the LB-LUDAS model.

Landscape carbon emissions

To calculate annual Carbon emissions from changes in land use, the book-keeping model approach of Houghton et al. (1983) is widely applied (Houghton and Hackler 1999; Achard et al. 2004; Gitz 2004; Ramankutty 2007; Gasparri et al. 2008). In the model, the annual per hectare changes in vegetation and soil following a land-use change are defined for different ecosystems and land uses. The model accounts for forest clearing and regrowth by tracking plant materials burnt at the time of clearing, carbon from slash decay, carbon accumulation from regrowth, and changes in soil carbon (Achard et al. 2004; Houghton and Hackler 1999). It has been used to estimate the net carbon fluxes in the study of land cover in the tropics, where soil carbon, decay from slash, and regrowths were accounted for (Achard et al. 2004). Houghton et al. (2000) also applied the model without accounting for the soil carbon in the region of Brazilian Amazon and Guyanas.

For this study and due to lack of information about the decay and soil carbon changes available at the study site, a very simple modeling approach was applied. Accounted for in the model are the changes in land cover derived from the overlay of 1993 and 2005 land-cover maps and the time-average carbon stocks (Table 5.1) assigned for each land class.

5.3 Results

5.3.1 Landscape characterization

Land-cover classification

From the 2005 land-cover map, eight major land-cover types were classified (Figure 5.4): forest, rubber agroforest, rubber monoculture, rice field, oil palm plantation, shrubland, settlement areas, and water body (Table 5.6 and 5.7). Forest remained the largest land-cover type with a 48% total cover.

It should be noted that the rubber monoculture in this classification is considered to have a 70% rubber tree cover. The rubber monoculture farms in the study site are less intensively managed compared to large scale rubber plantations and therefore includes a significant portion of non-rubber species (30%).

Table 5.6 Land-cover area in 2005

Land cover	2005 ha	2005 %
Forest	7,653	48
Rubber agroforest	2,265	14
Rubber monoculture	3,619	23
Oil palm	437	3
Rice field	237	2
Shrubland	260	2
Settlement	1,104	7
Water body	161	1
Total	15736	100

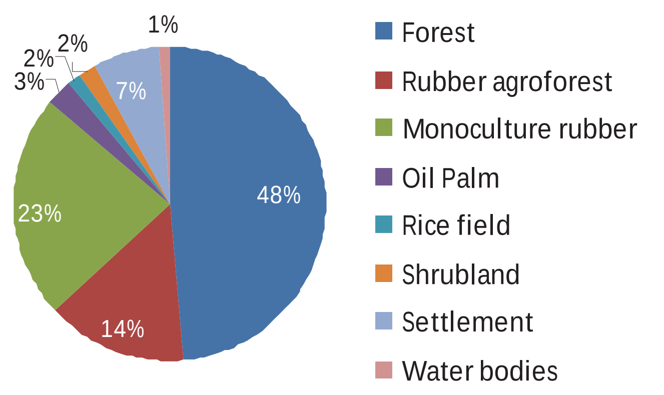


Table 5.7 Land-cover types

Land-cover type	Description
Forest	Characterized by more or less dense and extensive tree cover usually consisting of stands varying in characteristics such as species, structure, composition and age class, which may be exploited (partly logged). Excludes industrial tree plantations. Most areas are located in the highlands (>500 m.a.s.l), and only small patches in the lowland peneplains (as of 2002).
Rubber agroforest	Marked by the presence of rubber trees in fairly large numbers mixed with other tree species, forming a stand structure similar to forest. Also called 'jungle rubber' because of the presence of wild woody species that help to protect the rubber trees from weeds (Gouyon et al. 1993).
Rubber monoculture	Also called rubber plantation; characterized by single species of rubber trees covering most of the area, usually managed intensively. In some areas, plantations may also represent smallholdings, less intensively managed, rubber plantations mixed with non-tree species such as shrubs.
Oil palm	Characterized by oil palm as a single dominant species usually managed intensively.
Rice field	Covered with irrigated or non-irrigated (upland) rice field.
Shrubland	Woody herbs, grasses and non-woody herbs. Usually newly opened area, and is the first phase of land conversion into rubber or oil palm plantations.
Settlement	Residential areas including main roads and villages.
Water body	Area covered by water.

Table 5.8 Land-use change matrix for the period 1993-2005 (ha)

	Forest	**Rubber agroforest**	**Rubber monoculture**	**Oil palm**	**Rice field**	**Shrubland**	**Settlement**	**Total 1993**
Forest	**7653**	102	324	69	28	193	80	8450
Rubber agroforest	0	**1527**	1205	177	120	41	344	3414
Rubber monoculture	0	627	**2070**	79	79	23	329	3318
Oil palm	0	0	0	**0**	0	0	0	0
Rice field	0	3	1	0	**5**	0	0	0
Shrubland	0	0	0	0	0	**0**	17	26
Settlement	0	0	0	0	0	0	**309**	309
Total 2005	7653	2265	3618	437	237	260	1104	15736

Note: Column on far right is total area for each land-cover type in1993 and the bottom row of the table in 2005.

number of persistent land-use type in hectares between 2005 and 1993

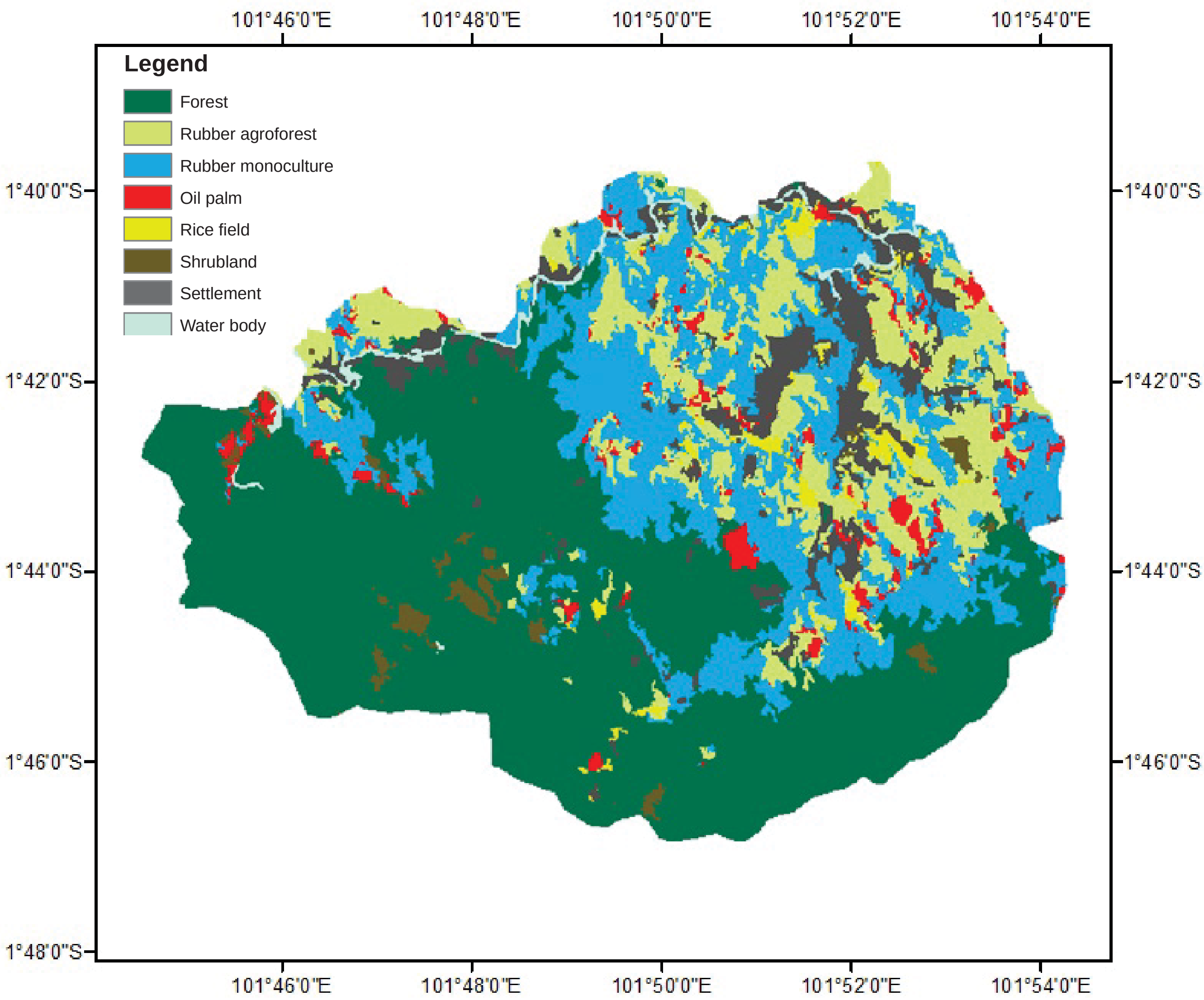


Figure 5.4 Land-cover map of 2005. Map coordinate system: Geographic projection (Long/Lat), Datum: WGS 1984 (Source: ICRAF)

The land-cover changes between 1993 and 2005 are summarized in Table 5.8. The loss[8] in forest cover dropped to 5% of the landscape, while rubber agroforest experienced the highest loss of 12.5% (see Appendix 1 for detailed analysis)

8 Loss of specific land-cover type is calculated by the total land-cover type of 1993 minus the total land-cover type of 2005 over the total area of the whole landscape. Gain of specific land-cover type is calculated based on the total land-cover type of 2005 minus the total land cover type of 1993 over the total area of the whole landscape.

Topographical characterization

Topographic wetness index

The wetness index ($P_{\_wetness}$) was calculated using the DEM of the study area (Figure 5.5). It describes the water accumulation in the soil through the combination effect of topographic slope and aspect. The higher $P_{\_wetness}$ value reflects the higher degree of water saturation. The highest $P_{\_wetness}$ recorded was 9.0 and the lowest was -15.0. It was observed that most of the rice paddies are located within areas with higher $P_{\_wetness}$ values whereas rubber farms are mostly located in the areas with lower values.

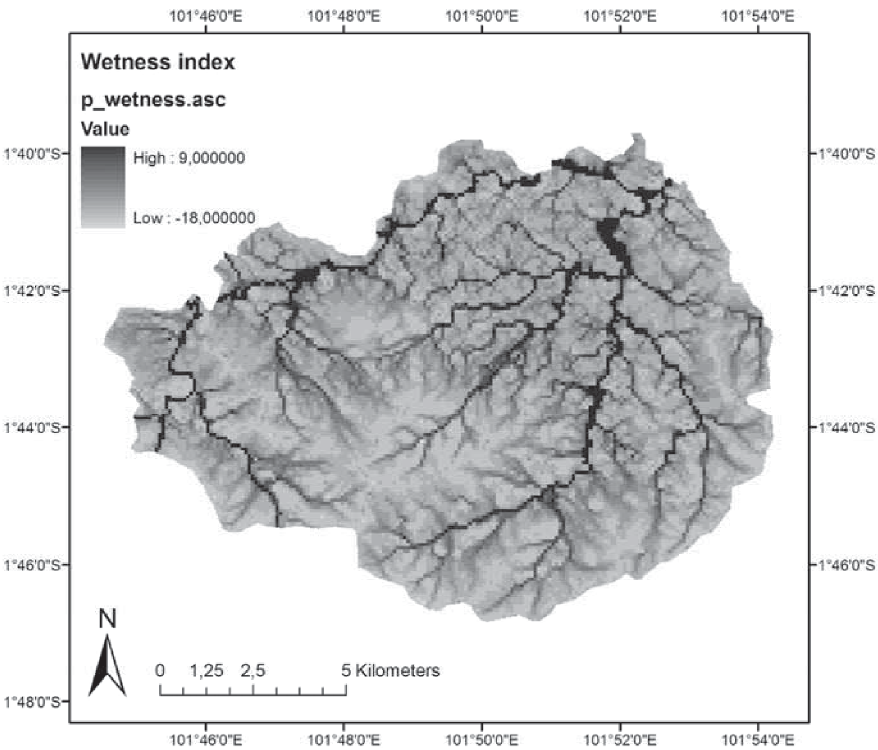
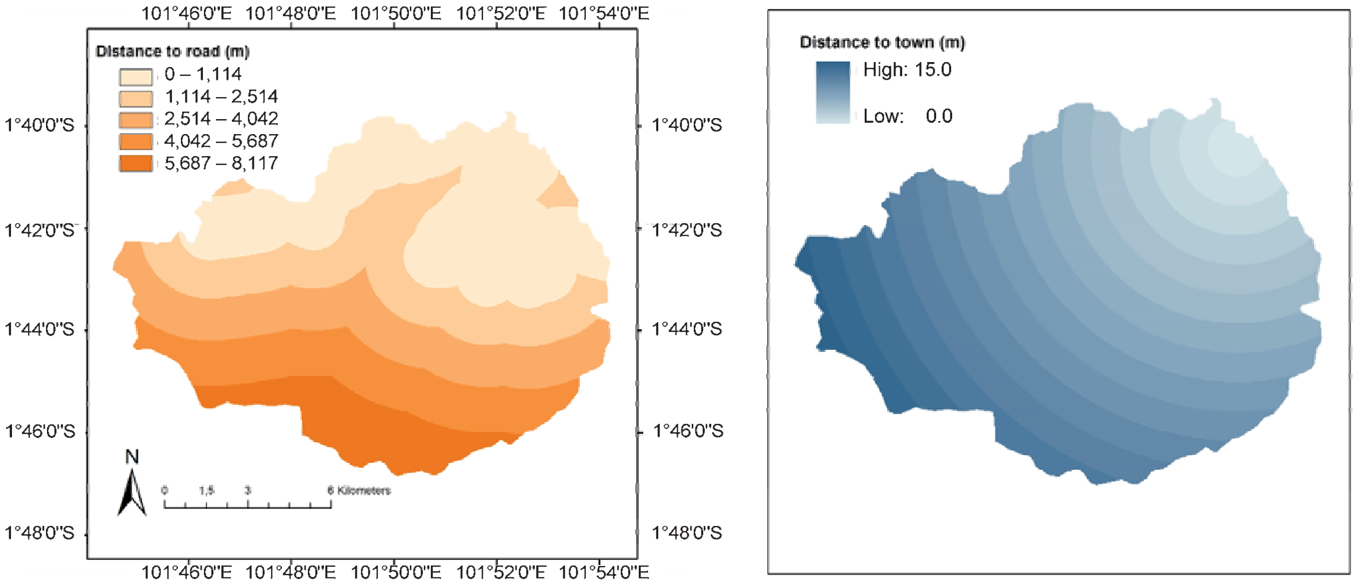


Figure 5.5 Raster image of wetness index at the study site. Map coordinate system: Geographic projection (Long/Lat), Datum: WGS 1984.

Spatial accessibility

The patterns of accessibility to roads and town center were relatively similar (Figure 5.6). Access to the nearest town and good roads to get there are important for the households' crop production. Distance to roads ($P_{\_droad}$) and town center ($P_{\_dtown}$) are significant variables affecting the land-use choice model, particularly for rice farmers (see Chapter 3).



(a) (b)

Figure 5.6 Raster images of a) proximate distance to roads (m), and b) proximate distance to the nearest town (m). Map coordinate system: Geographic projection (Long/Lat), Datum: WGS 1984.

Neighborhood interaction

The enrichment factors of land-use pattern ($P_{\_F2}$, $P_{\_F45}$, $P_{\_F6}$ & $P_{\_F8}$) are significant variables that influence the decision making of household agents. These variables are plugged in the land-use choice model (see section 3.3.2). Transition rules are developed based on the calculated states of the cell or patch (Figure 5.7). These variables could affect the transition rules, which consider whether to continue or discontinue the farming practices and/or open new land. In this way, the process of land-use change allocation through household-agent decision making can be explained. The enrichment factors of four land-use types, namely rubber agroforest ($P_{\_F2}$), upland/rice paddy ($P_{\_F6}$), settlement ($P_{\_F8}$) and other land uses ($P_{\_F8}$) may affect the decision making of household agents (Figure 5.7). Upland rice has the highest enrichment factor but is concentrated in small patches (Figure 5.7b) while the lowest is for other land uses and is widespread around the study area (Figure 5.7d).

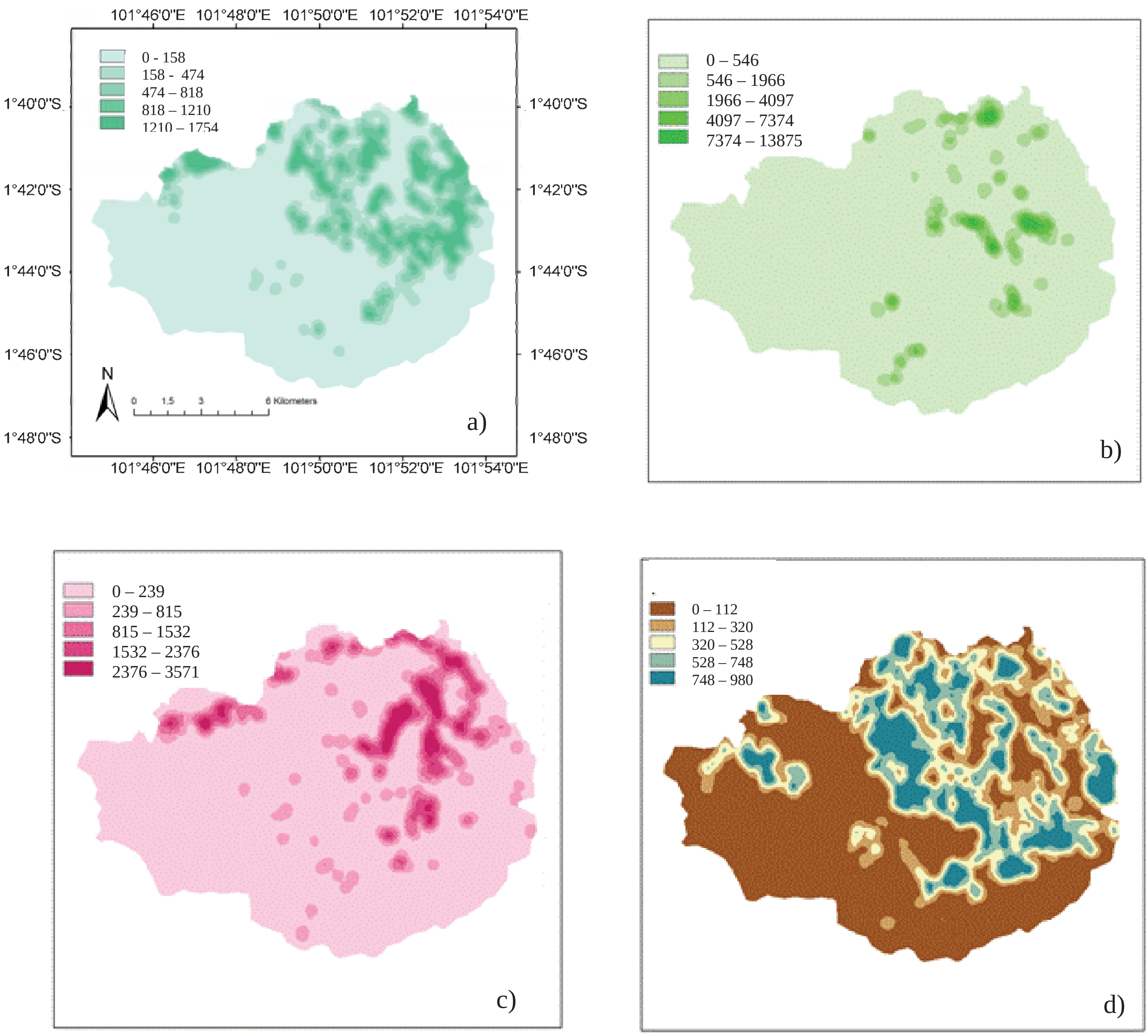


Figure 5.7 Raster images of enrichment factor of rubber agroforest ($P_{\_F2}$) (a), rice paddy/upland rice ($P_{\_F6}$) (b), settlement ($P_{\_F8}$) (c) and other land uses ($P_{\_F45}$) (d). Map coordinate system: Geographic projection (Long/Lat), Datum: WGS 1984.

5.3.2 Sub-model: species richness

Plot-level species richness

The results of the plot-level species richness analysis according to vegetation-age class were calculated using EstimateS (Colwell 2009) (Table 5.9). Data for higher plant species (DBH ≤ 10 cm) representing the pioneer species aged 0-5 years were not available. Thus, species richness for these species is assumed to be zero. For young secondary vegetation, the number of species recorded was 16 in the minimum plot area (200 m^2) and 79 in the maximum plot area (1000 m^2). For late secondary and forest species, the number of species recorded ranges between 23 and 33 in the smallest plot (2000 m^2) and, and between 115 and 166 in the largest plot (10,000 m^2). The number of species increases steadily with increasing area, and only curves using the Chao 1 richness estimator reached the asymptote level within the plot size ranges suggesting that the sampling effort is low (Table 5.9).

Table 5.9 Descriptive statistics of species richness at plot level based on EstimateS, 2009 in Lubuk Beringin, Jambi Province

Vegetation class by age	**Sample plot**	**Plot size (m^2)**	**Computed N (No. of individuals)**	**S_{obs} (Mao Tao) Mean**	**S_{obs} (Mao Tao) SD (σ)**	**Chao 1 Mean**	**Chao 1 SD (σ)**	**Jack 1 Mean**	**Jack 1 SD (σ)**
Pioneer (0-5 years)	-	-	-	-	-	-	-	-	-
Young secondary (5-20 years)	1	200	15.80	8.44	1.31	15.55	6.85	8.04	0
	2	400	31.60	13.40	1.60	22.77	8.73	17.73	0.57
	3	600	47.40	16.54	1.74	32.42	13.36	23.80	1.63
	4	800	63.20	19.38	1.83	33.13	11.47	27.05	2.11
	5	1000	79.00	21.00	1.94	28.20	6.44	28.02	2.93
Late secondary (20-50 years)	1	2000	23.04	8.66	1.43	25.28	12.10	8.44	0
	2	4000	46.09	15.72	2.08	32.93	13.17	20.28	2.44
	3	6000	69.14	20.16	2.58	37.95	13.83	26.09	5.57
	4	8000	92.19	23.86	2.96	36.44	10.98	29.91	5.92
	5	10000	115.24	26.26	3.28	33.40	6.91	33.29	6.70
Forest (>50years)	1	2000	33.20	16.54	1.74	41.31	17.44	18.10	0
	2	4000	66.40	30.92	2.72	58.75	16.71	45.71	4.17
	3	6000	99.60	40.32	3.39	70.91	16.44	63.20	7.08
	4	8000	132.80	49.90	3.90	77.75	14.79	75.45	7.77
	5	10000	166.00	57.00	4.37	80.4	11.90	85.00	6.57

Note: S_{obs} is the observed number of species expected in the pooled samples given by the empirical data (Colwell 2004).

The species accumulation curves for each vegetation-age class were plotted based on three richness estimator models namely, Chao 1, Jack 1and Mao Tao (Figure 5.8 and 5.9). From these estimator models, only the accumulation curve based on Chao 1 shows the asymptotic curves in young and late secondary stages. Thus, the Chao 1 richness estimator results were used for extrapolation. It should also be noted, especially in the taxon-rich species groups in the tropics, that observed richness rarely reaches an asymptote despite intensive sampling (Gotelli and Colwell 2001).

Extrapolation of S_{obs} for land-use type

The results of the correlation analysis (Table 5.9) were fitted to the power function formula $\boldsymbol{S = kA^z}$. The target is to calibrate the data to have a power function based on the patch area (900 m^2) for the LB-LUDAS model. The result of correlation analysis is presented in Table 5.10 and the species area curve in Figure 5.10.

Table 5.10 Correlation analysis of S_{obs} to determine the z and k coefficients in a log-log form using Chao 1 estimator results.

Vegetation class	**Slope (*z*-value)**	**β (log *k*)**	**R^2**
Young secondary (5-20 years)	0.44	0.203	0.890
Late secondary (20-50 years)	0.20	0.767*	0.808
Forest (>50years)	0.42	0.222***	0.980

*Note: ***, **, and * indicate significance at the 0.01, 0.05 and 0.1 level, respectively.*

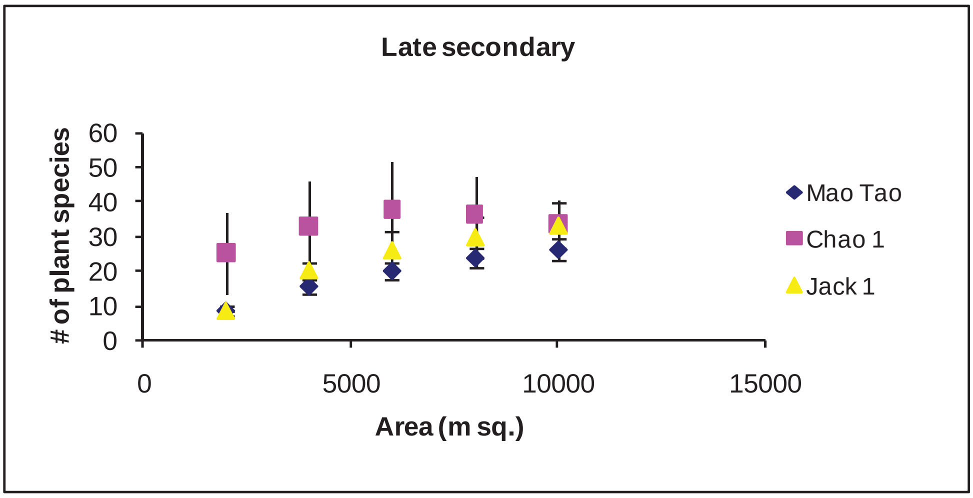


Figure 5.8 Species area curve (±SD) for late secondary stage of higher vascular plants (20-50 years) in the rubber agroforests

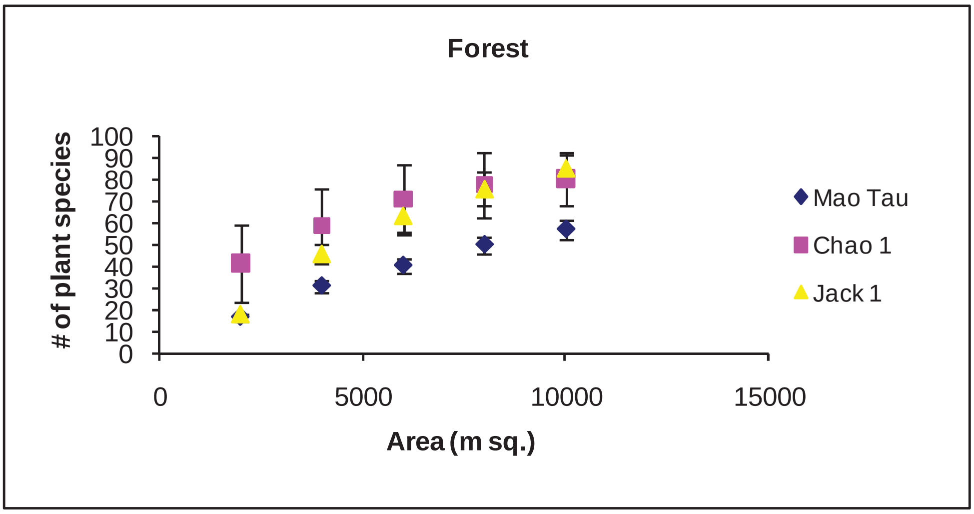


Figure 5.9 Species area curve (±SD) for forest (>50 years)

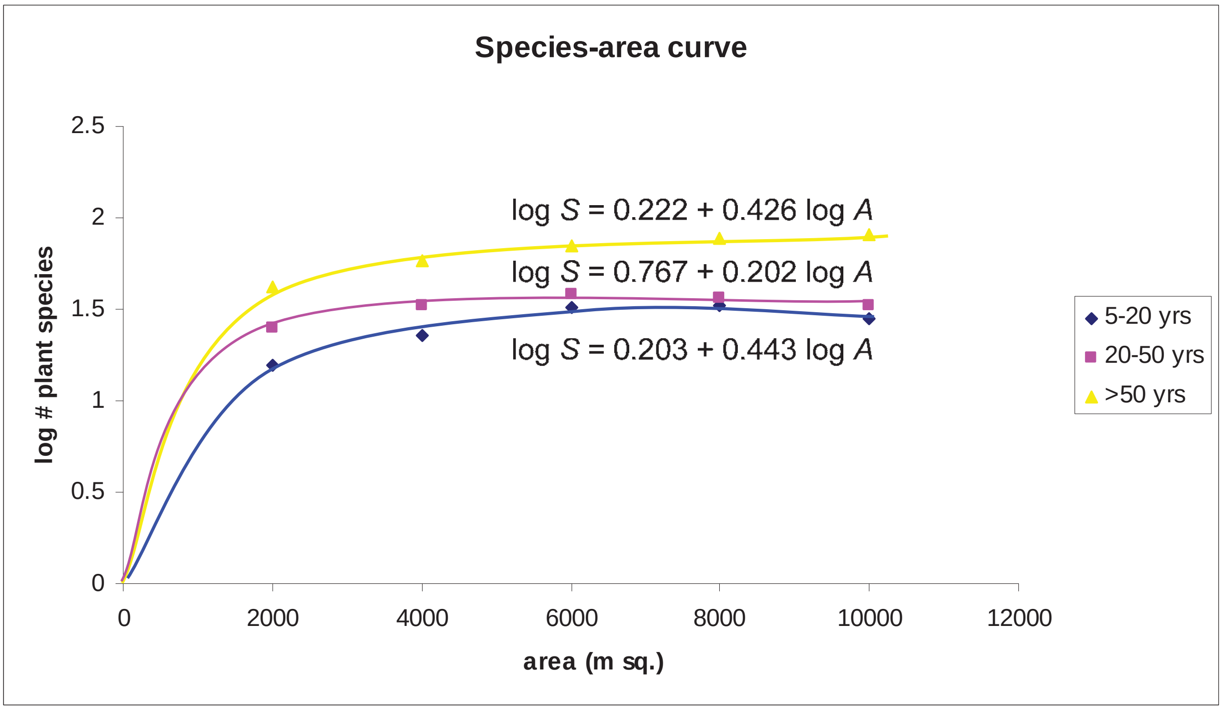


Figure 5.10 Species-area curves for three vegetation classes (by age) in Lubuk Beringin, Jambi, Sumatra, Indonesia. Data source: Rahayu (2009).

The power model (where log k is converted to $k = 10^{\beta}$) for species richness for each vegetative age class is derived as follows:

$$S_E = 1.60A^{0.44} \tag{5.22}$$

where S_E is the estimated species richness, and A is the area (m^2), if the vegetation class age (or P_t) is 5 - 20 years.

$$S_L = 5.84A^{0.202} \quad (5.23)$$

where S_E is the estimated species richness, and A is the area (m^2), if the vegetation class age (or P_t) is 20 - 50 years.

$$S_C = 1.66A^{0.426} \quad (5.24)$$

where S_E is the estimated species richness, and A is the area (m^2), if the vegetation class age (or P_t) is >50 years.

Diversity index

The diversity indices[9] of the plots were also calculated using EstimateS. The results show that the highest diversity index at plot level is found in the forest and ranges from 2.23 to 3.47 (Table 5.11). The indices at late secondary stage (where rubber-agroforest plant species predominate) are relatively similar to that of rubber agroforest in Jambi province observed by Tata et al. (2008) which is 2.6 (± 1.5).

Table 5.11 Index of species diversity using EstimateS (Colwell 2009) of Lubuk Beringin, Sumatra, Indonesia. Data source: Rahayu 2009.

Vegetation-age class	**Plot no.**	**Shannon diversity index (mean)**	**Standard deviation**	**Simpson diversity index (mean)**	**Standard deviation (SD)**
Young secondary (5-20 yrs)	1	1.86	0.15	-	-
	2	2.24	0.12	9.93	3.35
	3	2.46	0.10	11.31	2.21
	4	2.53	0.06	11.39	1.23
	5	2.61	0	11.98	-
Late secondary (20-50 yrs)	1	1.76	0.63	6.14	3.49
	2	2.18	0.54	7.83	4.18
	3	2.37	0.43	8.35	3.70
	4	2.57	0.35	9.36	3.39
	5	2.57	0.28	8.97	3.59
Forest (>50 years)	1	2.23	0.21	17.74	4.17
	2	2.48	0.43	14.87	10.66
	3	3.00	0.37	18.68	10.82
	4	3.37	0.09	18.71	2.14
	5	3.47	0	20.13	0

9 Diversity indices of Shannon (using natural logarithms) and Simpson (using the reciprocal form) are the two widely used diversity indices that combine information on richness and relative abundance in different ways.

5.3.3 Sub-model: agronomic-yield dynamics

Descriptive statistics of variables

The descriptive statistics of variables used for the agronomic yield sub-model in rice and rubber agroforest in 2010 are summarized in Table 5.12. Yield from upland rice production is around 605 ± 574 kg $ha^{-1}yr^{-1}$. Rice is harvested only once a year during rainy season. Labor (124 man-days $ha^{-1}yr^{-1}$) and fertilizers (6500 g $ha^{-1}yr^{-1}$) are the main inputs. The upland rice system is more labor demanding compared to rubber latex production.

Table 5.12 Descriptive statistics of variables for sub-model agronomic-yield dynamics of rice and rubber agroforest for 2010.

Model	Number of plots (n)	Mean	Standard deviation	Confidence interval at 95% level
a) Paddy/upland rice yield $P_{\_yieldrice}$ (kg $ha^{-1}year^{-1}$)	33	605	574	199
Labor $I_{ricelab}$ (man-day $ha^{-1}year^{-1}$)	33	124	72	25
Agrochemical input $I_{\_fert}$ (g $ha^{-1}year^{-1}$)	33	6501	14665	5106
Rainfall P_{rain} (mm)	33	1554	407	142
Wetness index $P_{wetness}$	33	-10.7	5.3	1.8
Rice plot area $P_{areaRICE}$ (m^2)	33	8560	4678	1628
b) Rubber agroforest (latex) yield $P_{yieldrubber}$ (kg $ha^{-1}year^{-1}$)	51	1090	1273	356
Rubber plot area $P_{areaRUB}$ (m^2)	51	41666	40726	11404
Wetness index $P_{wetness}$	51	-14.6	2.8	0.802
Labor I_{rublab} (man-day $ha^{-1}year^{-1}$)	51	106	23	6.534
Tree age T_{age}	51	15	8	2.490
Number of rubber trees I_{tree} (ha^{-1})	51	157	106	29.95
Seedling planted per plot $I_{\_seedling}$ ($ha^{-1}year^{-1}$)	51	3	4	1.621

For rubber latex production, the average latex yield is around 1090 ± 356 kg $ha^{-1}yr^{-1}$. The interviewed farmers reported that no agrochemical inputs were applied in the production system. However, the average yield was about 200 to 400 kg $ha^{-1}yr^{-1}$ higher compared to yields in a study conducted by Joshi et al. (2006), but still lower than in the labor-intensive rubber monoculture (1200-1800 kg $ha^{-1}yr^{-1}$). The average size of rubber agroforest farm plots is 4 ha (40,000 m^2) per household.

The yields from oil palm and rubber monoculture plantations were derived from the study conducted by ICRAF in 2009 (Figure 5.11). For oil palm, the (fruit) yield cycle is 25 years with peak yields in the years 11 to 18 of about 21 tons $ha^{-1}yr^{-1}$. For rubber monoculture plantations, the latex yield cycle is 29 yrs with peak yields in the years 8 to 17 of about 1800 kg $ha^{-1}yr^{-1}$. These yields were used to estimate the production per $ha^{-1}year^{-1}$ in the agronomic yield sub-model using the bounded-random rule.

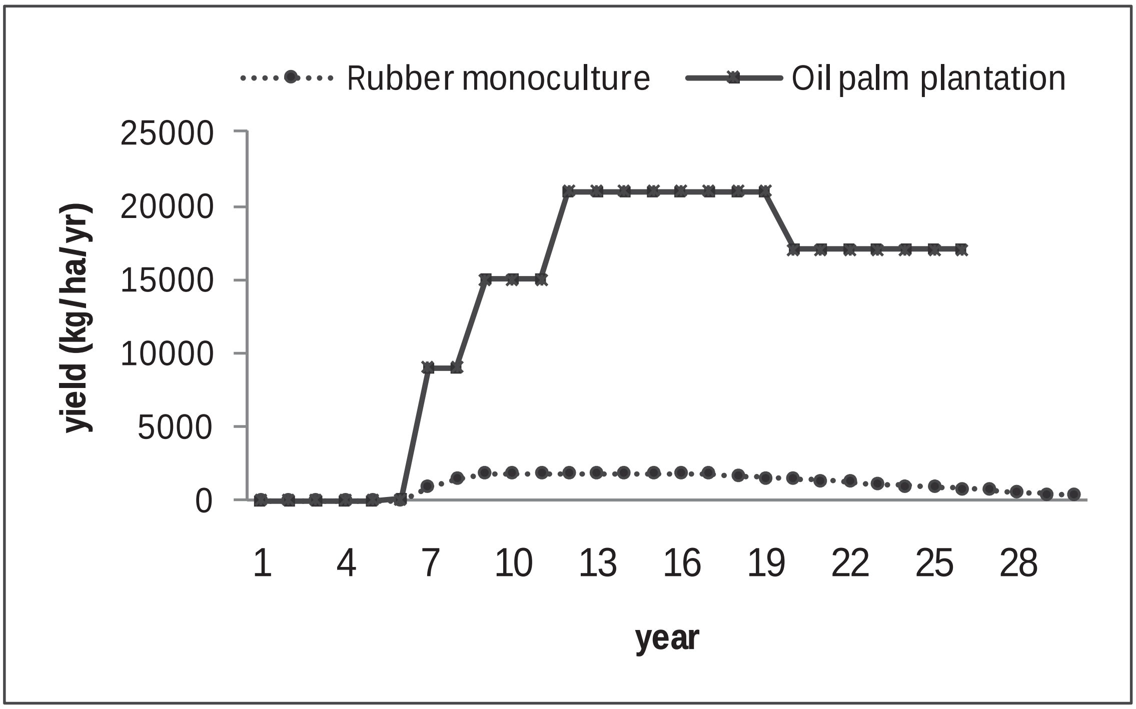


Figure 5.11 Yields of oil palm and rubber from monoculture plantations (Source: ICRAF 2010).

Modeling agronomic yield

The results of the log-linear regression analyses for the agronomic yield model of upland rice and rubber agroforest are summarized in Table 5.13.

Table 5.13 Results of log-linear regressions for yields of rice and rubber agroforest for 2010.

Agronomic yield model	Unstandardized coefficient (yield elasticity) (β)	Standard error of β (σ_β)	Confidence interval of β at 95% level
Ln of upland rice yield $ln(P_{\_y\text{-}rice})$ n= 33; mean $ln(P_{\_y\text{-}rice})$ = 6.0139 R^2 = 0.34; *mse* = 1.008; *p* = 0.039 (constant)	-5.464	6.889	13.778
Ln of labor input $ln(I_{ricelab})$	1.063**	0.473	0.946
Ln of agrochemical input $ln(I_{fert})$	0.093*	0.046	0.092
Ln of rainfall $ln(P_{rain})$	0.551	0.601	1.202
Wetness index (P_{wet})	-0.031	0.035	0.070
Ln of rice plot area $ln(P_{areaRICE})$	0.201	0.467	0.934
Ln of rubber agroforest yield $ln(P_{\_y\text{-}rubber})$ n= 51; mean $ln(P_{\_y\text{-}rubber})$ = 6.3764; R^2 = 0.471; *mse* = 0.921; *p* = 0.000 (*constant*)	3.154	3.449	6.898
Ln of rubber plot area $ln(P_{areaRUB})$	-0.601**	0.193	0.386
Wetness index $(P_{wetness})$	-0.074	0.052	0.104
Ln of labor $ln(I_{rublab})$	1.426**	0.673	1.346
Ln of tree age (T_{age})	-0.196	0.313	0.626
Ln of number of rubber trees $ln(I_{tree})$	0.535**	0.190	0.380
Ln of seedling planted per plot $ln(I_{seedling})$	-0.465**	0.158	0.316

*Note: The symbols *, **, and *** indicate statistical significance at the confidence level of 90%, 95%, and 99%, respectively. The symbol s refers to standard error of the regression model estimate. The bootstrap resampling method of 10,000 was conducted for both models and gave same* R^2 *results.*

Upland rice yield estimation

Labor $(I_{\_ricelab})$ and agronomic inputs $(I_{\_fert})$ are the significant explanatory variables in the rice yields. The yield elasticity or responsiveness to these variables indicates that an increase of 1% in labor and fertilizer input would increase the rice yield by 1% and 0.1%, respectively.

Rubber agroforest yield estimation

The explanatory variables significantly affecting the rubber agroforest yield are rubber plot area ($P_{\_areaRUB}$), labor ($I_{\_rublab}$), number of mature rubber trees ($I_{\_rublab}$), and number seedlings planted per farm plot ($I_{\_seedling}$). In relation to responsiveness of labor and capital inputs to the yield output, latex production from rubber agroforest is sensitive to labor input. A 1% increase in labor would lead to a 1.42% increase in output.

5.3.4 Sub-model: forest-yield dynamics

Basal area

The descriptive statistics of the stand basal area for four studied land-cover types based on 2009 and 2006 data are presented in Table 5.14. The average mean stand basal area is 41 ± 3.8 m^2 ha^{-1} for forest, 24 ± 8.9 m^2 ha^{-1} for rubber agroforest, 21 ± 5.2 m^2 ha^{-1} for logged-over forest, and 12 ± 3.3 m^2 ha^{-1} for rubber monoculture.

Table 5.14 Descriptive statistics of stand basal area for the four forest-like cover types in Jambi Province (Data source: Rahayu 2009; Rasnovi 2006)

Land cover	Number of plots surveyed	Mean stand basal area (m^2 ha^{-1})	Standard deviation	Confidence interval at 95% level (m^2 ha^{-1})	Confidence interval at 95% level	
					Lower bound (m^2 ha^{-1})	Upper bound (m^2 ha^{-1})
Forest	5	41	±7.76	3.88	37.1	44.8
Rubber agroforest [a]	17	24	±8.91	2.16	22.6	27.0
Logged-over forest [b]	5	21	±5.28	2.36	18.9	23.6
Rubber monoculture [c]	5	12	±3.73	2.15	10.6	14.9

Note: Only trees with ≥ 10cm DBH were considered and measured at 1.3m height.

[a] *Age of the rubber agroforest ranges from 30-60 years.*
[b] *Age of the logged-over forest is 25 years.*
[c] *Age of monoculture is 13 years.*

Based on this descriptive analysis (Table 5.14), the stand basal area of the study site was applied in LB-LUDAS model as a stand-alone sub-model using the bounded-random equation.

The average stand basal area was compared to that generated by Le (2005). The basal area in lowland forest of Jambi is higher. However, the result of the land-cover change analysis (see Appendix 1) shows that logging is mainly done in rubber agroforest monoculture rubber, especially if the trees are already matured. Based on local interviews, households meet their wood demand by cutting the old or matured rubber trees and at the same time planting new trees. Old matured rubber trees are cut when they are between 30 and 40 years old.

5.3.5 Natural transition sub-model: calibration for transition rules

The threshold values of stand basal area of rubber agroforest ($\theta_{tb\text{-}AF}$) and rubber monoculture ($\theta_{tb\text{-}RubMN}$) for the transition rule N1 are generated from the stand basal area (Table 5.14), and are as follows:

$$\theta_{tb\text{-}AF} = (24 + CI_{95\%}) = 27 \text{ m}^2 \text{ ha}^{-1} \tag{5.25}$$

$$\theta_{tb\text{-}RubMN} = (12 + CI_{95\%}) = 15 \text{ m}^2 \text{ ha}^{-1} \tag{5.26}$$

For the N2 transition rule, the rules were consistent with a study conducted by Gouyon (1993) in Jambi province, which documented the farming practice, e.g., *ladang* (fallow). Accordingly, due to labor needs and decreasing yields as a result of weed competition, farmers abandon the area after one to two years of cultivation, and after a fallow period of at least 15 to 20 years the area is similar to an agroforest. This analysis is similar to the vegetation-age class suggested in the FALLOW model (van Noordwijk 2002b). Here, it is assumed that the patch is not far from the forest, e.g., 20-30 m from the edge, and that there is no disturbance. Hence, the threshold parameters of the transition rules N2 are expressed as follows:

$$\theta_{d\text{-}forest} = 1 = 30 \text{ m x } 30 \text{ m} \qquad \text{(pixel length)} \tag{5.27}$$

$$\theta_{t\text{-}forest} = 41 \text{ m}^2 \text{ ha}^{-1} \qquad \text{(threshold basal area)} \tag{5.28}$$

$$\theta_{t\text{-}logged\text{-}over} = 50 + random_{int}(2) \qquad \text{(years for N2}_{logged\text{-}over}) \tag{5.29}$$

$$\theta_{t\text{-}AF} = 20 + random_{int}(2) \qquad \text{(years for N2}_{rubber\text{-}agroforest}) \tag{5.30}$$

where $random_{int}(2)$ returns randomly an integer number within [0,2], i.e., 0, or 1, or 2.

A stand-alone *NaturalTransition* sub-model is built in LB-LUDAS. The result of this sub-model per time-step is fed back to the biodiversity sub-model.

5.3.6 Carbon emissions

The land-cover transition matrix of 1993-2005 provides the information on the land-cover changes occurred within that period (Table 5.8). Based on this matrix, intensity of land-cover change including the rate of deforestation was determined (see Appendix 1). Between 1993 and 2005, around 66 ha year^{-1} of forest cover and 96 ha year^{-1} of rubber agroforests were converted to other land uses (see Appendix 1 for specific details of gains and losses of land covers). It is general knowledge that the conversion from forest and other high-carbon ecosystem to low-carbon ecosystems would lead to net carbon emission to the atmosphere, and vice versa would lead to carbon sequestration.

From the matrix, the net carbon emissions and sequestration were calculated (Table 5.15). It was estimated that the total carbon emission from land-cover changes in the period 1993-2005 was 10.5 Mg ha^{-1}, while annual emissions were 0.8 Mg ha^{-1}. The majority of the emissions were emitted through the conversion of forests (and later of rubber agroforests, see Appendix 1) to rubber monoculture with total emissions of 3.2 Mg ha^{-1} and to settlement areas with total emissions of 2.9 Mg ha^{-1}. These results (Table 5.15) will serve as the baseline for comparing results simulated in the LB-LUDAS model under different scenarios (see Chapter 7). Carbon emissions are linked to the impact module and monitored for every time-step (e.g., for every 5 years). The resulting land-cover change will be assessed to estimate carbon emissions and carbon sequestration.

Table 5.15 Estimates of total net carbon release and carbon sequestration based on land-cover change between 1993 and 2005 (Mg ha^{-1})

Land-cover type	Carbon parameter	Results	
	Time average C-density (Mg ha^{-1})*	**C-emitted from conversion (Mg ha^{-1})**	**C-sequestered (Mg ha^{-1})**
Emissions over 12 years			
Forest	150	0	0
Rubber agroforest	62	0.6	-0.6
Rubber monoculture	46	3.2	0
Oil palm	31	1.1	0
Rice field	1	0.9	0
Shrubland	26	1.8	0
Settlement	4	2.9	0
Total		10.5	-0.6

Land-cover type	Carbon parameter	Results	
	Time average C-density (Mg ha^{-1})*	C-emitted from conversion (Mg ha^{-1})	C-sequestered (Mg ha^{-1})
	Emissions over 12 years		
	Emissions year $^{-1}$		
Forest	150	0	0
Rubber agroforest	62	0	-0.1
Rubber monoculture	46	0.3	0
Oil palm	31	0.1	0
Rice field	1	0.1	0
Shrubland	26	0.1	0
Settlement	4	0.2	0
Total		0.8	-0.1

** Source: Tomich et al. 1998*

5.4 Conclusions

The integration of various ecological processes described above is a way to respond to one of the weaknesses of MAS/AB modeling, i.e., weak ecological integration (Cumming 2011). Here, the landscape agents were characterized to address the diversity, variability and heterogeneity of the ecological entities. In the context of rubber agroforests, among the important ecological functions and processes included are species richness per vegetation class (young and late secondary, and forest), and natural succession, which is based on the stand basal area against the threshold, plot age and distance to forest.

First, the past land-use changes and their trend (see Appendix 1) in the study site were considered. Next, the variables relevant to the productivity and land-use decision making were identified. Among them is the neighborhood characteristic of land-use patterns measured in this study. Rice field has the highest enrichment factor among the other land uses. The significance of the enrichment factor of neighboring land uses in the decision making of household agents is applied in Chapter 3, and later integrated in the simulation (see Chapter 7).

The fundamental methods of building sub-models used to describe the ES found in a rubber agroforest landscape were elaborated, i.e., biodiversity, natural succession, carbon sequestration and the agronomic yields from rubber agroforests, monoculture rubber and rice. Some of these sub-models explicitly reflect scale- and distance dependence and various temporal and spatial influences (e.g., species-area relationship, natural succession) coming into play that later would enforce various trade-offs.

Calibration of these sub-models and data was carried out. The final results were then translated for the LB-LUDAS model. In the following Chapter 6, the operationalization of the social-ecological systems using the LB-LUDAS model is addressed.

6 OPERATIONALIZING LB-LUDAS MODEL AND CHALLENGES OF EMPIRICAL MODELING

Science progresses from recognition of contextual patterns towards agency-based causal explanations, and the construction of an agent-based model that predicts emergent system behavior from realistic agent properties is a sign of significant scientific progress and internal consistency of model assumptions (Grimm et al. 2005). This part of the study tackles the construction and operationalization of the LB-LUDAS model using empirical data (Chapter 4 and 5). Empirical data for multi-agent simulation (MAS) modeling could provide relevant information to policy makers, scientists and stakeholders about the boundary conditions of rural development and uncertainties involved in land-use change (Parker et al. 2003; Berger and Schreinemachers 2006; Le et al. 2008; 2010). However, the caveat is that the researcher also moves into the problem of empirical modeling.

Thus, the aim is to address the following objectives:

1. To operationalize LB-LUDAS model as an integrated model and MAS model that simulates the socio-ecological components of a rubber agroforest landscape in Jambi province using empirical data,
2. To describe the unanticipated difficulty of applying MAS/AB model using empirical study that emerged during the initial simulation stage, and identify assumptions behind, and
3. To present alternative approaches to address the challenge of empirical MAS modeling for the case study, with potential wider applicability.

6.1.1 Operational LB-LUDAS: an integrated model using empirical data

The LB-LUDAS model was developed specifically for the context of the study site (see Chapter 3 and 5). This model has the basic functionalities of a negotiation-support system (NSS) to support the design of the land-use policies, as it can predict landscape level through the likely response of agents to changes in externally set rules and incentives. Parameters, inputs, calibrated data and transitional rules are discussed in Chapters 2, 3, 4, and 5. The model parameterization used a common sampling frame to randomly select observation units for both biophysical measurements and socio-economic surveys. These were extrapolated over the landscape based on the Monte Carlo simulation technique, assuming independence of parameters in a random process unless statistical relationships were explicitly specified (Atanassov and Dimov 2008). Thus, the resulting landscape and agent population are statistically consistent with empirical data, given the recognized patterns of correlations and stratification.

6.1.2 Graphic user interface

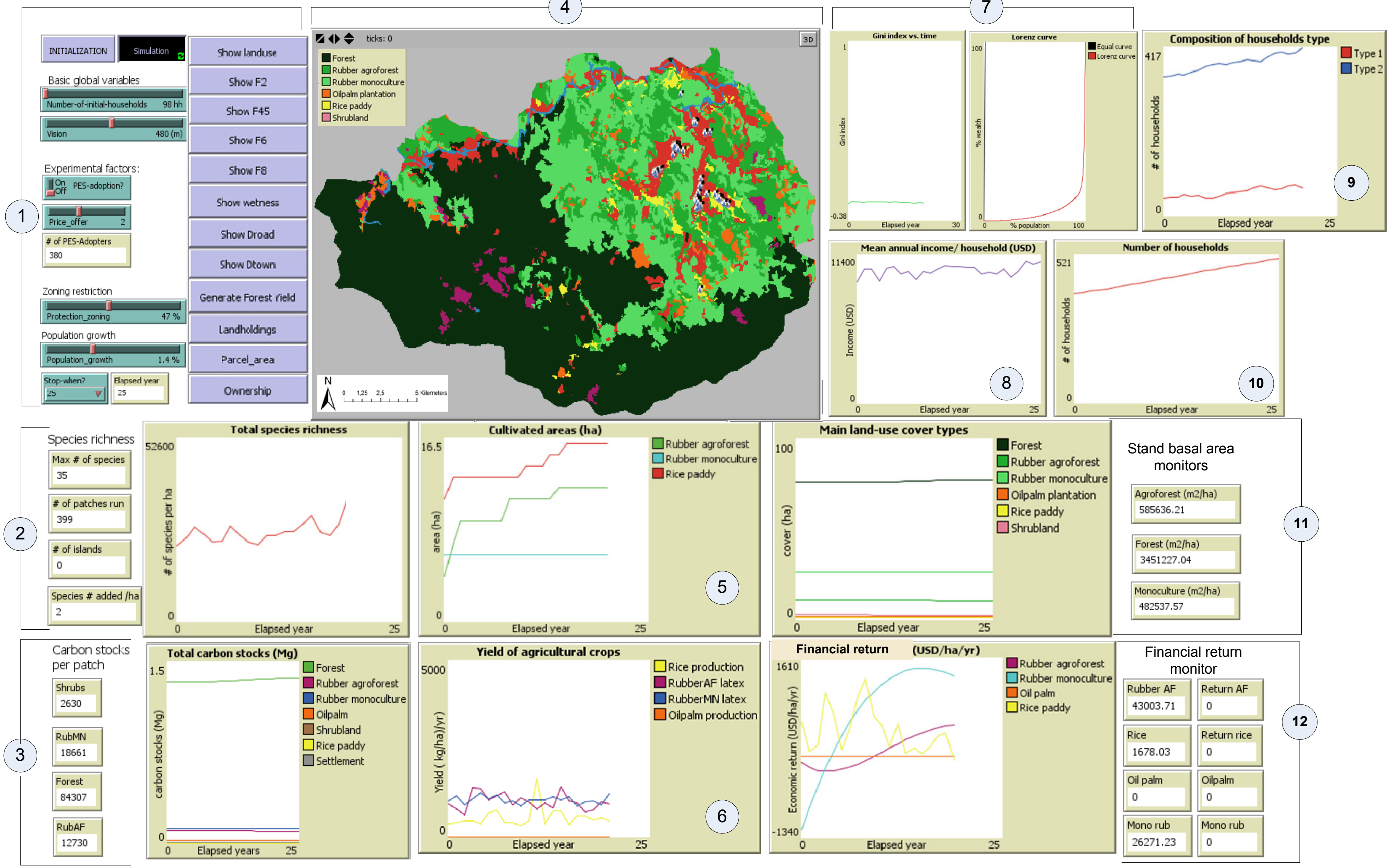
The following are the key components of the graphic user interface of the LB-LUDAS model (Figure 6.1):

1. User's input and global (experimental) parameters (part 1, Figure 6.1). Through the slider the user can adjust the parameter values to be tested.
2. Digital land-use/-cover map navigation window (part 4, Figure 6.1). This enables the user to visualize the land-use/-cover changes through time steps.
3. Time-series graphs of performance indicators of both biophysical and human systems (parts 2, 3, 5, 6, 7, 8, 9, 10, 11, and 12, Figure 6.1). These include the species number as specific land-use changes (part 2), the total carbon stocks of the target landscape (part 3), Gini index to monitor the wealth inequality (part 7), etc.
4. Monitors along with specific time-series graphs are included for further related calculations of indicators (parts 2, 3, 11 and 12, Figure 6.1).

The LB-LUDAS model is implemented in the Netlogo version 4.1 modeling environment (Wilensky 1999).

6.1.3 Baseline setting and stylized facts

In the baseline setting, the decision-making sub-model follows the empirical land-use choice model as the benchmark (section 3.3.2). For the socio-ecological parameters and variables under this scenario see Chapter 3.



1 Initializing and simulation command buttons, global parameters, policy factors inputs and spatial attributes	4 Spatio-temporal explicit land-use map	7 Income inequality and Lorenz curve	10 Population growth (by empirical function)
2 Time series graph: plant species richness (biodiversity)	5 LUCC – agricultural type graph	8 Change in household income	11 LUCC – Main land-cover types
3 Time series graph: carbon stocks of major land cover	6 Time series graph: agricultural yield of interest crops	9 Spatially correlated household types and interaction monitors	12 Annual financial return time-series graph and monitors

Figure 6.1 Operational LB-LUDAS graphic user interface

The land-use policy context of this baseline scenario and other key socio-economic conditions are the following:

1. The implementation of *Hutan desa* through Government Rule No. 6 (2007) and Government Rule No. 3 (2008), which stipulate the use of environmental services and use of timber (subject for approval) as part of the management rights granted to the villagers. However, the rule applies only to the 2,300 ha of the 7,600 ha forest land (30%). Hence, the zoning restriction for this scenario is 70%.
2. The land-cover map of 2005 (see Chapter 5 and Figure 5.4) is the initial state of the study site.
3. Initial simulated population of 1520 individuals (380 households), i.e., four times higher than those interviewed in the household survey (Chapter 3).
4. A price of rubber latex of USD 2.50 kg^{-1}; rice USD 1.0 kg^{-1}, and hired labor USD 2 day^{-1}.
5. A human population growth of 1.4% based on the 2003 Statistics of Rantau Pandan as a sub-district of the Bungo Regency where the study villages belong.

Using the context of the baseline setting and the outputs of the empirical analyses (Chapters 3, 4, and 5), 'stylized facts'[10] drawn from empirical observations were compared to the results of the simulations. Since empirical observations "*are always subject to numerous snags and qualifications*" (Kaldor 1961, p.178), the use of stylized facts provides guidance for model construction, in particular for formulating productive abstractions based on the observed characteristics or phenomena under investigation. Stylized facts differ from the simplistic assumption of *as if* or *what if* approach in that stylized facts refer to an earlier step of a scientific process and their purpose is to facilitate the choice of an appropriate level of abstraction (Heine et al. 2005). The aim of using stylized facts is to construct an adequate model that is parsimonious (efficient in use of sparse parameters) to avoid distraction by minor details and at the same time rich enough to capture relevant aspect of the phenomena. At the same time, stylized facts are used in empirical validation approaches, e.g., indirect calibration (Olsen 2004; Heine et al. 2005; Windrum et al. 2007).

[10] In this research, stylized facts were applied due to their significance for simulation models and for validation purposes (see Heine et al. 2005).

In this context, stylized facts are the simplified expression of statistical observations:

1. The land-use choice of the individual households is correlated with the following household characteristics and biophysical properties (see section 3.3.2), as follows:

   Type 1 households' decision to choose rice field is correlated with age of the household head number of dependents, household income and education, wetness index and neighborhood land-use pattern, and

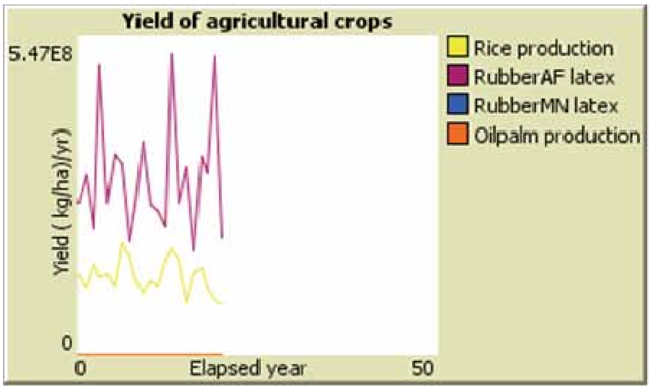
   Type 2 households' decision to choose rubber agroforest is correlated with age of the household head, number of dependents, education, wetness index, distance to road and town center, and neighborhood land-use pattern.

2. For rice yield, an increase of 1% in labor and fertilizer input would increase the rice yield by 1% and 0.1 %, respectively (see section 5.3.3).
3. For rubber agroforest yield, an increase of 1% in labor would lead to a 1.42% increase in output (see section 5.3.3).

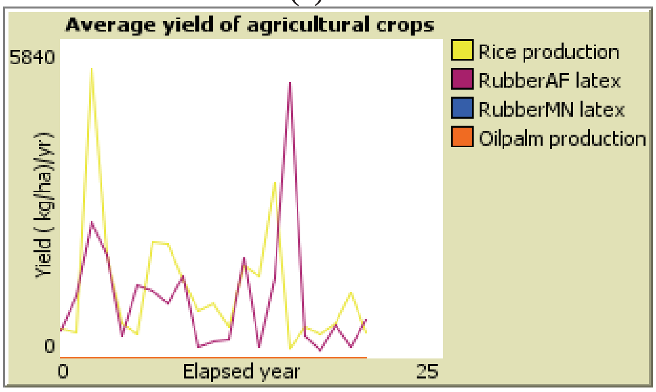
6.1.4 Initial simulation runs

During the initial simulations of the LB-LUDAS model, a problem with model behavior and output was frequently encountered, although most of the time-series graphs performed well, especially the graphics of the biophysical performance indicators. The problem was manifested by the dramatic oscillations (phenomena) reflected particularly in the crop yield graphs, and also in the economic return graphs (Figure 6.2).

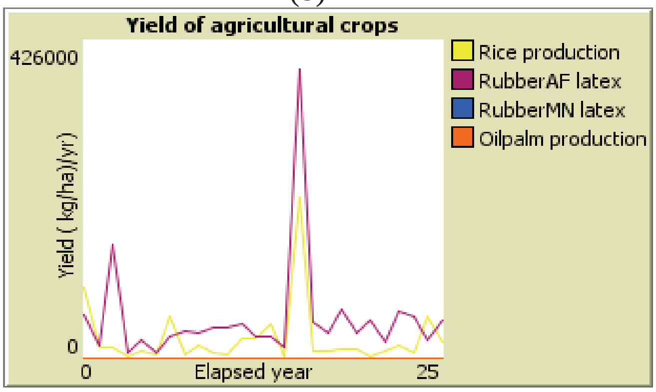
At first, it was suspected that the source of the problem originated from programming errors and/or wrong land-use choice and crop yield equations. Great efforts and time were invested in comparing the model outputs (Figure 6.2) to the set of stylized facts, which were very unmatched and unexplained. A series of tests over the space of initial conditions and parameters (which is already part of the sensitivity test), further analyses (e.g., model fitting and finding sources of variability, see Appendix 2 for results) and a literature review were conducted to address and explain the unwanted model output.



(a)



(b)



(c)

Figure 6.2 Examples of oscillation behavior in the crop yields generated from the preliminary simulation results using the baseline setting and the regression as the decision-making mechanism of agents. The oscillations were observed even in averaging the crop yields (b) and if the annual update of dynamic variables was only done every 3 to 5 years (c).

The expert suggestion to delay the annual updates of state variables of human and landscape agents (i.e., every 3 or 5 years) was also employed and helped to reduce the extreme oscillations and fluctuations, but once the update was executed the phenomenon occurred again (Figure 6.2c). The initial model output was presented to some experts/specialists[11], and it was agreed that the model output was atypical when compared to other model outputs.

Two specific cases are described and illustrated by Polhill et al. (2005; 2006) where dramatic changes in the model outcome were observed due to floating point arithmetic errors. The errors led to emergent effects with an entirely unwelcome element of surprise because of the high degree of non-linearity the errors introduces. Programming errors are not really uncommon, especially when the software platform is not user-friendly (see Gilbert 2008 for comparison of programs). Nonetheless, the oscillations[12] or resonance phenomenon observed may have a deeper source of explanations.

Oscillation phenomena are well known in the real world. Examples are periodic pulsating monotone growth (or resonance) until collapse processes, or chaotic processes.

Concerning our database, I do not feel entitled to make such assumptions simply because I only have cross-sectional data and therefore are unable to test such a hypothesis. On the other hand, oscillation phenomena could appear as arithmetic artifacts, i.e., a mere algebraic consequence or even technical restriction of the formulas or data used in our model.

And lastly, the observed oscillation might be the result of a model artifact, i.e., a consequence of a mis-specified model when relevant confounders are not included in the model.

In summary, the observed oscillation phenomena can be specified as follows:

1. Arithmetic artifact: Using recursively non-contracting functions in certain models. In such a case, the oscillation would appear as a monotone growth until a reset point when resources are exhausted thus a mimicry is created of a periodic pulsating growth until collapse. Also, it could be related to a 'butterfly effect' i.e., behavior of dynamic systems that are highly sensitive to initial conditions (Lorenz 1963).

[11] Presentations conducted in an Agent-based Modeling Workshop in Texel, Netherlands, held on 15-18 April 2011; and ZEFc seminar on 13 April 2011.

[12] In other MAS/ABM, this behavior is sometimes identified as non-ergodic during the process of validation (Windrum et al. 2007).

2. Model artifact: The oscillation as a result of a misspecification in modeling the agents' behavior when relevant confounders are not incorporated in the agent's modeling.

The first assumption requires a deeper level of understanding about the behavior and would involve not only a series of experimentation but also moving beyond into another scientific realm. Thus, the author proposes to address this in the future and treat them as a limitation of the present study.

For the time being, the second assumption is more realistic to tackle and is linked to the most pressing frontier of applying MAS/AB models with empirical data, i.e., the problematic relationship between MAS/AB models and empirical data. In this second assumption, the immediate question of "*is the oscillation or resonance phenomenon a manifestation that the regression analysis (i.e., frequently used tool for decision making) is inadequate of underlying variables?*" is raised. The following sub-sections introduce the background of the main frontier of empirical MAS modeling and recommendations for addressing the challenge.

6.2 Challenges

Researcher moves into the problem domain of empirical modeling whenever MAS/ABM is parameterized with empirical data. Heckbert et al. (2010, p. 46) pointed out that "*the field arguably suffers from a lack of success and effort in validating models … because of the difficult task of validating complex systems models and the response of many modelers to not sufficiently address validation. Thus, the field struggles with reputability, which is sometimes deserved*."

6.2.1 Weak theoretical representations of human decision making

The lack of success and the effort in validating the models can be traced to the weak theoretical representation of human decision making (Heckbert et al. 2010). This challenge lies in collecting empirical data on a system level and identifying its underlying causes.

Decision making of agents determines the overall functioning of multi-agent systems (Manson 2005a; Evans et al. 2006; Brown et al. 2007). Although there are different ways to explicitly formalize simple to complex human decision making (An

2011), the utility-seeking agents using preference functions calibrated with econometric techniques are the most common (Brown and Robinson 2006; Evans et al. 2006; Le et al. 2008; Feitosa 2010; Kaplan 2011; Villamor et al. 2011). However, one of the fundamental issues is to represent in a statistically consistent way a real-world situation of typically heterogeneous biophysical and socio-economic conditions (Berger and Schreinemachers 2006).

According to Evans et al. (2006), in empirical data analyses, statistical tools like logistic regression are commonly used to correlate particular actor attributes with specific land-use decisions either reported in a survey or observed from remotely sensed imagery. This approach identifies a statistically significant relationship between actor or landscape attributes and land-cover change but does not necessarily focus on the explicit land-use decision-making process. Moreover, these probability-based results do not necessarily provide clear insight into the actual decision-making process such as how an agent evaluates the benefits of a land-use change, the risks involved, and time frames considered for decision-making. Even if we capture as many variables as possible to describe the characteristics of human agents, the underlying causes are still unknown (Janssen and Ostrom 2006; Windrum et al. 2007; Heckbert et al. 2010).

In a statistical context, caution should be taken when using observational studies alone to model the agents' decision making, i.e., especially in predicting land-use decisions, since these kinds of models (i.e., the mere regress of observed decisions on observed data) *"do not carry the burden in the causal argument nor give much help in controlling for confounding variables"* (Freedman 2010, p.46). According to Rothman et al. (2008), given the observable nature of association measures, it is tempting to substitute them for effect measure and even more natural to give causal explanations for observed associations in terms of obvious differences. It is a well known textbook fact that - outside the realm of experiments - observed associations of variables do not automatically imply causality (Moore and McCabe 2004, p.160) and therefore cannot establish a law that could predict outcomes.

Another caveat that was posed by Gilbert and Troizsch (1999) is related to the concept of retrodiction, that even if the results obtained from simulation match those from the target (i.e., presumed social processes), there may be some aspects of the target which the model cannot reproduce (Gilbert and Troitzsch 2005). The authors give an example using the growth of the world's population "*where predictions for the next 50 years looked plausible, but retrodiction of the population to the situation 20 years in the past using the same model and the same parameters was completely wrong when compared with the actual world population then* (Gilbert and Troizsch 1999, p.22)." Thus, the use of longitudinal data (against cross-sectional data) or asking questions that are time-related is a rule of thumb to establish causal mechanisms (van Belle 2008).

Back to the finding presented above (section 6.2.2), the question of "*is the oscillation or resonance phenomenon a manifestation that the regression analysis (i.e. frequently used tool for decision-making) is inadequate regarding underlying variables?*" could be translated that the inadequate underlying variables are the confounders. Furthermore, in the context of modeling decision making, the factors of the decision process itself can be seen as confounding factors between the observed socio-economic data and the production decision. Because such factors are associated with both the socio-economic status and the selected production, such factors could be the risk-aversion of the decision maker, long term decision and alike. In order to estimate the central decision process more prospectively and so reduce confounding, one could estimate some parameters of the decision process directly. The next sub-section introduces the options to address this challenge.

6.3 Process-based decision making: an alternative

One method of addressing structural validation[13] is to develop a better understanding of the component relationships in the model, including the decision-making dynamics and processes (Evans et al. 2006).

In dealing with uncertainty of assumptions in models and data, an accepted way of reducing uncertainty or showing the influence of uncertainty processes on model results is by modeling the actual processes (Barthel et al. 2008). Process-based decision models, accordingly, are those capturing the triggers, options, and temporal and spatial aspects of an actor's reaction in a (relatively) direct, transparent and realistic way. An (2011) advocates that substantial efforts should be invested in process-based decision-making mechanisms or models to better understand socio-ecological systems.

[13] Decision making is considered the primary structural component in agent-based models (Evans et al. 2006)

While several options to address the issue discussed in this chapter are proposed (see Appendix 4), in this research a process-based decision sub-model is applied where the decision process as a confounding factor is integrated in the decision-making mechanism of LB-LUDAS. The empirical data generated from the future land-use preference (section 3.3.3), and the P/RES adoption (Chapter 4) are good estimators for the decision processes of the human agents. These two decision-making sub-models are treated as key important element in the scenarios instead of changing or setting up the environmental parameters or agents' state and global variables at the onset of initialization, which is the common way of testing scenarios. Instead, each scenario has its specific own decision-making sub-model where the decision process is built in.

6.3.1 Two-stage decision making

Using the land-use choice model alone could not give the underlying causes in the decision making of the agents. To better incorporate the human behavior component (i.e., decision making process), two-stage (or layered) decision-making routines were developed for the LB-LUDAS model. In the decision module of LUDAS, the *Preferred-land-use* and *PES-adoption* sub-models are integrated within the *FarmlandChoice* (see Chapter 2) as a household decision-making mechanism (Le 2008). The new routines are illustrated in Figure 6.3 and Figure 6.4.

In Figure 6.3, the decision process 'to adopt or not adopt P/RES schemes' is highlighted in gray, and is based on the results of the logistic regression developed in Chapter 4. On the other hand, in Figure 6.4, the first stage of decision is derived from the land-use choice model (see section 3.3.2) which performs the decision-making of the household agents in a retrospective manner. The *Preferred-land-use* under certain conditions (i.e., if supported by financial investment or subsidies, and in the coming 5 to 10 years) sub-model is integrated in the moving phase (highlighted in gray). In this way, the agents have already available labor to open new land.

With these decision making sub-models, time-related question (i.e., land-use preference in the next 5 to 10 years) and possible behavior of the agents (i.e., if PES schemes will be adopted based on the real pilot PES projects) form a new basis of more realistic decisions of the agents. Comparing the results of these two alternative decisions would provide a more rigorous strategy for modeling agent decisions (Grimm et al. 2005).

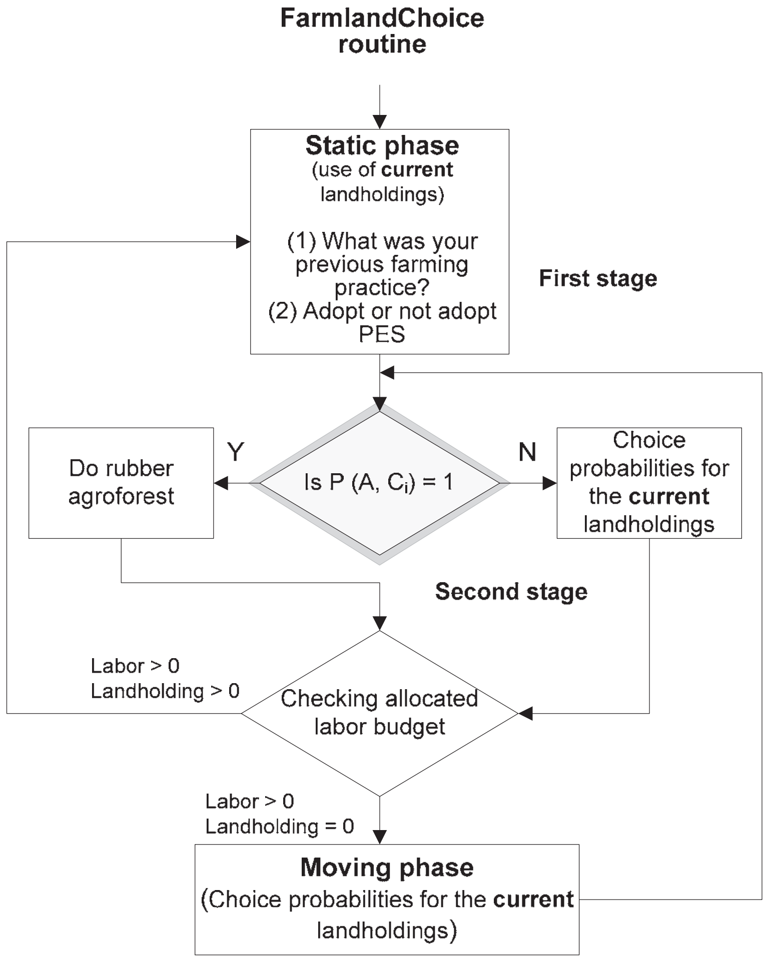


Figure 6.3 Schematic representation of the two-stage decision making for PES scenario wherein the *PES-adoption* sub-model is integrated in the first stage of the *FarmlandChoice* routine. P (A, C_i) refers to the probabilities (P) for agent (A) to choose the choices (C_i).

Figure 6.5 shows the example outputs of the new decision-making routine where the two-stage decision making for PES adoption is incorporated. The graphs demonstrate a considerable reduction in dramatic oscillations compared to those in Figure 6.2. The mathematical evidence of the concept is beyond the scope of this study and is considered as a limitation. However, one key issue that is addressed in this chapter is the introduction of a more adequate description of the underlying causal mechanism described in section 6.3.

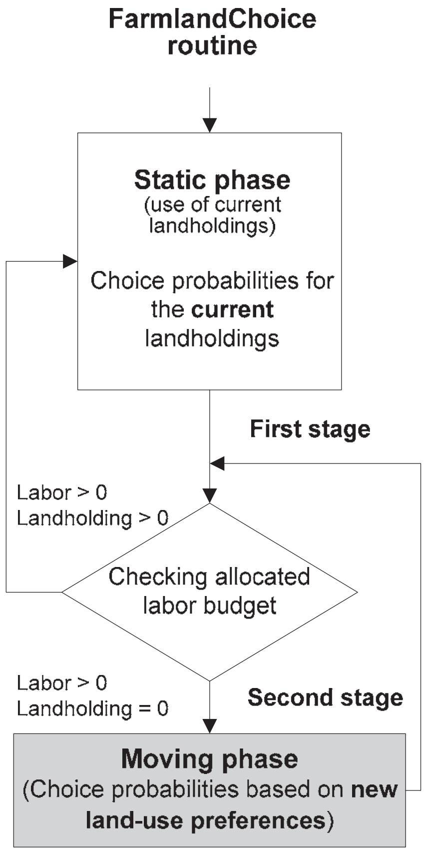


Figure 6.4 Schematic representation of the two-stage decision making for SUB scenario (or with financial investments or subsidies) wherein *Preferred-land-use* sub-model is integrated in the second stage of the *FarmlandChoice* routine.

Another important aspect is to strengthen the scenario analysis of future options of combined social and ecological systems (Chapter 7). According to Swart et al. (2004), the development of scenarios in the context of sustainability of social-ecological systems includes characterization of current conditions and processes driving change, and of human and environmental response under contrasting future conditions. In quantitative modeling of scenarios, the results of analyses of possible future events become illegitimate when the state description of the system is uncertain, causal interactions are poorly understood, and non-quantifiable factors are significant (Swart et al. 2004).

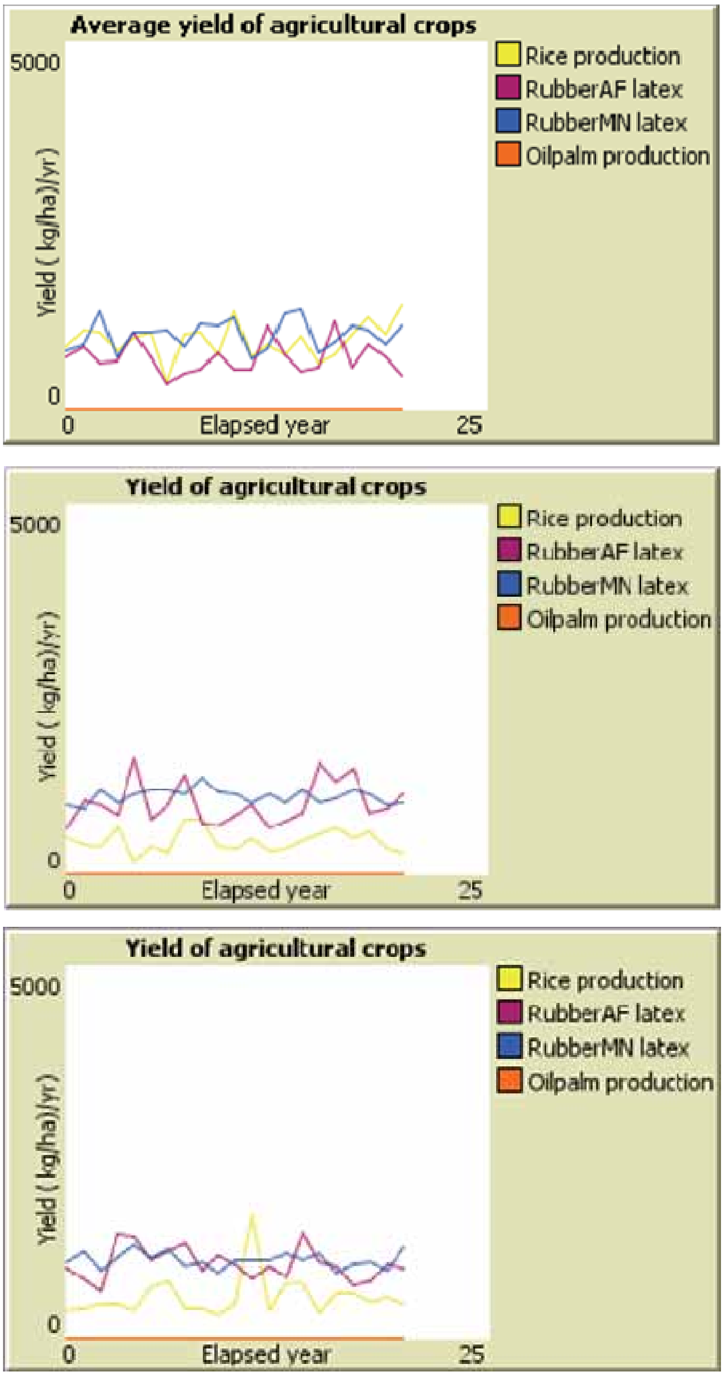


Figure 6.5 Initial test results after incorporating the *PES-adoption* sub-model in the *FarmlandChoice* routine, exported from the Netlogo.

In the next chapter, these sub-models are applied to answer the overall research questions and achieve the objectives of this study.

7 SCENARIO ANALYSIS OF LAND-USE/COVER CHANGE AND ECOSYSTEM SERVICE TRADE-OFFS

The need to incorporate ecosystem services (ES) into resource management decisions is fully recognized, but quantifying the levels and values of these services has been proven difficult (Nelson et al. 2009; De Groot et al. 2010). Accordingly, without quantification of these benefits and lacking incentives for landowners to provide them, these ES tend to be ignored by those making land-use and land-management decisions.

Global loss of ES has many causes, including dysfunction of institutions and policy, gaps in scientific knowledge, unpredictable events, and other factors (Carpenter et al. 2009). On the other hand, policies and practices intended to improve ES and human well-being e.g., Payments for Ecosystem Services (PES) schemes are based on untested assumptions and limited information because the basic information of the dynamics of social-ecological systems (SESs) and the relationships of ES to human wellbeing are also missing (see Chapter 1 and 2). Carpenter et al. (2009) call for research that considers the full ensemble of processes and feedbacks for a range of biophysical and social systems to be able to understand and manage the dynamics of the relationship between humans and ecosystems. In fact, there is urgency for an accelerated effort to understand the dynamics of coupled human-natural systems. Accordingly, explicit models of SESs are essential for research, synthesis, and projection of the consequences of management actions.

Thus, this chapter addresses the following:

1. Apply the LB-LUDAS model (with process-based decision-making sub-models) to understand the SESs of a rubber agroforest landscape,
2. Understand the temporal and spatial impacts of PES schemes as policy interventions and possible resulting emergent properties, and
3. Compare the PES and future land-use preferences if supported by financial investments or subsidies and their impacts on the ES trade-offs.

In the process, new insights are provided on how ES can in turn benefit humanity, and how human actions alter ecosystems and the services these provide.

7.1 Scenarios

Scenarios in this study are tools to reveal and explore the consequences, trade-offs and synergies of different policies with respect to conservation of ES. In contrast to prognoses, scenario analysis does not extrapolate information from the past, but rather considers possible developments and turning points, which may be merely connected to the past. It is also a process of analyzing possible future events by considering alternative outcomes. The Millennium Ecosystem Assessment (MA) presents scenarios on the future prospects for ES to create an understanding of ecosystem management by considering a set of possible future paths. In this study, the tested scenarios are in line with the 'real' local and national policies currently in pilot tests and under negotiation (Table 7.1). The aim is to compare the two opposing scenarios, i.e., payments for ecosystem services schemes (PES) as an environmental conservation pathway, and the condition 'if financial investment or subsidies are provided' (SUB) as an economic development pathway, and to explore the possible temporal and spatial impacts on ES trade-offs.

The key difference in these scenarios is the use of different decision-making sub-models integrated in the decision-making mechanism (see Chapter 6). It is assumed that using this approach, agents' behavior could be better explained.

Table 7.1 Policy scenarios

Scenario	**Scenario description**
I. Baseline (BAS)	• Current trend (see section 6.1.2)
II. PES	• Under the proposed REDD strategy of Indonesia (see section 4.1.3), *Hutan desa* is considered a policy instrument for communities with revenue sharing of 20% for the government, 30% for the developer, and 50% for the community. But the specific guidelines are still under negotiation, thus this sharing rule is not incorporated. Instead, a 70% protection zoning is applied in the forest. • Under an eco-certification scheme, the price of rubber latex is 50% (upper case limit) higher than the baseline price, i.e., about USD 3-4 kg $^{-1}$ (Akiefnawati pers.com.), but it is only granted if the biodiversity criteria are met (see section 7.2.2), and the price of rice is approximately USD 1 kg $^{-1}$ (see section 6.1.2).

Table 7.1 continued

Scenario	Scenario description
	• A population growth of 1.4% per year, based on low out-migration rates. • The decision-making sub-model for the simulation follows the routine illustrated in Figure 6.3. • The actual land-use map of 2005 is used as a base for simulating the next 20 years.
III. SUB (with financial investments / subsidies)	• The prices of rubber agroforest latex and rice are the same as in the baseline scenario, i.e., USD 2.5 kg $^{-1}$ and USD 1 kg $^{-1}$, respectively (see section 6.1.2). • The assumption is that credit facilities or subsidies would be provided (either by government or private entities) to cover the initial financial investment of the farmers. • *Hutan desa* policy of 70% zoning restriction is also implemented. • A population growth of 1.4% per year. • The decision-making sub-model for the simulation follows the routine illustrated in Figure 6.4. • The actual land-use map of 2005 is used as a base for simulating the next 20 years.

7.2 Methodology

7.2.1 Stylized facts

PES scenario

The stylized facts extracted from the empirical findings of PES adoption (Chapter 4) are as follows:

1. The decision of a household to adopt a PES scheme is correlated with the household characteristics, which are:

   Type 1 household: decision is correlated with the education of the household head, size of the household and number of dependents, and

   Type 2 household: decision is correlated with the age of the household head, number of household group memberships, size of the household, and number of dependents.

   Although only a few empirical studies exist that document factors driving people's participation in PES, findings from related empirical research on technology adoption, e.g., agroforestry systems, are well documented and useful for supporting the above stylized facts (see section 4.2.1). Also, factors such as prior information on and involvement in the PES activities are found important in the participation or adoption (Zbinden and Lee 2005).

2. Both household types would participate in PES schemes if income from rice and rubber is low. Findings from empirical studies show the same trend (see Table 4.2 and 4.3). For example, farmers' participation in PES schemes was influenced by PES contribution to household income and land opportunity costs (Wunder 2005); in Latin America, PES incentives have contributed up to 30% of the household income (Miranda et al. 2003; Alban and Arguello 2004; Echavarria et al. 2004).
3. Only households who could meet the PES criteria and eligibility would be rewarded or paid. Pagiola et al. (2005) explained the sequential reasoning process before getting involved in a PES scheme. These include eligibility requirements such as if the farmer is located in the target area and follows the required resource management practices, if PES practices are profitable (related to the second stylized fact) and fit in the current farming system, and if the household is able to meet investment needs. Under the PES scenario, one of the main criteria set for PES adopters is to meet the biodiversity requirement as proposed by Tata et al. (2007) and is translated into rules for the LB-LUDAS model (see section 7.2.2).

SUB scenario: with financial investments or subsidies

The following are the stylized facts generated from the statistical observations (see Section 3.3.3) for this scenario:

1. The preferred land use of individual households under the condition of financial investment or subsidies is correlated with the following household characteristics and biophysical properties:

   Type 1 households' decision to choose rubber agroforest is correlated with the age of the household head, household income and education, and distance to household's house and town center, while

   Type 2 households' decision to choose rubber agroforest is correlated with the age and education of household head, landholdings and neighborhood land-use pattern.

2. The probability of type 1 households to keep to rubber agroforests is 87%, suggesting that they are risk-averse households.
3. Lightly more than half of the (53%) Type 2 households are willing to convert their rubber agroforestry farms into a more profitable land-use monoculture, i.e., oil palm and rubber (see section 3.3.3) only under the provision of subsidies that would cover initial investments, suggesting income diversification.

In reality, initial investments from the private sector and state-owned companies were provided to the villages such as agricultural support and extension services to speed up the pace of development in the area (Martini et al. 2010).

7.2.2 Biodiversity performance measurement

Supporting the third stylized facts under the PES scenario, PES adopters would be offered a higher latex price if the criteria for eco-certification are met. So far, no rules or specific guidelines exist that are approved for certifying rubber latex from sustainably managed sources. Yet, empirical studies have proposed ways to meet rubber latex production while conserving biodiversity specifically in Jambi province (Tata et al. 2007; Bennett 2008). These criteria based on empirical studies were translated into biodiversity rules for LB-LUDAS simulation (Table 7.2).

Table 7.2 Proposed criteria for eco-certification of rubber agroforest based on Tata et al. (2007) and criteria fitting for LB-LUDAS model.

Proposed criteria for eco-certification of rubber agroforest	**Fitting for LB-LUDAS model**	**Data source**
o *Criteria 1*: At least 4 tree species (> 10 cm DBH) in a circle with 8 m radius around a random starting point within the plot – average of 5 observations	At least 27 species of trees in a 900 m^2 patch using Eq. 5.23 and 5.24 (Chapter 5)	Calibrated using plant species inventory (Rahayu 2009)
o *Criteria 2*: If the number of species is <6, determine the relative basal area of rubber trees, with 2/3 as threshold; in case the number of species > 6, (this step can be skipped)	Basal area requirement per patch as generated by the forest dynamic model (see section 5.3.4)	Calibrated using plant species inventory (Rahayu 2009)
o *Criteria 3*: Assure that there is at least 1 tree with DBH > 40 cm per circle of 25 m radius – average of 5 observations	1 tree with DBH of >40cm for every 2 patches (1800 m^2)	Calibrated using plant species inventory (Rahayu 2009) and generated in forest dynamic sub-model

7.2.3 Simulations

For each scenario, a total of five simulation runs were conducted. Each run has 20 time steps (or simulated years). All scenarios started with initial population of 380 households (1520 individuals). The averages (with 95% confidence interval) of each performance indicator (both social and ecological) were plotted as time-series graphs (while some required additional calculations) to compare scenarios.

7.2.4 Financial opportunity costs

The opportunity costs of major land uses in each scenario were calculated using the net present value (NPV). NPV is a measure of estimated returns to land and is expressed as:

$$NPV = \sum_{t=1}^{T} \frac{R_t}{(1+i)^t} \quad (7.1)$$

Where t is the number of years, i is the interest (discount) rate (20%)[14], and R_t is the net cash flow or net revenue

The NPV of the three land uses (upland rice, rubber agroforest and rubber monoculture) was calculated. Data on the establishment costs of each crop were taken from Wulan et al. (2008) and others were from the field survey (see Chapter 3). It is assumed that a positive cash flow will start at year 9 for rubber agroforests and at year 6 for monoculture rubber, while establishment costs are based on the number of labor days.

7.3 Results

7.3.1 Impact of PES on land use/cover

The following are the apparent trends observed when comparing the PES scenario with the baseline scenario (Figure 7.1 and 7.2). These were:

1. Forest cover slightly increased after year 13;
2. Rubber monoculture slightly decreased after year 15; and
3. Both rubber agroforest and rice field were the most actively changing land uses/covers under the baseline scenario.

[14] Wibawa et al. 2005

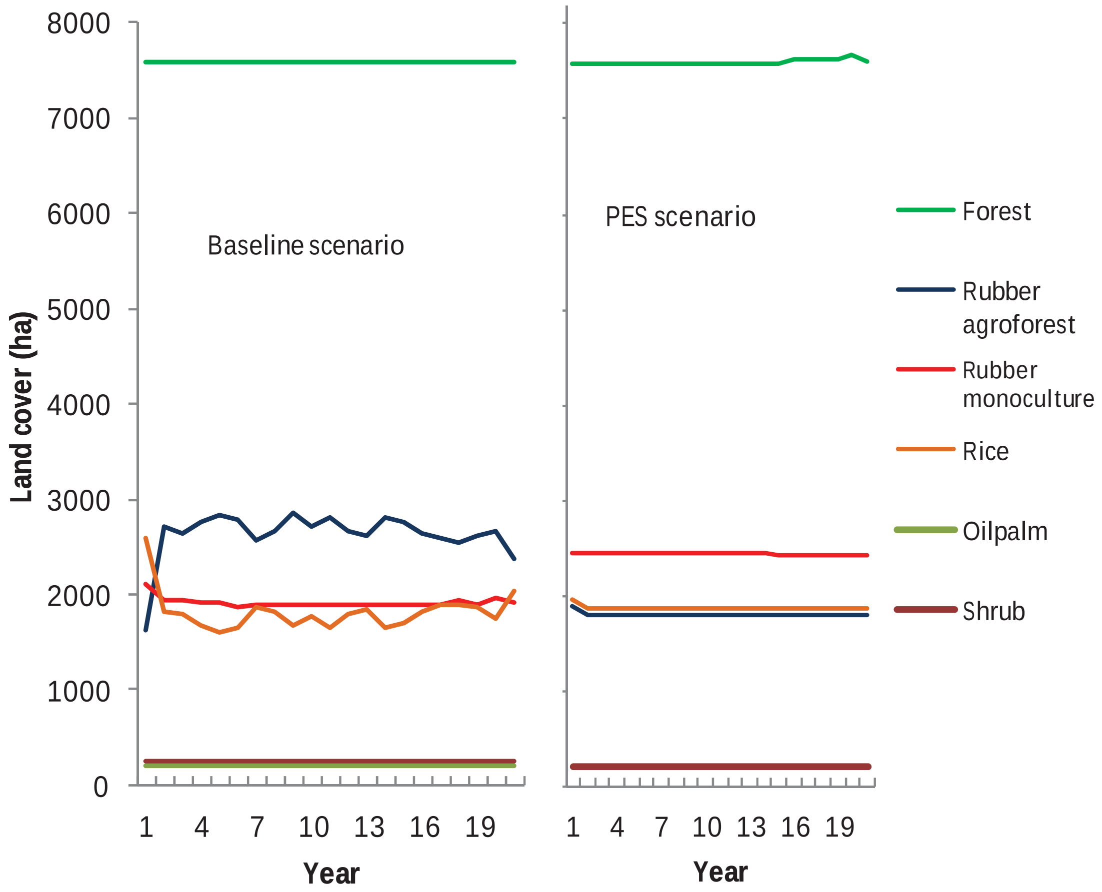


Figure 7.1 Simulation of land-use/ cover change in PES scenario compared to baseline scenario.

In Figure 7.2, the shrubland (dark pink areas) in the 2005 map (year 0) was mostly converted to either rubber agroforest or rice fields after year 5 under the baseline scenario, but under the PES scenario, it had either transformed naturally to forest or was converted to rice paddies. The same trend was observed under the SUB scenario (Figure 7.4). For specific land-cover changes in three scenarios with confidence intervals (95%) of the means, see Appendix 6.

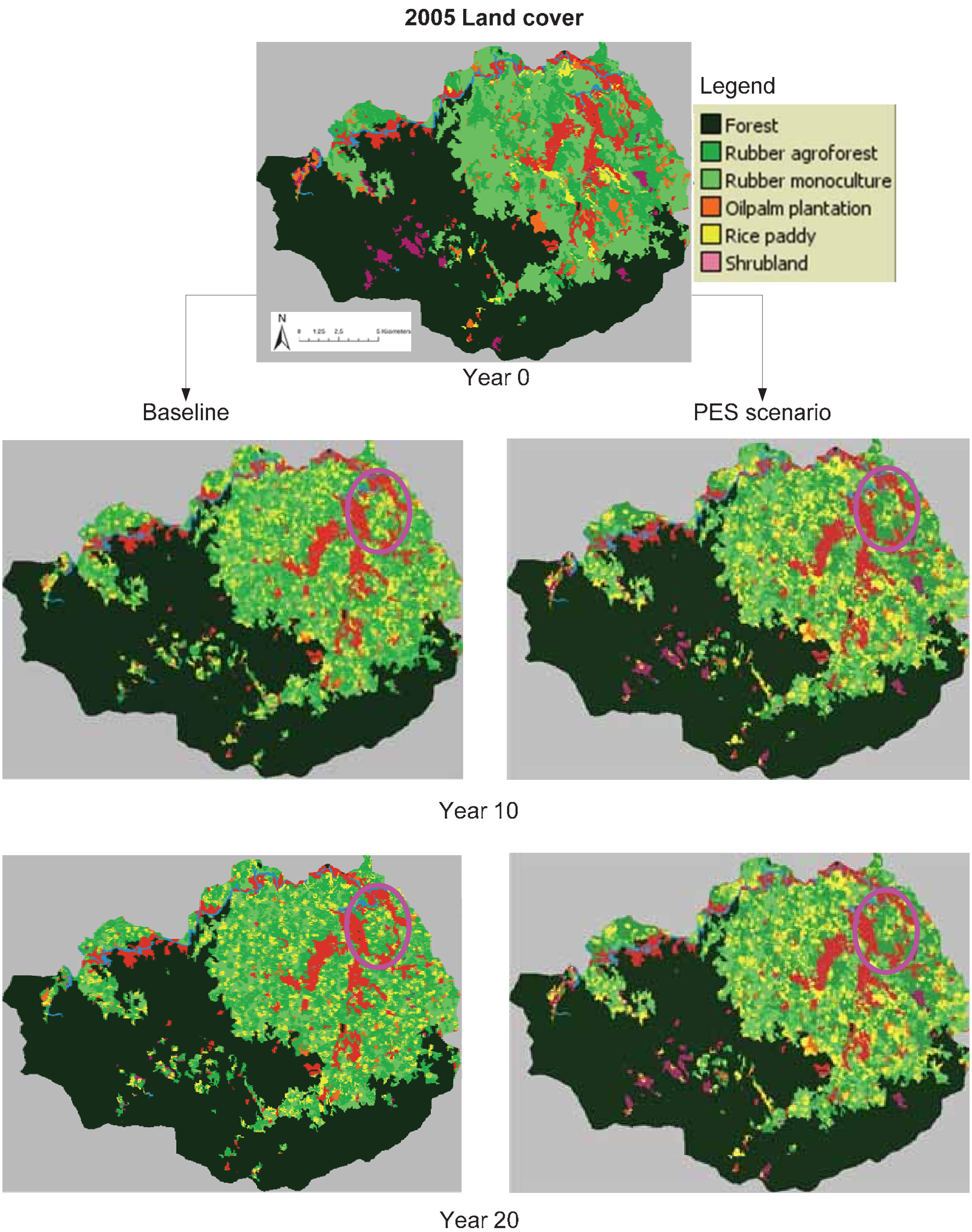


Figure 7.2 Comparison of simulated spatio-temporal land-use/cover change between PES scenario and baseline scenario (current trend) (Note: red patches are settlement areas)

7.3.2 Impact of financial investment/subsidies (SUB) on land use/cover

For the SUB scenario, the following major trends were observed when compared to the baseline scenario (Figure 7.3 and 7.4):

1. Forest cover increased slightly after year 13,
2. Rubber agroforest and rice field are the two most actively changing land uses/ covers under both scenarios, but the gap between the two land uses is wider under the SUB scenario. Both of the changes between these two land covers reflect a mirror-like image of change, and
3. Both rubber monoculture and shrub slightly decreased after year 15.

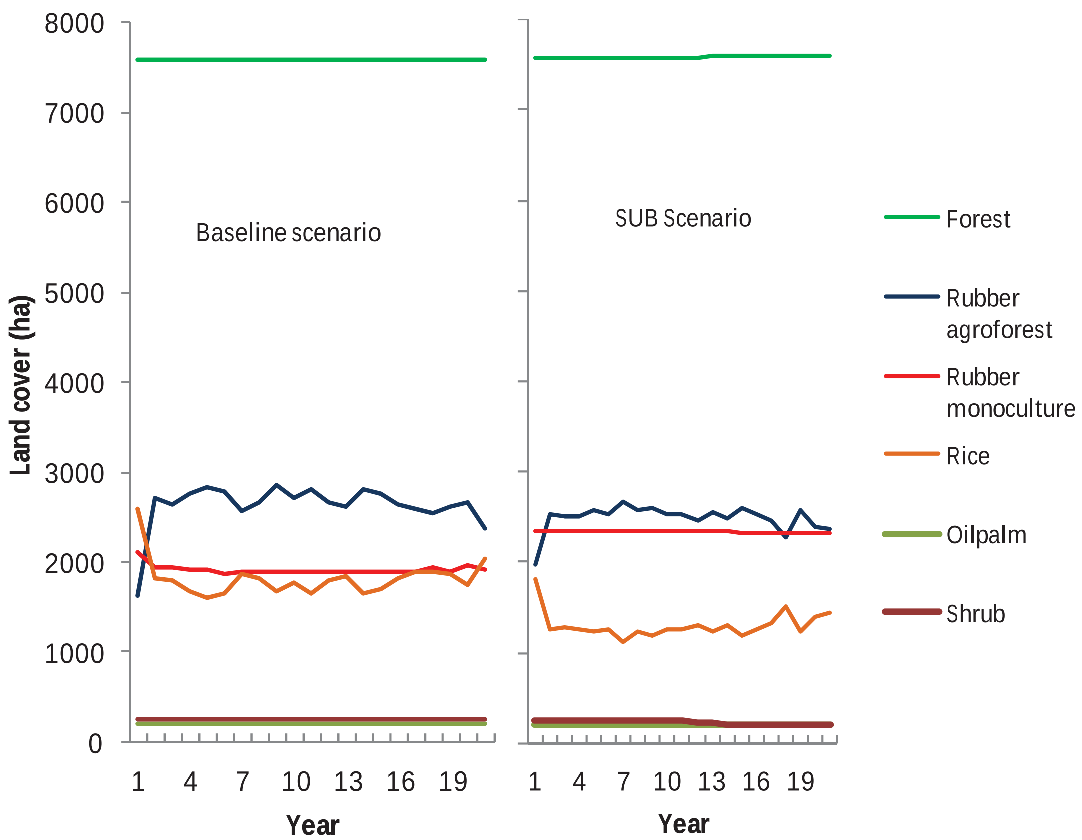


Figure 7.3 Simulation of land-use/ cover change with initial financial investments compared to baseline scenario.

In the cultivated areas (Figure 7.5), two major findings were: 1) both SUB and baseline scenarios have gradually increasing cultivated areas, and 2) under the PES scenario, there was hardly a decrease or increase in cultivated areas except during the initial year of rubber monoculture (Figure 7.5c).

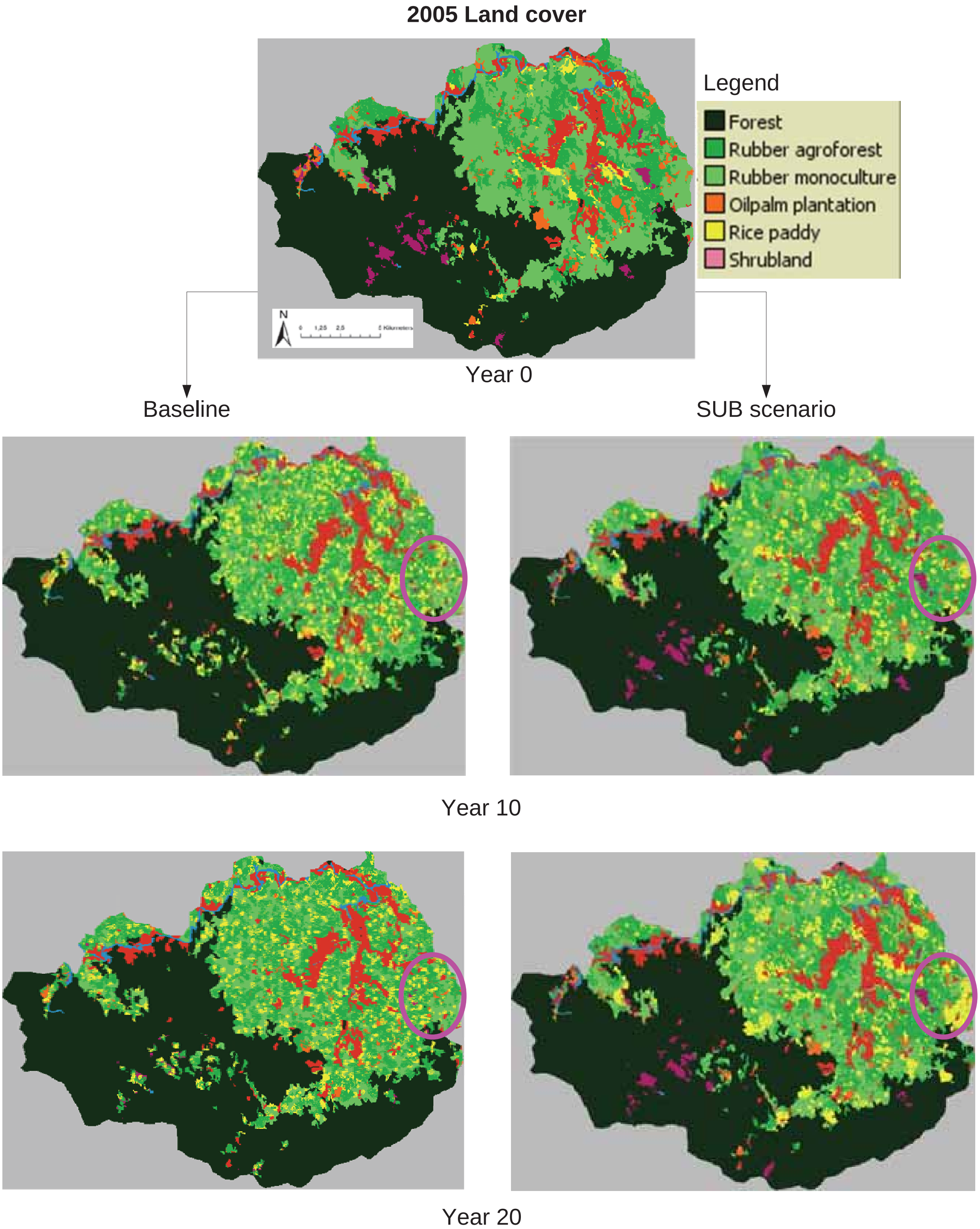
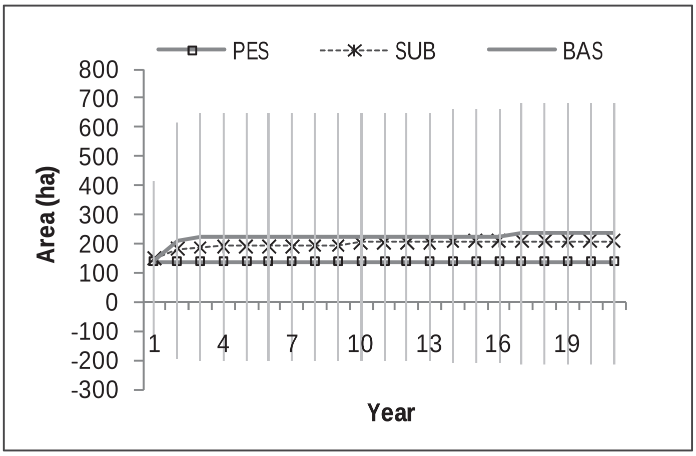
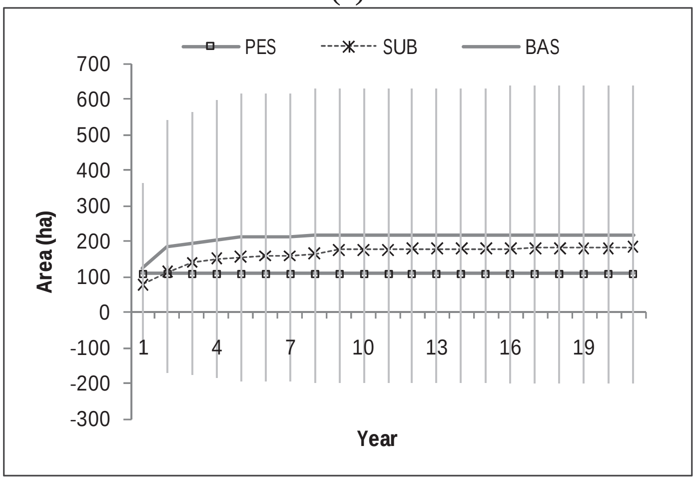


Figure 7.4 Comparison of simulated spatio-temporal land-use/cover between SUB scenario and baseline (current trend) (Note: red patches are settlement areas)

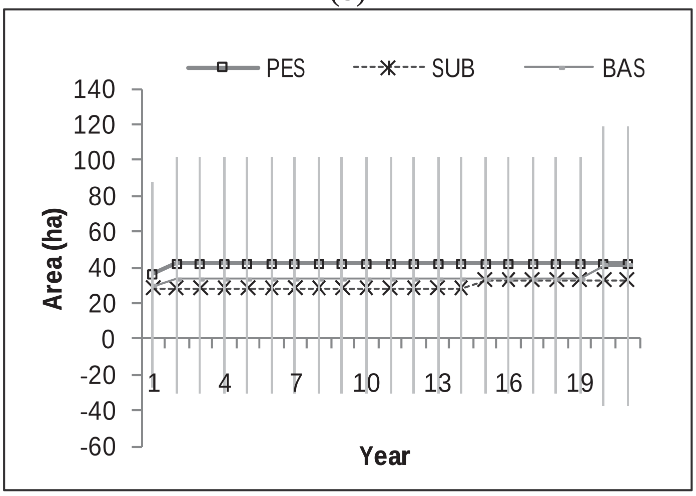
Cultivated area



(a)



(b)



(c)

Figure 7.5 Area (ha) cultivated for rice (a), rubber agroforest (b), and rubber monoculture (c) in three scenarios (PES, SUB, BAS (baseline)).Vertical segments are the confidence interval (95%) of the means. For uncertainty of yield prediction, see Appendix 5.

7.3.3 Impact on species richness

Under the three scenarios, the average species richness (ha^{-1}) in the rubber agroforest is slightly higher under the SUB and baseline scenarios (Figure 7.6). Rubber agroforest is one of the dominant land covers in the area and is also the preferred land use under the two scenarios (see Figure 7.1 and 7.3). While there were no changes in the rubber agroforest area under the PES scenario over the 20-year period, an increase in the average species number occurred particularly after year 19. This may be due to the effect of the natural transition process in the abandoned rubber monoculture plots (see section 5.3.5). The same trend was also observed under the SUB and baseline scenarios.

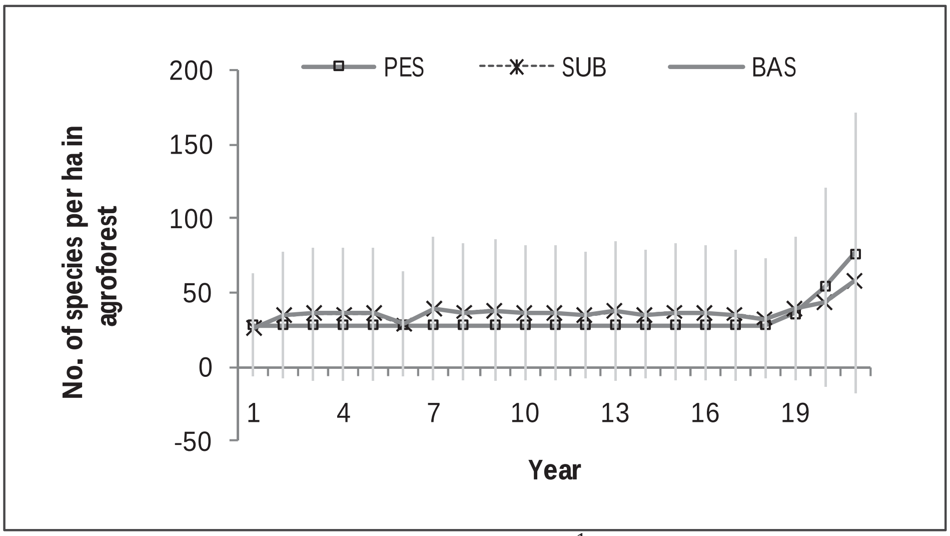


Figure 7.6 Average tree species number (ha^{-1}) in rubber agroforests in three scenarios (PES, SUB, BAS (baseline)). Note: vertical segments are the confidence interval (95%) of the means.

Species loss

Using the equations 5.4 and 5.5 (section 5.2.2), the proportion of the species that had survived after the conversion of rubber agroforest, i.e., to rice or rubber monoculture, was calculated for the three scenarios. Assuming that the average total area of rubber agroforest (at year 0) is the *original area or habitat*, and the average total area of rubber agroforest converted to rice and rubber monoculture (Figure 7.5) over 20 years is the *area of habitat destroyed*, the proportion of remaining original species and species loss in the rubber agroforest could be estimated. Findings (Figure 7.7) show that under the PES and SUB scenarios, habitat destruction could be avoided and thus an average of

22% and 6% of the species, respectively, would remain in the rubber agroforests under these scenarios.

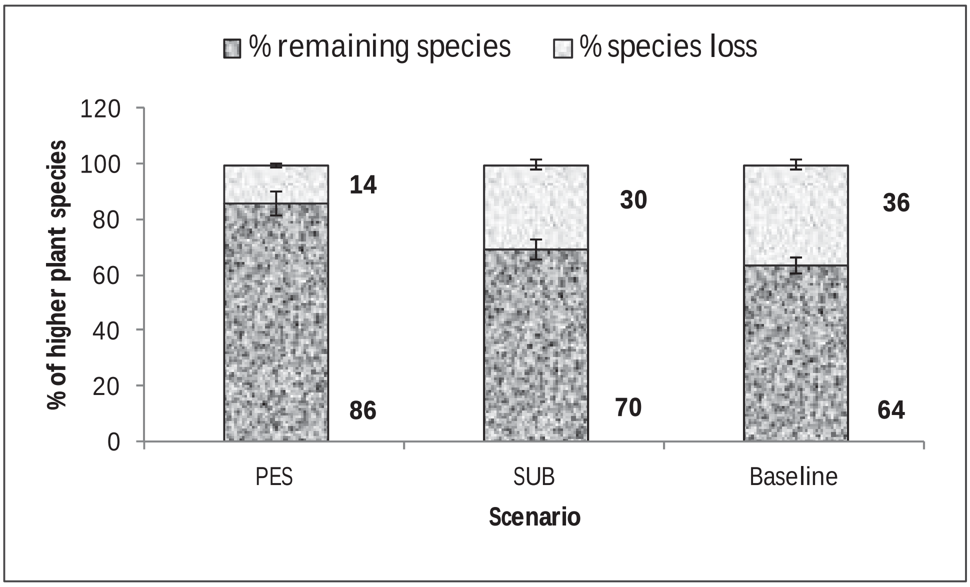


Figure 7.7 Average percent of remaining tree species after habitat destruction/conversion. Note: vertical segments are the SEM.

7.3.4 Impact on carbon emissions

The estimated carbon emissions under the PES and SUB scenarios were compared to the 1993-2005 emissions (Figure 7.8; see also Table 5.15).

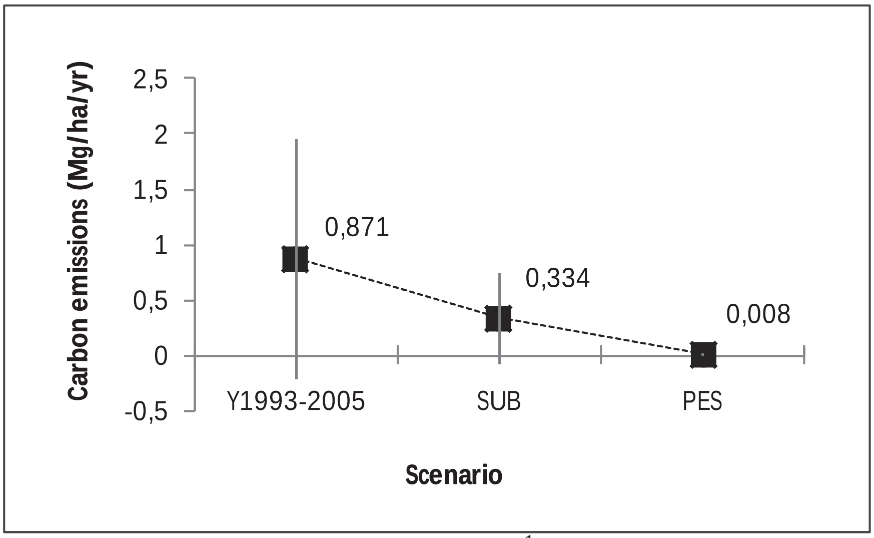


Figure 7.8 Annual carbon emissions (Mg ha^{-1}.yr) in simulated scenarios against calculated 1993-2005 carbon emissions (see section 5.3.6). Note: vertical segments are the confidence interval (95%) of the means.

The results show that the PES scenario has the lowest annual emissions of about 0.01 Mg $ha^{-1}yr^{-1}$.

Under the SUB scenario, the carbon emissions are 97% higher compared to the emissions under the PES scenario. This is mainly due to the conversion of rubber agroforest (high carbon) to rice paddies (low carbon). Compared to the 1993-2005 emissions, they are 47% lower due to the increase in forest cover and decrease in shrubland and rubber monoculture areas (Figure 7.3).

The findings suggest that under the PES scenario (through REDD using zoning restriction of 70%) carbon emissions could be greatly reduced.

7.3.5 Impact on socio-economic household dynamics

Simulated crop yields

The simulated average crop yields from upland rice (a), rubber agroforest (b) and rubber monoculture (c) are summarized in Table 7.3. Comparing these results to those of other studies, the rice yield is comparatively low (800 kg $ha^{-1}yr^{-1}$ in ICRAF data 2009; 1200 kg $ha^{-1}yr^{-1}$ in Wulan et al. 2008 under extensive practices); agroforest rubber latex yields are relatively higher (~600 kg $ha^{-1}yr^{-1}$in Joshi et al. 2006), while yields from rubber monoculture are consistent with the yields cited from literature.

Table 7.3 Average annual crop yield in three scenarios

Crop	Baseline	PES	SUB
Upland rice (kg ha^{-1} yr^{-1})	667 ± 122	511 ±104	456 ± 92
Latex from rubber agroforest (kg ha^{-1} yr^{-1})	1026 ± 222	1080 ± 241	1192 ± 185
Latex from rubber monoculture (kg ha^{-1} yr^{-1})	1026 ± 173	1037 ± 61	988 ± 99

Note: Values are mean ± SD of outcome variable for 5 simulation runs.

Using the (i.e., over lapping or non-over lapping) confidence intervals of each crop (Table 7.4), the average rice yield under the baseline scenario is significantly higher than under the PES and SUB scenarios. For latex production from rubber agroforests, the average latex yield under the baseline scenario is significantly lower than that under the SUB scenario. On the other hand, the average latex yield from monoculture plantations under the SUB scenario is significantly higher under the PES and BAS scenarios. It should be noted that the uncertainty in the crop yield prediction is accounted for in the LB-LUDAS model (see Appendix 5).

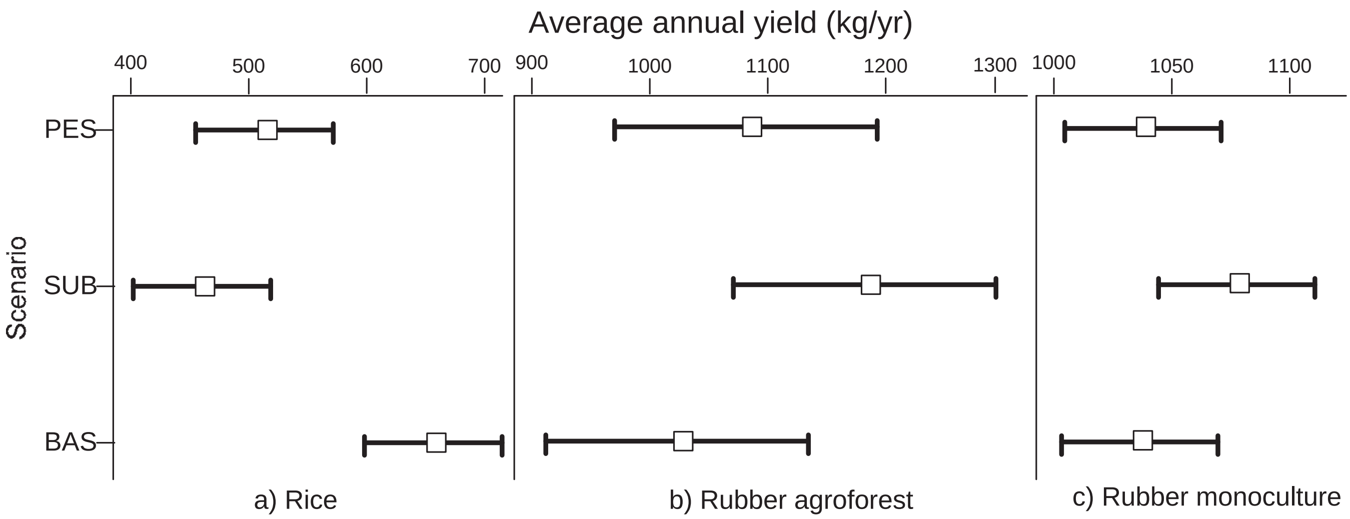


Figure 7.9 Average yields of rice (a), latex from rubber agroforest (b) and latex from rubber monoculture (c) in three scenarios (PES, SUB, BAS (baseline)). Horizontal segments are the confidence interval (95%) of the means. (Note: CIs are used to show the degree of over-lap).

Table 7.4 Comparative analysis of the average yields per major crop under the three scenarios using the Bonferroni method.

Comparative scenario	**Contrast (kg/ha/yr)**	**Bonferroni *t***	**Sig.**
(a) Rice (*Std. error* = 32.9)			
SUB vs. PES	-54.6	-1.65	0.310
BAS vs. PES	155.6	4.72	**0.000**
BAS vs. SUB	210.2	6.37	**0.000**
(b) Rubber agroforest (*Std. error* = 67.1)			
SUB vs. PES	110.8	1.65	0.312
BAS vs. PES	-54.4	-0.81	1.000
BAS vs. SUB	-165.2	-2.46	**0.050**
(c) Rubber monoculture (*Std. error* = 20.7)			
SUB vs. PES	46.2	2.23	**0.089**
BAS vs. PES	-0.6	-0.03	1.000
BAS vs. SUB	-46.8	-2.25	**0.084**

Household income

Of all three scenarios, the highest average revenue per household over the 20-year period is under the SUB scenario, while the lowest is under the baseline scenario (Table 7.5 and Figure 7.10). The average revenue under the SUB scenario is slightly higher than that under the PES scenario. It should be noted that the establishment cost for opening new plots (as a negative income for households) is taken into account in estimating the household income per year in the LB-LUDAS model.

Table 7.5 Simulated gross income per household (USD) in three scenarios over 20 years

Income typology	Scenarios		
	Baseline	**PES**	**SUB**
Revenue (USD household^{-1})	130,954 ± 6082	184,874 ± 2484	197,326 ± 8534
Present revenue at 20% discount rate[15] (USD household^{-1})	30,109 ± 1398	38,719 ± 1449	45,818 ± 2008

Note: Values are mean ± SD of outcome variable for 5 simulation runs.

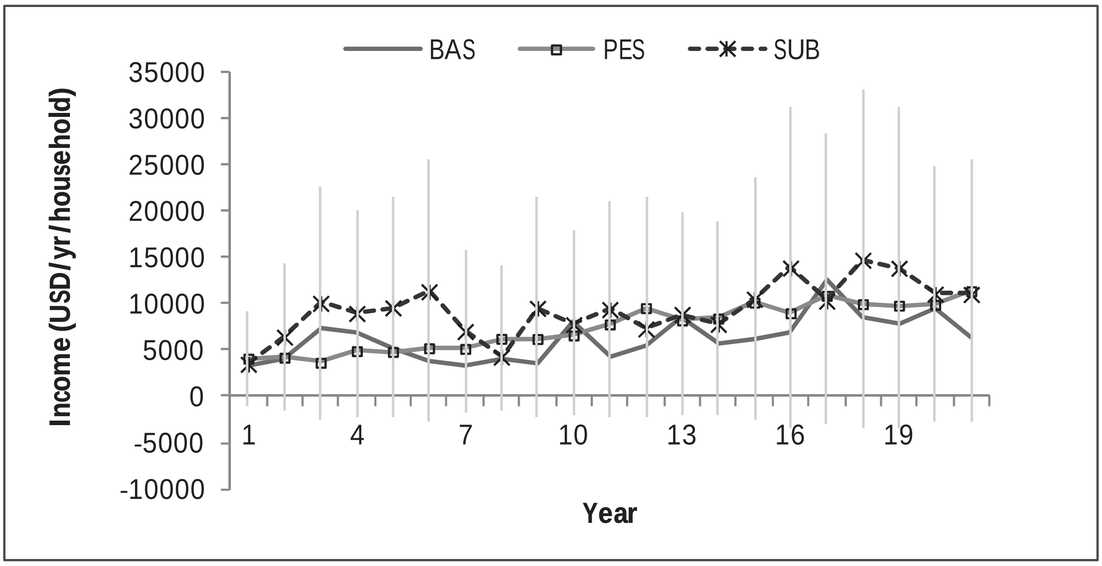


Figure 7.10 Annual revenue in three scenarios. Note: vertical segments are the confidence interval (95%) of the means.

The PES adopters averaged between 30-40% of the mean total simulated population (Figure 7.11). These PES adopters preferred rubber-agroforest system.

[15] The discount rate for Indonesia used by Wibawa et al. 2005.

However, they have to meet the biodiversity criteria to get the price premium for latex. Hence, not all of the 30-40% PES adopters received the 50% higher price.

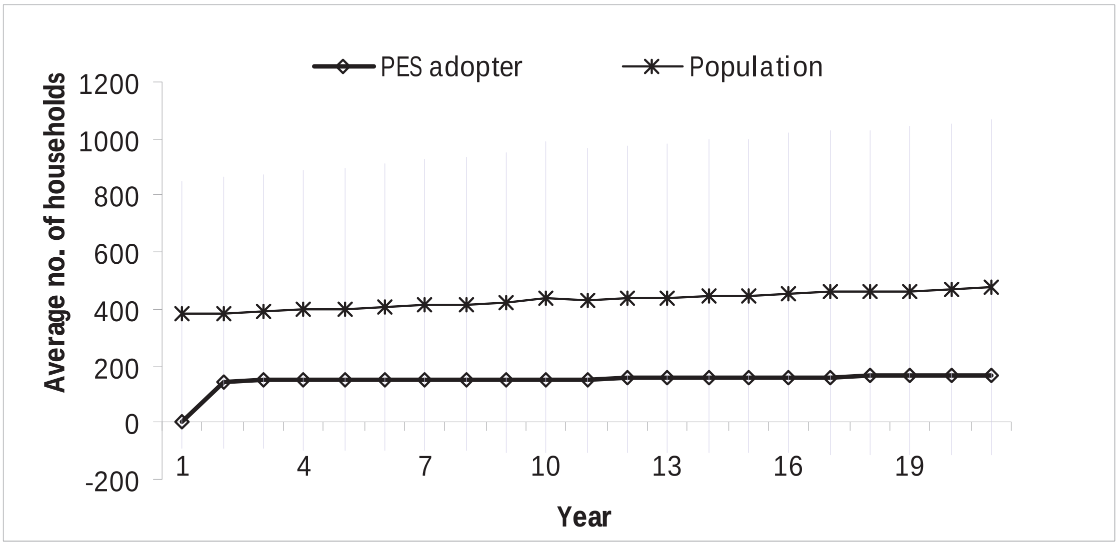


Figure 7.11 Number of PES adopters against average total population. Note: vertical segments are the confidence interval (95%) of the means.

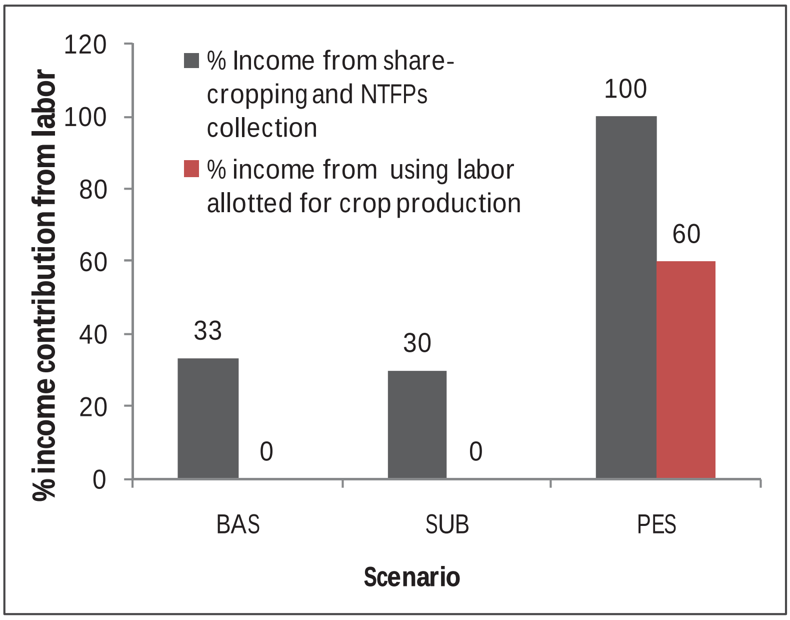


Figure 7.12 Income contribution from share cropping and NTFPs (non-timber forest products) collection

The percent contribution from hired or paid labor to household income is depicted in Figure 7.12. It shows that under the PES scenario, the bulk of the income comes from share cropping and the man-days used for collecting non-timber forest products (e.g., forest fruits such as durian), while 60% of the labor assigned to crop production was also diverted to share cropping and NTFPs (see section 7.4.1), whereas in the other scenarios it remained zero. This could be the reason for the change in wealth inequality of the agents as shown in the Gini index (Figure 7.13).

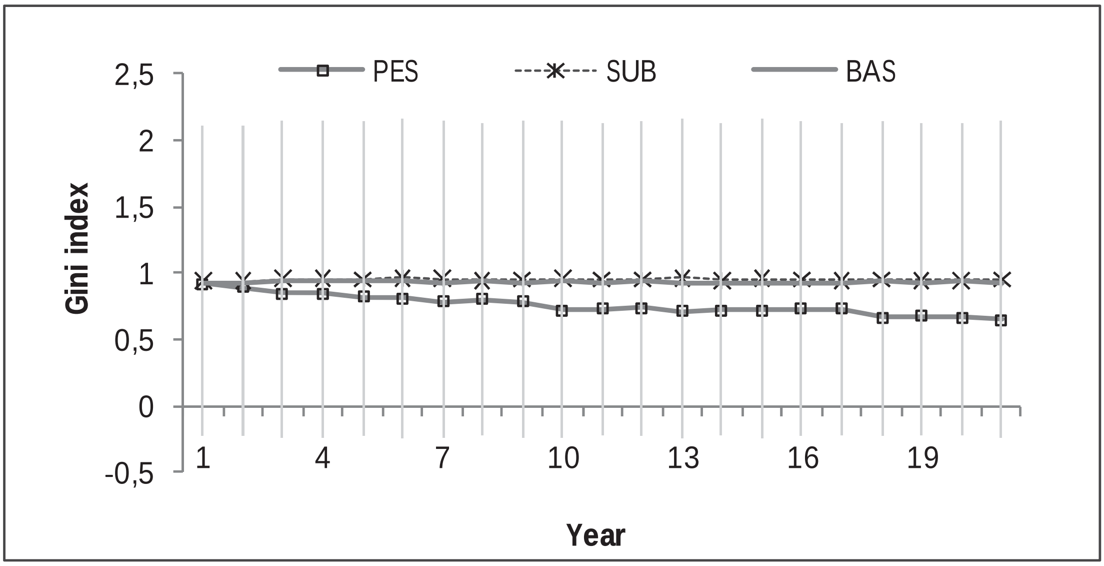


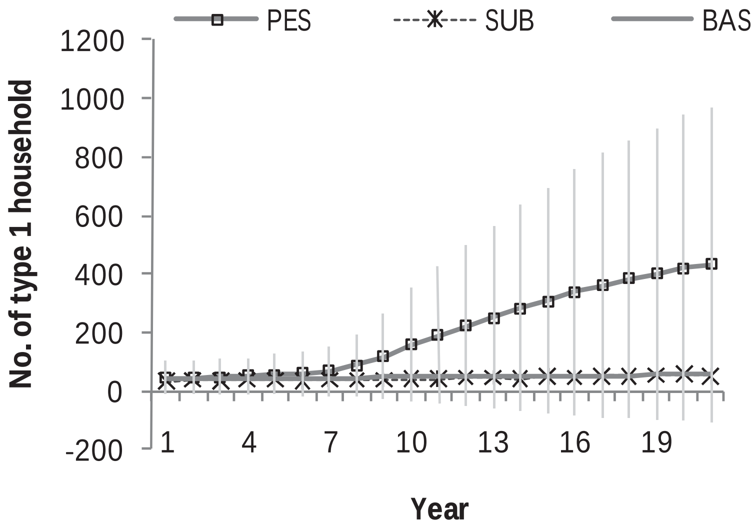
Figure 7.13 Gini index generated for three scenarios. Note: vertical segments are the confidence interval (95%) of the means.

The Gini index under the PES scenario gradually moved towards 0.5 over the 20-year period. On the other hand, under the SUB and baseline scenarios, the Gini indices stayed between 0.95 and 0.98 over this period.

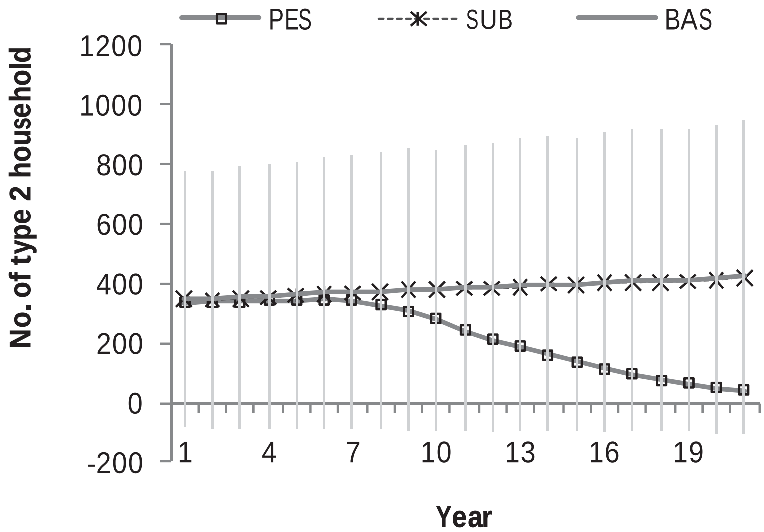
Household livelihood typology

The characterization of household types simulated under the three scenarios is depicted in Figure 7.14. Apparent changes were observed under the PES scenario, where a significant increase in household type 1 ('better-off' farmers; Figure 7.14a) and a decrease in household type 2 ('relatively poor' farmers; Figure 7.14b) occurred.

Based on the simulation results of the wealth inequality (Figure 7.13), it appears that under the SUB and baseline scenarios very few households (i.e., type 1) received almost all the income, whereas large part of the households (i.e., type 2) received a very low income. In contrast, under the PES schemes, the status of both household types changed significantly after year 7, when the household types received quite similar incomes. This suggests that the livelihoods of the type 2 farmers would be better under the PES schemes (see discussion section for further analysis).



a)



b)

Figure 7.14 Time-series change of rice-rubber farmers (type 1), and rubber-based farmers (type 2). Note: vertical segments are the confidence interval (95%) of the means.

Financial opportunity costs

Based on the labor requirement (ha^{-1}) (Table 7.6), average yield (kg ha^{-1}) simulated in the LB-LUDAS model (Table 7.3), and costs per cropping system (USD ha^{-1}) (Table 7.7), the return for land investment (i.e., using NPV) for each scenario was estimated. The results show that return for land investment differs in each scenario. Of all the land uses, under the baseline scenario, rice is the most profitable (Table 7.8).

Table 7.6 Labor requirement for rice, rubber agroforest and rubber monoculture

Main farming system	Establishment (man-days ha^{-1})	Mean total (man-days ha^{-1})	Source
Rice	-	130	Wulan et al. 2008
Rubber agroforest[a]	828	107	Wulan et al. 2008 and field survey
Rubber monoculture[b]	1239	130	Wulan et al. 2008 and field survey

Note: [a] *using the medium weeding rubber agroforest system*
[b] *using the private monoculture system*

Table 7.7 Estimated total costs for rice, rubber agroforest and rubber monoculture

Main farming system	Total establishment and operational costs (USD ha^{-1})	Source
Rice	260	Field survey
Rubber agroforest	640	Wulan et al. 2008
Rubber monoculture	770	Wulan et al. 2008

Because the conditionality set under the PES scenario does not apply to almost 60 to 70% of the simulated population and also to agents who did not adopt PES, sub-scenario under PES without the price premium was estimated. The rubber agroforest under this scenario with eco-certification becomes the most profitable land use, and also under the other two scenarios. On the other hand, rubber agroforest becomes the least profitable under the PES sub-scenario without eco-certification as well as under the other two scenarios.

Under the SUB scenario, rubber agroforest is slightly more profitable than rice production and rubber latex from rubber monoculture.

Table 7.8 Net present value of rubber latex production and rice production for three scenarios at annual discount rate of 20%

Scenario and typology	**Main farming system**		
	Rice	**Rubber agroforest**	**Rubber monoculture**
1) Baseline (current trend)			
Average yield (kg ha^{-1})	667 ± 104	1026 ± 222	1036 ± 82
NPV (USD ha^{-1})	2527	1778	1342
2) PES scenario (without eco-certification)			
Average yield (kg ha^{-1})	511 ± 105	1080 ± 241	1037 ± 61
NPV (USD ha^{-1})	1630	1193	1452
PES scenario (with eco-certification)			
Average yield (kg ha^{-1})	511 ± 105	1080 ± 241	1037 ± 61
NPV (USD ha^{-1})	1630	2626	1452
3) SUB scenario			
Average yield (kg ha^{-1})	456 ± 92	1192 ± 185	988 ± 99
NPV (USD ha^{-1})	1256	1729	1360

Note: Values are mean ± SD of outcome variable for 5 simulation runs. The estimated NPVs are at upper case limit.

Assessment of overall trade-offs

Based on the results presented above, under the PES scenario (Figure 7.15, *green line*), the key objectives of ecosystem services such as agro-biodiversity conservation and carbon emission mitigation are better achieved than in the other two scenarios. In terms of household livelihoods, the generated revenues under this scenario are competitive compared to the SUB scenario. Since rubber agroforest under the PES sub-scenario (with eco-certification) is much more profitable (Table 7.6) than the other scenarios, the non-PES adopters' household (specially the type 2 household) should be encouraged to adopt PES schemes with-eco-certification. It also suggests that the PES schemes, including the proposed design, i.e., biodiversity targets, protection zoning, are appropriate in the rubber agroforest landscape context.

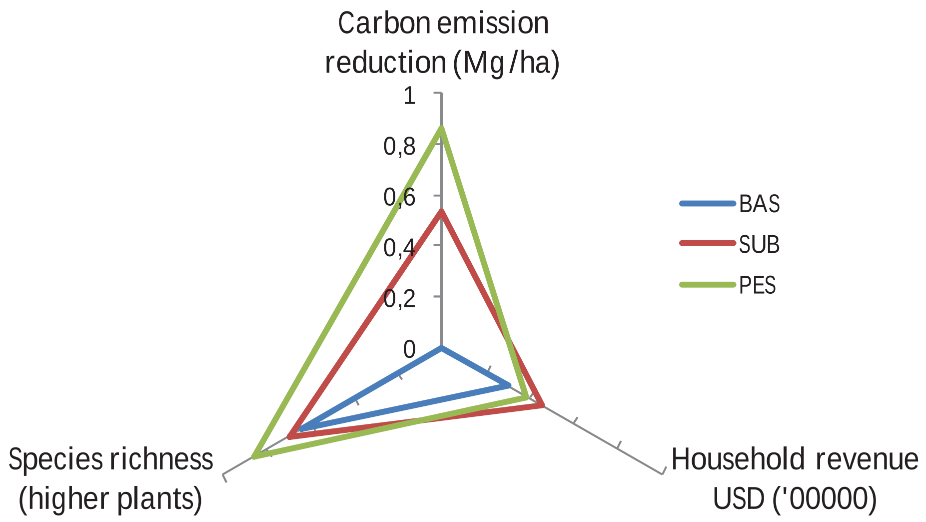


Figure 7.15 Overall trade-offs for the three study scenarios over 20 years.

7.4 Discussion

7.4.1 Emergent properties: spatial feedback or adaptation

Cumming (2011) defines *emergent properties* as properties or behaviors of complex systems arising from the combination of system components and relationships and feedbacks, or feedback loops, as a situation in which an effect influences its cause. *Spatial feedbacks* in particular are feedbacks that occur between spatial variation and systemic processes (e.g., migration, settlement, competition).

Under the PES scenario, one intriguing outcome is the interactions between the agent behavior and land-use change. It was observed that there was almost no opening of new land and that the number of cultivated plots actually being used by the agents is less than the number of the household's total landholdings, and yet the income is relatively high when compared to baseline scenario where opening of new land was observed.

Numerous empirical studies attest the labor shortage situation in Jambi province as one of the constraints in rubber production, which actually triggers the development of rubber monoculture to rubber agroforests. In the simulations, this observation was captured as a result of the interaction between the agents' decision and land-use change. Basically, not all of the household agents in the model have their own farm plots. Households without rubber or rice farms work as share tappers or in share cropping. This is an important labor strategy in the rubber agroforests in Sumatra.

Under the share-tapping scheme, the owner of the rubber farm lets the share-tapper harvest latex from his rubber plots in a profit-sharing scheme of 60% for the share tapper and 40% for the plot owner. This concept was not incorporated in the initial version of the LB-LUDAS model. However, the results of the initial runs generated a very low average income, which differed greatly from the initial average household income at the initialization stage (year 0). Therefore, the concept was integrated but not on the basis of the profit-sharing scheme mentioned, i.e., very simple decision rules were used. Below is one example:

$$\text{if } h_{\_landholdings} = < 0\text{, set } h_{\_incl} \text{ [labor-spent}\cdot\text{\%L-NTFP or \%L-crop]} \qquad (7.1)$$

where $h_{\_landholdings}$ is the total land holdings of the household agent
$h_{\_incl}$ is the household income from hired labor
%L-ntfp is the percent labor allotted to harvesting NTFPs
%L-crop is the percentage labor allotted to crop production

All scenarios have these decision rules pertaining to labor (and according to various land uses demanding a different number of man-days), but under the PES scenario, a different observation emerged (see Figure 7.12) as described below.

Land expansion or opening of new land mainly depends on two conditions: 1) household decisions (and based on labor and land availability, see section 6.3.1), and 2) population growth. With these conditions in mind, it would be interesting to know what may have triggered the change in the socio-economic conditions (e.g., income, household livelihood typology, and wealth inequality) of the household agents (after year 7). Also, with this change alone, biodiversity and ecosystem services were enhanced (as a negative feedback). Currently, there are two assumptions to explain the observed simulated behavior: 1) there is a *spatial feedback* as a result of the interactions between the decisions made by agents, i.e., not to open new land and labor and land availability, and 2) there is adaptation through the agents as a result of the two-stage decision making. A better decision rule (i.e., labor sharing or share-tapping schemes) is obviously needed to refine the model. For now, it is yet to be explained whether there was such adaptation and whether spatial feedbacks were operating. Since this behavior is unintentionally modeled, more tests (including different scenarios) are needed to establish said interactions.

7.4.2 Model validation

Pattern-oriented: structural model validation

According to Grimm et al. (2005), the use of pattern-oriented modeling attempts to make MAS/AB models more rigorous and comprehensive. Pattern in this context is defined as characteristics of a system and often, therefore, an indicator of essential underlying processes or structures. Although formulated in ecology, the use of patterns in this study is highly applicable, thus gauging the rigor and comprehensiveness of the LB-LUDAS model. The above authors provide two questions as guides to check whether the observed patterns of the real system are tied in the model structure:

1. Which observed patterns seem to characterize the system and its dynamics? and
2. Which variables and processes must be in the model so that these patterns could, in principle, emerge?

The answers to the first question are given in Chapter 3, 4 and 5 where social and ecological system dynamics are extensively characterized. The second question can be answered by the fact that: 1) the stylized facts (see section 7.2.1) identify the variables correlated with the decisions of the household agents, and 2) the decision processes integrated in the decision-making mechanism represent the important processes that reflect the characteristics of the real system. In addition, one pattern (i.e., labor pattern in rubber agroforest system) that was unintentionally modeled emerged.

Role playing games (RPGs): input validation

One way to approach the validation of a MAS model of a real-world system is input validation, i.e., ensuring that the structural conditions, institutional arrangements, and behavioral dispositions incorporated into the model capture the salient aspects of the actual system. In the MAS modeling approach, role-playing games (RPGs) are widely used as a tool to validate both the model construction and the simulation outputs (Barreteau et al. 2001; Barreteau et al. 2003; Etienne 2003; Castella et al. 2005; Guyot and Honiden 2006; Pak and Brieva 2010). RPGs validate the MAS models by finding a match between observed and simulated results as well as between modeled and real processes (Guyot and Honiden 2006).

Here, the simulated results generated from the LB-LUDAS model were validated with the results of the RPG conducted in the rubber agroforest of Jambi province by Villamor and van Noordwijk (2011). The RPG was conducted to deepen the understanding of the system properties and dynamics, which are hardly communicated through interviews and surveys. Also, the RPG was designed to understand the behavior or reactions of the households if buyers (e.g., PES negotiators, oil palm companies, logging companies, etc.) were interested in converting their rubber agroforests or maintaining them through PES schemes. The land-use game boards were used to represent the rubber agroforest landscape of Jambi province, and the players were the same farmers as those in the survey (Chapter 3).

Using the RPG coupled with the survey, Villamor and van Noordwijk (2011) explored the following questions, which were of paramount importance for the development of the LB-LUDAS model:

1. How are current conservation agreements perceived at household level? Are the household plans and ambitions aligned with village level planning and commitments? Are differences between household strategies apparent?
2. What are the responses to land-use options in a social setting with competing agents that promote conversion and conservation? Do these social responses match individual preferences?

One of the main findings of the RPG that validates the LB-LUDAS output (i.e., under the PES scenario) is that no land-use change was observed throughout the whole game including the spatial land-use arrangement that was set by the players. Interestingly, "*during the game, all the financial bids by external agents to secure an oil palm foothold in the village were rejected despite indications of declining income in the village*". This statement supports the LB-LUDAS simulation results regarding the fact that some land uses did not change (Figure 7.1 and 7.3).

Indirect calibration

The LB-LUDAS model was also validated using the indirect calibration. With this approach, empirical evidence is indirectly employed to identify sub-regions in the potential parameter space. Within sub-regions, a model is expected to replicate some relevant statistical regularities or stylized facts (Windrum et al. 2007). The empirical validation using this approach was carried out following the four main steps enumerated by Windrum et al. (2007):

1. Identify set of stylized facts interested in reproducing and/or explaining the model (see section 6.1.2 and 7.21)
2. Gather all possible evidence about the underlying principles that inform on real-world behavior (see also Chapter 3, 4, 5, and Appendix 1)
3. Use of empirical evidence on stylized facts to restrict the space of parameters and determine whether the statistical regularities derived from simulation are consistent with the empirically-based stylized facts of interest. Chapter 6 provides insights for this step in which patterns derived from stylized facts were unable to replicate or explain the initial model results (i.e., Figure 6.2).
4. To deepen the understanding of the causal mechanisms that underlies the stylized facts being studied and/or explores the emergence of fresh stylized facts. Due to the weak causal mechanism established using the land-use choice model alone, two sets of stylized facts were generated (section 7.2.1), which were considered as good estimators for the agents' behavior.

7.4.3 Model comparison

To the author's knowledge, the application of MAS/AB modeling to explore the possible impact of land-use policies, i.e., PES and ES trade-offs, is novel. However, it is also interesting to compare this model with models other than MAS/AB models that also quantify ES trade-offs. For example, the Integrated Valuation of Ecosystem Services and Trade-offs (InVEST) as a spatially explicit modeling tool (Tallis et al. 2011) predicts changes in ecosystem services, biodiversity conservation, and commodity production levels (Nelson et al. 2009). From the model application in the Willamette Basin, Oregon, little evidence was found of trade-offs under scenarios where scores for ES (i.e., carbon sequestration, storm peak mitigation, water quality, and soil conservation) and biodiversity were high. In contrast, in scenarios that involved more development and had higher commodity production values but lower levels of ES and biodiversity, the high trade-offs could be alleviated through payments for carbon sequestration.

Though a similar trend/pattern was also observed in the LB-LUDAS application, I wasn't able to run the INVEST model. Thus, it is not possible to comprehensively compare the two models.

7.5 Conclusions

The improved version of LB-LUDAS model was applied for understanding the SESs of a rubber agroforest landscape in Jambi province. Three scenarios namely, PES (for conservation pathway), SUB (development pathway) and baseline (current trend) scenarios were simulated. Findings show that under the PES scenario, LUCC was very minimal (mostly due to natural transition processes). On the other hand, LUCC under the SUB scenario was very evident, particularly in the rice paddies and rubber agroforests.

Regarding socio-economic and environmental impacts, under the PES scenario household livelihoods would be better off, and ecosystem services (i.e., carbon emission reduction) and biodiversity would be enhanced, suggesting synergies among them. While under the SUB scenario, synergies are also evident between income and ES when compared to baseline scenario, improvements in terms of wealth inequality and livelihood welfare could not be achieved.

Furthermore, the third hypothesis is found to be acceptable, i.e., *dramatic and unexplained oscillations (specifically in crop yields) were results of a misspecification in modeling the agent's behavior when relevant confounders were not incorporated in the agent's model* (section 6.1.3). Incorporating the decision processes as the confounders (i.e., PES adoption and with financial investment provision) not only reduced the oscillations but also provided relevant factors that could explain the outcome. Moreover, new emergent behavior was also observed (section 7.4.1).

8 CONCLUSIONS AND RECOMMENDATIONS

The aim of this study is to contribute to the research on the understanding and management of the dynamics of the relationships between humans and ecosystems that consider various processes and feedbacks of socio-ecological systems. It also assessed the potential spatial and temporal impacts of payments for ecosystem services schemes (PES) as a widely recognized management or policy instrument for land use. Four key aspects of these relationships are provided.

First, the gap between agricultural production and agro-biodiversity protection can be bridged. The rubber agroforest is an example of a man-made ecosystem, which is considered a multi-functional landscape system that could serve agricultural production and agro-biodiversity conservation. However, it requires a management regime or policy interventions to survive in a continually changing social environment.

Second, PES schemes (i.e., eco-certification and 70% protection zoning for reduced emission from deforestation and degradation (REDD) strategy) as land-use policy interventions offer synergies among ES (i.e., carbon emission reduction), biodiversity and household livelihoods. Management schemes such as these reduced the trade-offs by enhancing ES as a result of the interactions between household agents' livelihood dynamics and their land-use decisions.

Third, the use of MAS/AB models is a highly valuable framework to tackle the complexity of social-ecological systems (SESs). However, essential patterns and processes of the systems should be incorporated to provide sound outputs while reflecting the real-world systems.

Fourth, the LB-LUDAS model (with process-based decision-making sub-models) as an integrated and multi-agent system (MAS) model was able to represent the dynamics and interactions as well as the processes between the human and landscape systems of a rubber agroforest landscape. It is a tool that quantifies and estimates possible impacts of land-use change policies, e.g., species loss, carbon emissions, opportunity costs, etc. Also, it has the basic functionalities of a negotiation-support system (NSS) tool to support the design of the land-use policies, as it can predict landscape level through the likely response of agents in externally set rules and incentives.

8.1 Where from here?

In the following, the background of the above conclusions is summarized. Chapter 1 describes the fundamental concepts of SESs and inherent challenges of understanding the coupled systems. In Chapter 2, the details of one of the frameworks for studying the SESs of a rubber-agroforest-dominated landscape are presented. The multi-agent system model, i.e., LB-LUDAS (Lubuk Beringin – Land Use DynAmic Simulator) model as the framework of this study, is described using the standard ODD (Overview, Design and Details) protocol.

Chapter 3 characterizes the human system of the rubber agroforest landscape in Jambi province and addresses its heterogeneity. It also identifies the factors affecting the decision making of the human agents, including the decision process under specific conditions. Having set up the human system, Chapter 4 explores and describes the land-use policy interventions, i.e., PES schemes such as REDD and eco-certification or eco-labeling. The factors affecting the participation or adoption in PES schemes of the human agents are identified and a sub-model for decision making developed.

Chapter 5 has a strong focus on building ecological sub-models for the bio-physical system of the model. In this way, the criticism about the weak incorporation of ecological processes in most MAS/AB models is addressed. Data generated from empirical studies were calibrated and parameterized, and incorporated the important patterns and processes of the biophysical system reflecting the real rubber-agroforestry landscape as far as possible, i.e., species richness, forest and agronomic yields, natural succession and carbon sequestration.

Chapter 6 presents the operationalization of the LB-LUDAS model. During this process, challenges were encountered regarding the calibration and validation of the empirically based MAS/AB model as manifested in the model outputs. Two assumptions were identified as explanations of the observed phenomenon: 1) the recursive use of a non-contracting function that mimics the natural oscillation, and 2) mis-specification of agents' behavior when relevant confounders are not incorporated in the agent's modeling. To resolve the latter hypothesis, process-based decision making sub-models were proposed and integrated in the LB-LUDAS' decision-making mechanism.

Chapter 7 is the final empirically based chapter where the LB-LUDAS model with improved decision-making mechanisms was applied. Three scenarios were simulated: 1) PES (conservation pathway), 2) SUB (economic development pathway), and 3) baseline or current trend. As an overall result of the three scenarios, PES was found to be a highly desirable scenario, as it could not only reduce the trade-offs between ES and biodiversity but also bridge the gap between conservation of rubber-agroforest and the livelihoods of human agents.

8.1.1 Policy implications

Three important aspects on the effectiveness and design of PES were revealed by the simulation results:

1. *Conditionality* that links environmental context to environmental effectiveness: Setting up the biodiversity criteria ensures that the desired ES and biodiversity in rubber agroforest landscape are achieved. According to Jack et al. (2008), the long-run viability of PES schemes may depend on techniques that estimate ES from easily observable ecosystem properties. Here, the criteria are based on the species richness and basal area of the rubber agroforest plots (as simple ES proxies) which were captured by the LB-LUDAS model (as pattern and process) and used to estimate biodiversity and carbon stocks for payments in the form of price premium. However, as mentioned in Chapter 4, the market for eco-certified rubber latex is still premature and eco-certification for rubber latex needs to be recognized by the certifying authorities, e.g., Forest Stewardship Council.
2. *Social inefficiency*: Engel et al. (2008) point out that social welfare in PES schemes is reduced if households fail to adopt practices where benefits exceed the costs, or if households adopt practices where benefits are smaller than the costs. In practice, this could be judged from the type and payments provided by the PES schemes. The simulation results show that a price premium was assigned to those PES adopters who met the biodiversity criteria; the probability that the biodiversity criteria are met is high for rubber-based farmers (household type 2), who are the relatively poor households. This also suggests that the simulated PES scheme design is favorable for supporting the socially desirable land-use practices (see Chapter 3) and at the same time poor households. However, this research did not consider the transaction

costs for setting up rubber agroforests, which would affect the desirability of land-use practices.

3. *Distributional implications*: According to Jack et al. (2008), the overall viability of PES schemes is determined by the preferences of all relevant stakeholders, in this case the household farmers. In Chapter 4, preference coefficients were identified that would determine if the household agent would or would not adopt and were used in the simulation. About 30-40% adoption success was simulated, and only this percentage of households would realize the rewards or payments. Thus, if one would propose to up-scale such PES schemes, factors affecting the decision to adopt or participate in PES schemes should be seriously considered. However, the factors used in the simulation only provide the observable patterns of adoption, but what caused the decision is not known.

8.1.2 Limitations

The overall aim of applying LB-LUDAS is to understand the possible ES trade-offs of land-use change policies spatially and temporally. However, the model does not provide accurate values for identifying the best policies. Rather, it is a tool to support the design of land-use policies. Aside from specific limitations mentioned in the respective chapters, additional shortcomings are as follows:

1. Biodiversity equation application: The estimation of species richness was limited to the rubber agroforest. This was done to reduce the running time of the simulation. The uncertainty measurement of species richness estimates is only limited to the standard error of the mean. The use of biodiversity intactness variances could improve the biodiversity uncertainty estimates (Hui et al. 2008).
2. Running speed (or speed of execution): Although Netlogo is one of the most user-friendly modeling platforms, its drawback is the long running time of the simulation. It is not recommended for models that consider the landscape type of simulations with various patterns and processes that operate simultaneously. Mason and Repast are alternatives; however, the disadvantages are in the documentation and ease of learning and programming (Gilbert 2008).
3. Data demanding model: The LB-LUDAS model demands a large amount of data that reflect different aspects, patterns, and processes to capture as much as possible

the real world system. Therefore, it is suggested to apply various data collection techniques such as role-playing games and semi-structured interviews.

4. ES target: The impacts on ES trade-offs were limited to carbon sequestration, though important ecosystem processes (i.e., natural succession, forest, rubber agroforest, and shrub growth) and higher plant diversity were included.

8.2 Where to from here?

8.2.1 Theoretical development

The LB-LUDAS model set an entry point to contribute to the science of coupled human-environment systems (CHES or SESs) and land-use change. However, there are specific areas of this complexity that are greatly in need of further development.

Identifying thresholds is the most intriguing part for CHES scientists. So far, the indications of the potential system shifts in the simulated rubber agroforest landscape have not yet been observed. Thus, it is suggested that the rubber agroforestry system under the simulated conditions and assumptions is stable or at a certain metastable equilibrium. However, to explore this concept, further scenarios, including other behavioral preferences of household agents, and testing of different parameters are planned for the future.

Assuming that the behaviors identified, i.e., adaptation, learning and spatial feedbacks, are clearly operating in the model (which are rare if not absent in most of MAS/AB models), answering the following research questions should be the next step to better understand the key components of SESs:

1. Are there positive or negative feedbacks between spatial processes? To what extent does a system change its external environment?
2. If learning is occurring, is it active or positive? What mechanisms reinforce it? Does adaptation occur proactively through deliberate management towards a goal or passively as a result of action of selective processes?

Answers to these questions would further contribute to the understanding that a SES is a co-evolving system through two-way feedbacks. With this, a window of theoretical development is opened by linking the macro-outcomes of the LB-LUDAS model to emergent macro-patterns, e.g., labor shortage situation.

8.2.2 Methodological development

One of the main improvements in the LB-LUDAS model is the incorporation of the process-based decision making. Though the *PES-adoption* and *Preferred-land-use* sub-models produce useable estimators for the agents’ behavior, the decision-making routine would likely be more realistic if more direct decision estimations derived from, for example, multi-choice experiments would be incorporated into the modeling of agent's decisions (see Appendix 4). Such extended models would incorporate intended decisions of agents in various situations. A comparison between a simple and such an extended model as a standard feature in studies could help modelers to decide whether extended models should be preferred.

Generally, in studying SESs, a combination of different approaches, e.g., role-playing games, surveys, semi-structured interviews, use of historical accounts, census data, direct participant observation, and laboratory experiments, seems a promising way to model and estimate agent behavior. From this study, it was also learned that longitudinal data should be included to establish causal relationships and to build strong inference. If this is not feasible, the above proposed direct agent's decision estimation might be a substitution as it covers projective information.

Stylized facts are widely applied in economic MAS/AB models to provide a point of reference for a comparative analysis of models intended to explain an observable phenomenon. Its application in this study was experimental and novel, but was found very useful in dealing with the questions simulation researchers are confronted with. The author believes that the use of stylized facts will be part of most MAS/AB modelers for land-use change in the years to come.

8.2.3 Research outlook

The following topics emerging from this study will be further studied by the author:

1. Test the first hypothesis regarding the oscillation phenomenon (see Chapter 6);
2. Analyze and ascertain the emergent properties, i.e., spatial feedback, learning and adaptation, that were observed under the PES scheme, and
3. Test and compare the different proposed methods (see Appendix 4) to improve the decision making of agents and other validation techniques.

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10 APPENDICES

10.1 Appendix 1: Land-cover change in Jambi Province: intensities of change speed, and transition

This supplementary chapter of the thesis presents how to detect the dominant landscape changes and patterns (i.e., the spatial configuration of land-use), and to understand the process of change (and its dynamics) through its land cover change intensity, speed and transition. A statistical method developed by Aldwaik and Pontius (2012) was implemented to answer the following questions:

1. In which time intervals is the overall annual rate of change relatively slow versus fast as revealed by time interval analysis (speed of change)?
2. Which land-cover types are relatively dormant versus active in a given time interval as revealed by an intensity analysis of land-cover types, and is the pattern stable across time intervals? and
3. Which transitions are intensively targeted by a given land-cover type in a given time interval as revealed by the transition intensity analysis, and is the pattern stable across time intervals?

10.1.1 Historical background

At the beginning of the 20th century, rubber trees (*Hevea brasiliensis*) were introduced in Indonesia from Brazil by the Dutch. Because of the similar climate of Sumatra, rubber trees thrived well and rapidly replaced the farming systems (shifting cultivation) in the island (Gouyon et al. 1993). Forests in the area were transformed into agroforests through local rules by assigning property rights where rubber trees had been planted (van Noordwijk et al. 1995; Murdiyarso et al. 2002). Sumatra benefitted from the rubber boom in the 1920s and people planted more trees. The Batanghari River was used for transportation. Labor availability has been the primary constraint in rubber production (Suyanto et al. 2001), and in the periods of high rubber prices, the labor force was increased by migrant labor from the Kerinci Mountains and Java.

In the 1970s, there was a big change in the island, when the government took up logging as a commercial activity, completed the Trans-Sumatran highway, and brought in a transmigrant population coming mostly from Java, which was followed by the establishment of large-scale oil palm plantations in the 1990s (Martini et al. 2010). Van Noordwijk et al. (1995) and Tomich et al. (1998a) described the land-use change in the early 1990s, which saw the end phase of commercial logging and the transition of the transmigration villages from a production of food crops to livelihoods based on rubber and oil palm (Martini et al. 2010).

In 2006, 4.7 million ha of oil palm were newly planted in Sumatra (van Noordwijk et al. 2008). At the same time, rice-paddy cultivation increased in response to a near-doubling of the rice price from 4,500 rupiah kg^{-1} (USD 0.50) in 2004 to 8,000 rupiah kg^{-1} (USD 0.90) in early 2007.

10.1.2 Methodology

Site description

The study site in Sumatra includes three villages (or *dusun*) namely Laman Panjan, Lubuk Beringin and Buat covering an area of around 16,000 ha of land belonging to Bathin III Ulu sub-district in Jambi province. It is located between 101° 50’ to 101° 53’ east longitude and 01° 40’ to 01° 43’ south latitude. The terrain is flat to undulating with elevations ranging from 110 to 1316 m.a.s.l. The area is dominated by lowland forests and mixed rubber agroforests. There are three main rivers in the area, namely the Sungai Buat, Sungai Letung, and Sungai Mengkuang Rivers. Surrounding these rivers are rice fields and settlement areas. The distance from Muara Bungo, the capital of the Bungo District, is about 12 km^2.

The Bungo district has a total rubber plantation area of 91,470 ha and oil palm plantations with a total area of 47,606 ha. Rubber latex is the main crop produced in the area. Fruits such as *durian*, *duku* and *rambutan* and cinnamon are also produced for additional income. The majority of the people are rubber tappers and rice farmers.

10.1.3 Data sources

Land-cover maps of the study area for 1973, 1993 and 2005 were prepared from Landsat MSS, Landsat TM, and Landsat ETM images, respectively (Ekadinata et al. 2010) under the Landscape Mosaic Project of ICRAF. Accuracy of the land-cover classes varies between 77.8% for settlement and 90.8% for the forest class. For rubber agroforest, the classification accuracy is 80.7%, while most of the misclassification occurred between rubber agroforest, forest and monoculture rubber (Ekadinata and Vincent 2010). Map boundaries and validation were done with the participation of local farmers between January and March 2010.

10.1.4 Land-cover transition matrix

Land-cover transition matrices are useful conventional tools to identify key patterns of land-cover change. The analysis used land-cover maps for three points in time, i.e., 1973, 1993 and 2005. All maps have a 30 m x 30 m resolution. For the first interval, the 1973 map was overlaid with the 1993 map, and for the second interval the 1993 map with the 2005 map to produce two matrices (Table 10.1 and 10.2). The results of the overlays are presented in terms of percentage of the study area. In each matrix, the gross loss and gain of land-cover type between the beginning and end of the period is shown. Braimoh (2006) used the transition matrix with gross gain and loss for an in-depth analysis to reveal swap or location, i.e., simultaneous gain and loss, of a given land-cover type, and to distinguish between random and systematic transitions (Pontius et al. 2004).

Table 10.1: Land-cover change 1973-1993 (%)

1973	**1993**								
	Forest	**RAF**	**Mono R**	**Rice field**	**Shrub land**	**Settle-ment**	**Water bodies**	**Total 1973**	**Loss**
Forest	**55.6**	12.8	12.6	0.0	0.4	0.3	0.2	82.0	26.4
Rubber agroforest	0.1	**6.4**	3.9	0.0	0.1	0.6	0.1	11.2	4.8
Monoculture rubber	0.0	0.9	**1.0**	0.0	0.1	0.3	0.0	2.3	1.3
Rice field	0.0	0.5	0.3	**0.0**	0.0	0.3	0.1	1.2	1.2
Shrubland	0.0	1.0	1.8	0.0	**0.0**	0.0	0.0	2.9	2.9
Settlement	0.0	0.0	0.0	0.0	0.2	**0.2**	0.2	0.2	0.0
Water body	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**	0.1	0.1
Total 1993	55.8	21.7	19.7	0.0	0.7	1.7	0.5	100.0	36.6
Gain	0.2	15.2	18.7	0.0	0.6	1.5	0.4	36.6	

RAF = rubber agroforest; Mono R= monoculture rubber; Sett= settlement, Water= water bodies.

Table 10.2: Land-cover change 1993-2005 (%)

		2005									
		Forest	**RAF**	**Mono R**	**Oil palm**	**Rice field**	**Shrub land**	**Settle-ment**	**Water bodies**	**Total 1993**	**Loss**
1993	**Forest**	**48.6**	1.0	2.8	0.7	0.2	1.3	0.9	0.2	55.8	7.2
	RAF	0.0	**9.2**	7.1	0.8	1.0	0.3	2.8	0.4	21.7	12.4
	Mono R	0.0	4.0	**12.6**	1.2	0.2	0.1	1.4	0.2	19.7	7.1
	Oil palm	0.0	0.0	0.0	**0.0**	0.0	0.0	0.0	0.0	0.0	0.0
	Rice field	0.0	0.1	0.3	0.1	**0.0**	0.0	0.1	0.0	0.7	0.6
	Shrubland	0.0	0.0	0.0	0.0	0.0	**0.0**	0.0	0.0	0.0	0.0
	Settlement	0.0	0.0	0.0	0.0	0.0	0.0	**1.7**	0.0	1.7	0.0
	Water bodies	0.0	0.0	0.1	0.0	0.0	0.0	0.1	**0.2**	0.5	0.3
	Total 2005	48.6	14.4	23.0	2.8	1.5	1.7	7.0	1.0	100.0	27.6
	Gain	0.0	5.2	10.4	2.8	1.5	1.7	5.3	0.8	27.6	

RAF = rubber agroforest; Mono R= monoculture rubber; Sett= settlement, Water= water bodies.

10.1.5 Land-cover change analysis

To analyze the size and intensity of change in order to address the research questions, three levels of analyses were applied (Note: the term category refers to land-cover type).

1. *Interval level* examines how the size and annual rate of change varies across the time interval and is given by the following equations (Aldwaik and Pontius 2012):

$$U = \frac{100 \times \sum_{t=1}^{T-1}\left\{\sum_{j=1}^{J}\left[\left(\sum_{i=1}^{J} C_{tij}\right) - C_{tij}\right]\right\} / \left\{\sum_{j=1}^{J}\left(\sum_{i=1}^{J} C_{tij}\right)\right\}}{Y_{t+1} - Y_1} \qquad (10.1)$$

$$= \frac{100 \text{ x area of change interval} [\text{Yt, Yt} + 1] / \text{area of study region}}{\text{duration of interval} [\text{Yt, Yt} + 1]}$$

$$S_t = \frac{100 \times \left\{\sum_{j=1}^{J}\left[\left(\sum_{i=1}^{J} C_{tij}\right) - C_{tjj}\right]\right\} / \left\{\sum_{j=1}^{J}\left(\sum_{i=1}^{J} C_{tij}\right)\right\}}{Y_{t+1} - Y_t} \qquad (10.2)$$

$$= \frac{100 \text{ x area of change during all intervals / area of study region}}{\text{duration of all interval}}$$

where U = value of uniform line for time intensity analysis
S_t = length of bar for time interval $[Y_t, Y_{t+1}]$
J = number of categories ≥ 2; $i \equiv$ index for a category = 1, 2… J
j = index for a category = 1, 2, … , J
m = index for the losing category in transition of interest
n = index for the gaining category in transition of interest

T = number of time points ≥ 2
t = index for a time point = 1, 2, … T
Y_t = year at time point t
C_{tij} = number of cells that changed from category i at time Y_t to category j at time Y_{t+1}

If $(S_t) > (U)$, then the change is relatively fast for the given time interval; if $(S_t) < (U)$, then the change is relatively slow for the give time interval; and if $(S_t) = (U)$ for all time intervals, then the annual rate of change is stationary.

2. *Category level* examines each land-cover type to measure how the size and intensity of both gain and loss varies across space and is given by the following equations (Aldwaik and Pontius 2012):

$$P_t = 100 \times \frac{\left\{\sum_{j=1}^{J}\left[\left(\sum_{i=1}^{J} C_{til}\right) - C_{tjj}\right]\right\} / \{Y_{t+1} - Y_t\}}{\sum_{j=1}^{J}\left(\sum_{i=1}^{J} C_{tij}\right)} \tag{10.3}$$

$$= 100 \times \frac{\text{area of change}\left[Y_t, Y_{t+1}\right]/\text{duration of } [Y_t, Y_{t+1}]}{\text{area of study region}}$$

$$L_{ti} = 100 \times \frac{\left\{\left(\sum_{i=1}^{J} C_{tij}\right) - C_{tii}\right\} / \{Y_{t+1} - Y_t\}}{\sum_{i=1}^{J} C_{tij}} \tag{10.4}$$

$$= 100 \times \frac{\text{area of gross loss of category i during}\left[Y_t, Y_{t+1}\right]/\text{duration of } [Y_t, Y_{t+1}]}{\text{area of category i at time } \mathrm{Y_t}}$$

$$G_{tj} = 100 \times \frac{\left\{\left(\sum_{i=1}^{J} C_{tij}\right) - C_{tjj}\right\} / \{Y_{t+1} - Y_t\}}{\sum_{i=1}^{J} C_{tij}} \tag{10.5}$$

$$= 100 \times \frac{\text{area of gross gain of category j during}\left[Y_t, Y_{t+1}\right]/\text{duration of } [Y_t, Y_{t+1}]}{\text{area of category j at time } \mathrm{Y_{t+1}}}$$

where P_t = value of uniform line for time interval $[Y_t, Y_{t+1}]$ for category intensity analysis, L_{ti} = length of bar for time interval $[Y_t, Y_{t+1}]$ for gross loss of category i for category intensity analysis, and G_{ti}= length of bar for time interval $[Y_t, Y_{t+1}]$ for gross gain of category j for category intensity analysis

The observed intensities of categories are compared to the uniform intensity of annual change that would occur if the change within each interval were distributed uniformly over the entire study area. If the intensity bar of a category does not reach the uniform line, then the change is relatively dormant for that category during that interval. If the intensity bar extends farther than the uniform line, then the change is relatively active for that category during that interval. If the change were distributed uniformly across the landscape, then all the bars would end at the uniform line.

(3) *Transition level* examines how the size and intensity of the transition varies among categories available for that transition and is given by the following equations (Aldwaik and Pontius *in review*):

Given the empirical gross gain of category *n*, the following equations identify which categories are intensively *avoided* versus *targeted* for takeover by category *n* in a given time interval.

$$W_{tn} = 100 \times \frac{\left\{\left(\sum_{i=1}^{J} C_{tin}\right) - C_{tnn}\right\} / \left\{Y_{t+1} - Y_t\right\}}{\sum_{j=1}^{J}\left[\left(\sum_{i=1}^{J} C_{tij}\right) - C_{tnj}\right]} \tag{10.6}$$

$$= 100 \times \frac{\text{area of gross grain of category n during } [\mathrm{Y_t}, \mathrm{Y_{t+1}}] / \text{ duration of } [\mathrm{Y_t}, \mathrm{Y_{t+1}}]}{\text{area that is not category n at time } \mathrm{Y_t}}$$

$$R_{tin} = 100 \times \frac{C_{tin} / \left\{Y_{t+1} - Y_t\right\}}{\sum_{j=1}^{J} C_{tij}} \tag{10.7}$$

$$= 100 \times \frac{\text{area of transition from i to n during } [\mathrm{Y_t}, \mathrm{Y_{t+1}}] / \text{ duration of } [\mathrm{Y_t}, \mathrm{Y_{t+1}}]}{\text{area of category i at time } \mathrm{Y_t}}$$

where W_{tn}= value of uniform intensity of transition to category *n* from all non-*n* categories at time Y_t during time interval $[Y_t,Y_{t+1}]$ for transition intensity analysis; and R_{tin}= length of bar of transition from category *i* to n during time interval $[Y_t,Y_{t+1}]$ for transition intensity analysis where $i \neq n$

Given the empirical gross loss of category *m*:

$$V_{tm} = 100 \times \frac{\left\{\left(\sum_{j=1}^{J} C_{tmj}\right) - C_{tmm}\right\} / \left\{Y_{t+1} - Y_t\right\}}{\sum_{i=1}^{J}\left[\left(\sum_{j=1}^{J} C_{tij}\right) - C_{tim}\right]} \tag{10.8}$$

$$= 100 \times \frac{\text{area of gross loss of category m during } [\mathrm{Y_t}, \mathrm{Y_{t+1}}] / \text{ duration of } [\mathrm{Y_t}, \mathrm{Y_{t+1}}]}{\text{area that is not category m at time } \mathrm{Y_{t+1}}}$$

$$Q_{tmj} = 100 \times \frac{C_{tmj} / \{Y_{t+1} - Y_t\}}{\sum_{i=1}^{J} C_{tij}} \tag{10.9}$$

$$= 100 \times \frac{\text{area of transition from m to j during } [\mathrm{Y_t}, \mathrm{Y_{t+1}}] / \text{ duration of } [\mathrm{Y_t}, \mathrm{Y_{t+1}}]}{\text{area of category j at time } \mathrm{Y_{t+1}}}$$

where V_{tm} = value of uniform intensity of transition from category *m* to all non-*m* categories at time Y_{t+1} during time interval $[Y_t, Y_{t+1}]$ for transition intensity analysis where $j \neq m$; and Q_{tmj}= length of bar of transition from category *m* to category *j* during time interval $[Y_t, Y_{t+1}]$ for transition intensity analysis.

If the intensity bar of a category does not reach the uniform line, then the transition systematically avoids that category. If an intensity bar extends farther than the uniform line, then the transition systematically targets that category.

10.1.6 Results

Past land-cover changes and pattern

Three main land-cover changes can be observed at the three points in time 1973, 1993 and 2005, namely decrease in forest area, increase in monoculture rubber areas, and an initial increase and then subsequent decrease in rubber agroforest (Figure 10.1).

Between 1973 and 1993 (Table 10.3b), forest experienced the highest loss in over 26% of the total landscape area. This is likely due to the conversion to monoculture rubber and rubber agroforest, which had the highest gain with 18% and 15% of the landscape, respectively. The gain-to-loss ratio of 14.3 was highest in monoculture rubber, indicating that monoculture rubber experienced a 14 times higher gain than loss. This gain can be associated with the boom of rubber prices (up to more than 100% of the normal price), which made it profitable for the farmers to convert their complex rubber agroforest into a monoculture system (Martini et al., 2010). The change attributable to quantity (net change) is highest for forest (99% of total change), while change attributable to location (swap) is highest for monoculture rubber (47% of total change).

Between 1993 and 2005, the loss in forest dropped to 7% of the landscape, while rubber agroforest experienced the highest loss in over 12%. Monoculture rubber experienced the highest gain of over 10%. Oil palm, as a new land-cover type, emerged in very small areas during this period, while settlement increased in over 5%. The changes in rubber agroforest and monoculture are both swap (change attributable to location) and net change (in quantity). The swap change is highest in monoculture rubber (81% of the total change), while net change is highest in rubber agroforest (41% of the total change). It is most likely that the loss of monoculture rubber was swapped to the gain of 5% of rubber agroforests. Swap change dynamics accounted for 50% of the total land change.

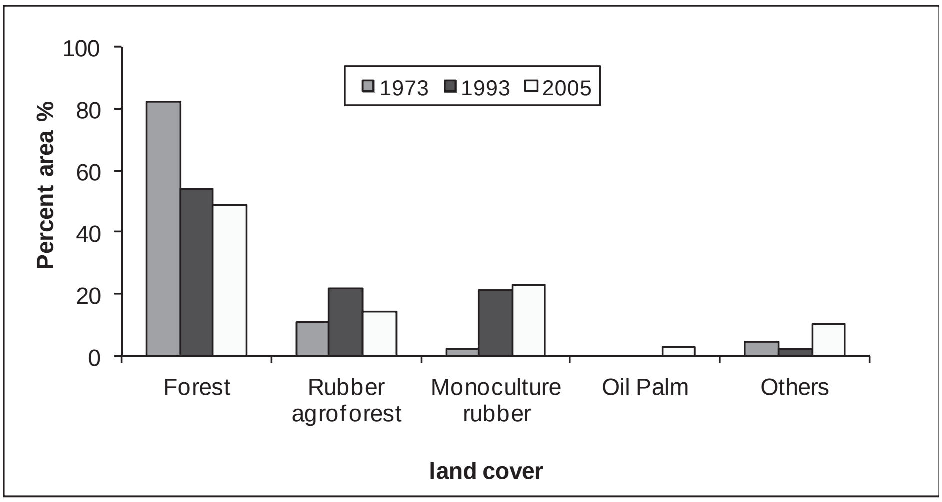

Figure 10.1: Land-cover changes in the study site between 1973 and 2005

Table 10.3: Summary of land-cover changes (a) 1993-2005 and (b) 1973-1993 (%)

(a)	**Total 1993**	**Total 2005**	**Gain**	**Loss**	**Total change**	**Swap**	**Absolute net change**
Forest	55.8	48.6	0.0	7.2	7.2	0.0	7.2
Rubber agroforest	21.7	14.4	5.2	12.4	17.6	10.3	7.3
Monoculture rubber	19.7	23.0	10.4	7.1	17.5	14.2	3.3
Oil palm	0.0	2.8	2.8	0.0	2.8	0.0	2.8
Rice field	0.7	1.5	1.5	0.0	1.5	0.0	1.5
Shrubland	0.0	1.7	1.7	0.6	2.3	1.3	1.0
Settlement	1.7	7.0	5.3	0.0	5.3	0.0	5.3
Water body	0.5	1.0	0.8	0.3	1.1	0.5	0.6
Total	100.0	100.0	27.6	27.6	27.6	13.2	14.4

Table 10.3 continued

(b)	Total 1973	Total 1993	Gain	Loss	Total change	Swap	Absolute net change
Forest	82.0	55.8	0.2	26.4	26.6	0.3	26.3
Rubber agroforest	11.2	21.7	15.2	4.8	20.0	9.5	10.5
Monoculture rubber	2.3	19.7	18.7	1.3	19.9	2.5	17.4
Rice field	1.2	0.0	0.0	1.2	1.2	0.0	1.2
Shrub land	2.9	0.7	0.6	2.9	3.5	1.2	2.3
Settlement	0.2	1.7	1.5	0.0	1.5	0.0	1.5
Water body	0.1	0.5	0.4	0.1	0.5	0.1	0.4
Total	100.0	100.0	36.6	36.6	36.6	6.9	29.8

10.1.7 Land-cover change process

Time interval intensity

A comparison of the land area changed per year ***(S_t)*** with the uniform speed of the change (***U)*** shows that in the time interval between 1993 and 2005, the speed of land-cover change is faster (2.18%) than between 1973 and 1993 (1.83%) (Table 10.4).

Table 10.4 Time intensity analysis of land-cover change for the study site (%)

Time interval ***[Y_t, Y_{t+1}]***	Area changed per interval	Area changed per year ***(S_t)***	Uniform speed of land-cover change (***U***)
1993, 2005	27.60	2.30	2.01
1973, 1993	36.63	1.83	2.01

Land-cover type (category) intensity

This intensity analysis examined each land-cover type to measure how the size and intensity of both gross losses and gross gains varies across space. The results indicate whether the land-cover types are active or dormant when compared to the uniform distribution of change *(S_t)* (table 10.5 and figure 10.2). Monoculture has highest annual gain, but this slightly slowed down from the first interval to the second interval. Forest has the largest loss during the first interval, but this slowed down during the second interval. Rubber agroforest during the second interval has the highest annual loss (4.8%) with an intensity of transition (4.78%) above the uniform intensity of distribution (2.30%), thus making it the most active land-cover type in terms of transition to other land uses.

Rice field (8.33%), settlement (8.33%), and shrubland (8.24%) are also active categories in transition (gain); however, the values (in size) cannot be compared to monoculture rubber with its 3.77 % annual gain. Thus, monoculture rubber is the most active in terms of annual gain in the period 1993-2005.

Table 10.5 Land cover change intensity analysis for the study site in size (pixel)

Time interval **[Y_t, Y_{t+1}]**	Category/ land-cover type	Gross loss (numerator of L_{ii})	Intensity of losses (L_{ii}) (%)	Gross gain (numerator of G_{tj})	Intensity of gains (G_{tj}) (%)	Uniform distribution of change (S_t)
1993-2005	Forest	**1042**	0.00	0	0.00	***2.30***
	Rubber agroforestry	**1811**	**4.78**	**751**	**2.99**	
	Monoculture rubber	**1037**	**3.01**	**1516**	**3.77**	
	Rice field	0	0.00	405	**8.33**	
	Others*	93	**8.13**	337	**7.40**	
1973-1993	Forest	**2309**	1.61	14	0.01	***1.83***
	Rubber agroforest	415	**2.13**	**1333**	**3.52**	
	Monoculture rubber	111	**2.74**	**1631**	**4.73**	
	Rice field	106	**5.00**	0	0.00	
	Others*	87	**4.03**	75	**4.54**	

*(Note: *Others are average due to the small changes)*

Transition intensity

This analysis examines how the size and intensity of the transition varies among land-cover types available for that transition. The results show the transition of the key land-cover types, i.e., rubber agroforest, monoculture rubber, and rice field in 1993-2005, and also which land-cover types were targets (Table 10.6 and 10.7; Figure 10.3 to 10.5).

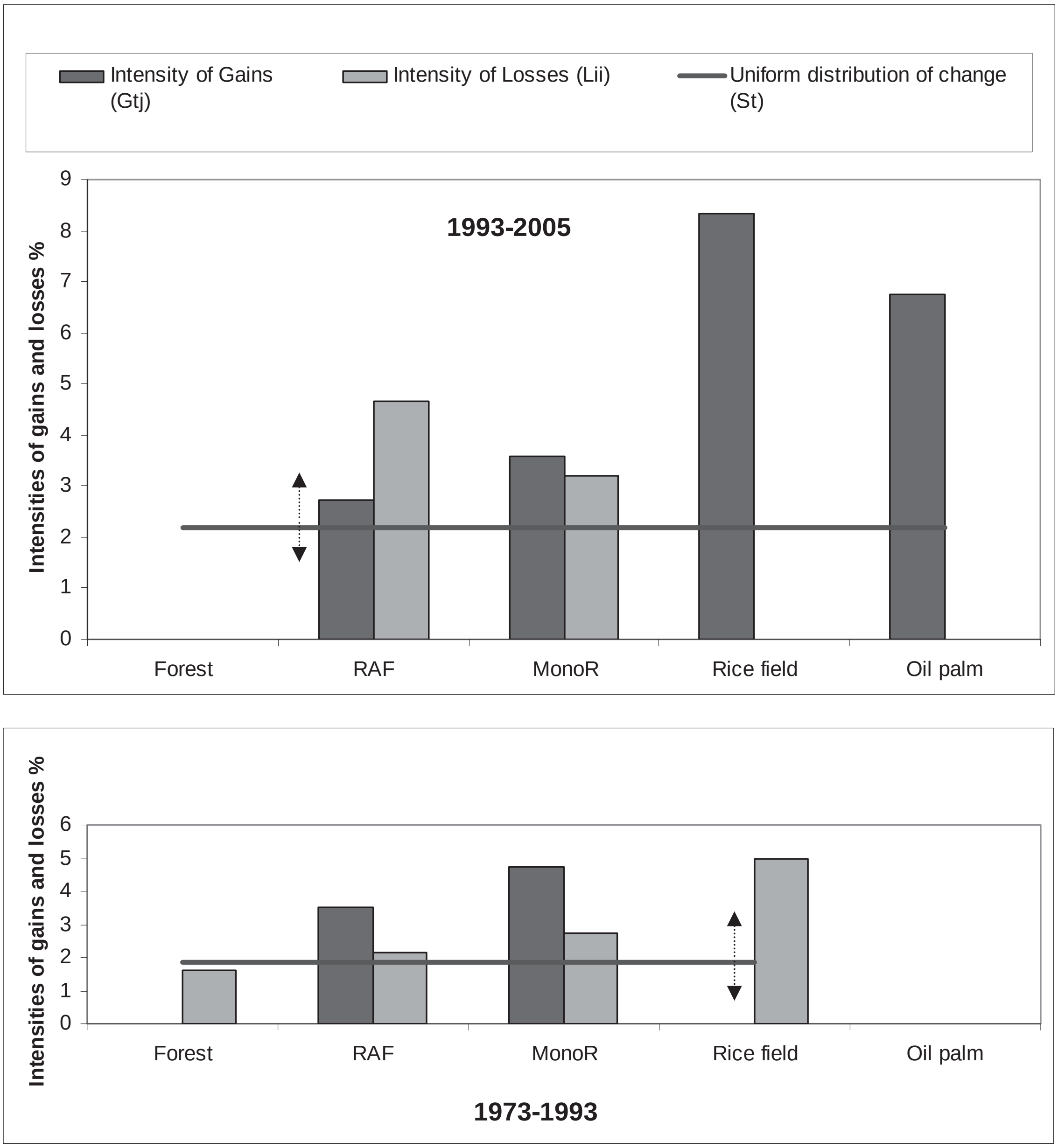

Figure 10.2 Land-cover type intensity analysis for 1973-1993 and 1993-2005. Red lines show uniform distribution of change (if bar extends *above* this line, land use is *active*, if is *below*, then it is *dormant*).

Table 10.6: Annual (gain) transition in size (pixel) and intensity (%) between 1993 and 2005

Gaining land-cover type	Land-cover transition from	Observed transition (numerator of Q_{tmj})	Intensity of transition (Q_{tmj})	Uniform distribution of transitions (V_{tm})
Rubber agrofo	Forest	94	0.10	
	Monoculture rubber	**581**	**1.56**	
	Rice field	0	0.00	***0.50***
Mono-culture	Forest	300	0.32	
	Rubber agroforest	**1115**	**2.89**	
	Rice field	0	0.00	***1.04***
Rice field	Forest	64	0.07	
	Rubber agroforest	**164**	**0.43**	
	Monoculture rubber	**175**	**0.47**	***0.23***
Oil palm	Forest	14	0.01	
	Rubber agroforest	**50**	**0.13**	
	Monoculture rubber	**37**	**0.10**	***0.06***
	Rice field	0	0.00	

Table 10.7: Annual (loss) transition in size (pixel) and intensity (%) between 1993 and 2005

Losing land-cover type	Land-cover transition to	Observed transition (numerator of Q_{tmj})	Intensity of transition (Q_{tmj})	Uniform distribution of transitions (V_{tm})
Forest	Rubber agroforest	94	0.37	
	Monoculture rubber	300	0.75	
	Rice	0	**1.32**	***0.84***
	Others (settlement)	**178**	**6.17**	
Rubber agroforest	Forest	0	0.00	
	Monoculture rubber	**1115**	**2.77**	***1.20***
	Rice	**164**	**3.38**	
Mono-culture rubber	Forest	2	0.00	
	Rubber agroforest	**78**	**0.21**	
	Rice field	0	0.00	***0.08***
Rice field	Forest	0	0.00	
	Rubber agroforest	0	0.00	
	Monoculture rubber	0	0.00	
	Shrubland	0	0.00	***0.00***
	Settlement	0	0.00	

Rubber agroforest was annually converted to monoculture rubber at 2.77% intensity, and rice field at 3.38% intensity (Table 10.6). Some of the monoculture rubber areas also were converted to rubber agroforest, but the rate (size of change) is less than 50% of the rate of rubber agroforest transition to monoculture. For monoculture rubber, aside from rubber agroforest, shrubland areas were target areas, and forest was the avoided land-cover type (Figure 10.3). The conversion of monoculture rubber to agroforest is usually attributed to labor availability (Suyanto et al. 2001). For rice fields, farmers mostly targeted the rubber agroforest and shrubland, and some of the monoculture rubber areas, while forest was avoided (Figure 10.4). There is a high transition intensity in rubber agroforest to rice fields (3.38% annually) (Table 10.7), whereas oil palm targeted areas where rubber agroforest, monoculture rubber and shrub were located (Figure 10.5).

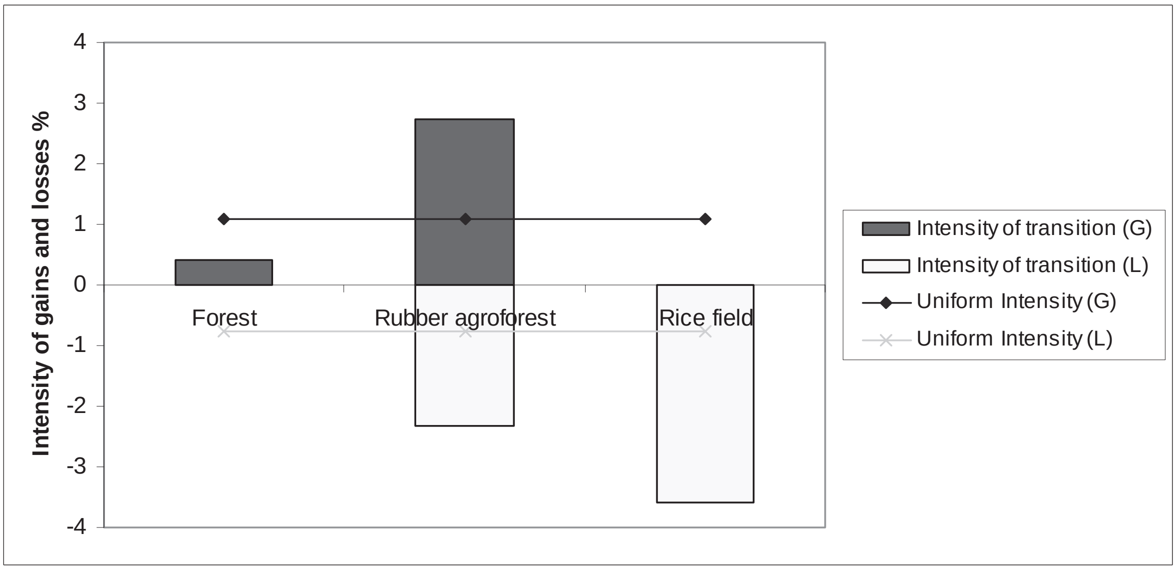

Figure 10.3 Intensity of monoculture rubber's gain (+) and loss (-) in 1993-2005. (Dark and light blue lines are uniform intensities of gain and loss, respectively. Bars that extend above line indicate the land cover targeted for transition, and bars below line indicate avoided land cover).

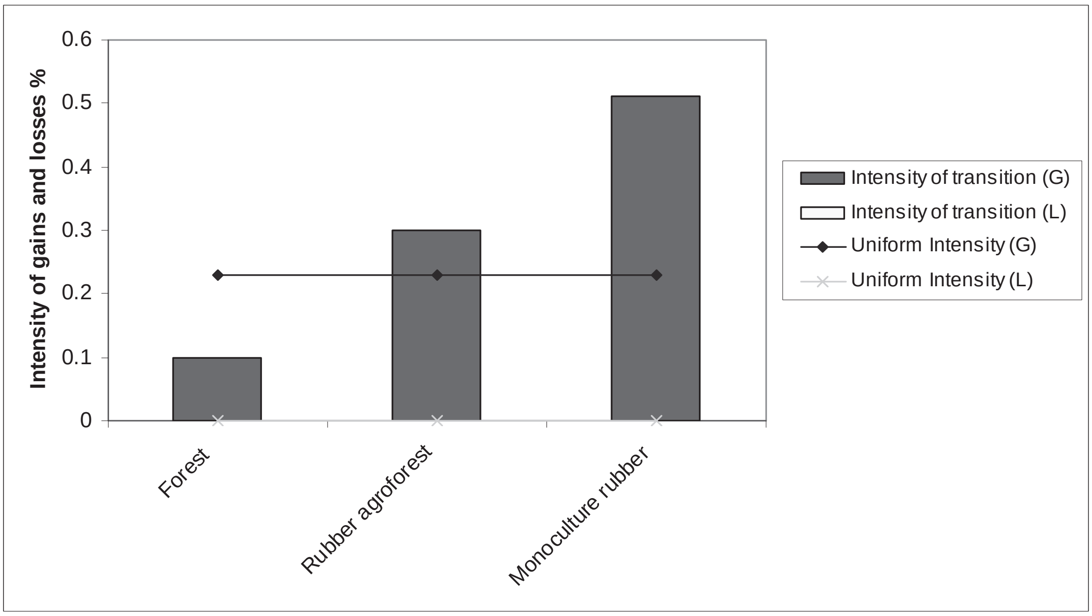

Figure 10.4 Intensity of rice field's gain (+) and loss (-) in 1993-2005. (Dark and light blue lines are uniform intensities of gain and loss, respectively. Bars that extend above line indicate the land cover targeted for transition, and bars below line indicate avoided land cover).

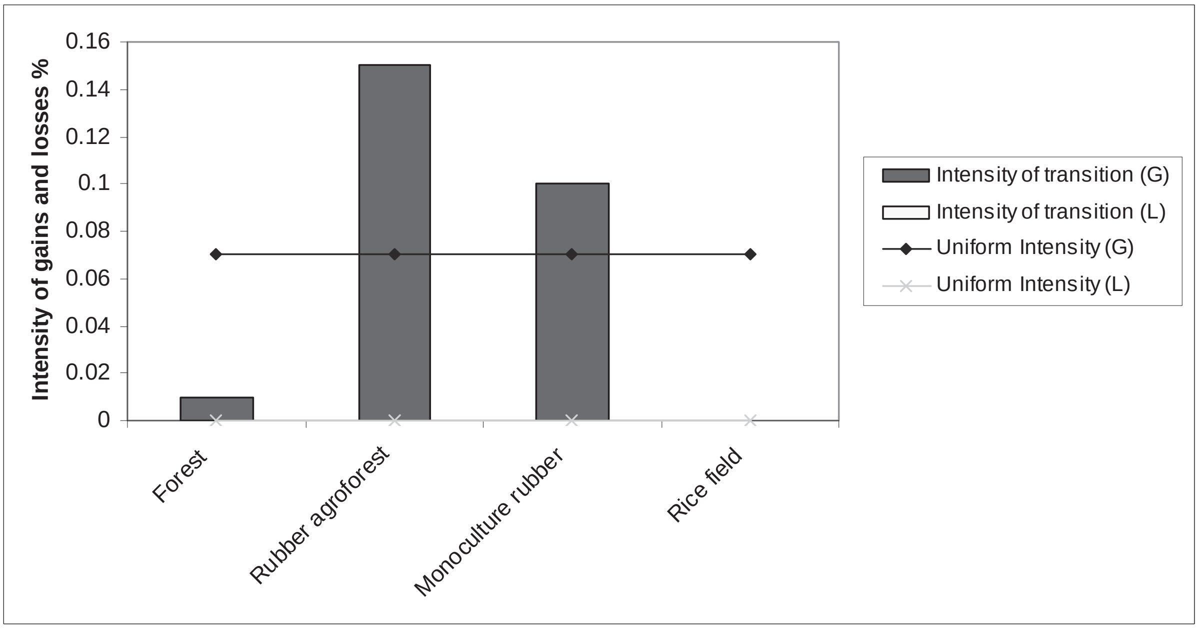

Figure 10.5 Intensity of oil palm's gain (1993-2005). (Dark and light blue lines are uniform intensities of gain and loss, respectively. Bars that extend above line indicate the land cover targeted for transition, and bars below line indicate avoided land cover).

10.1.8 Conclusion

Going back to the three questions addressing the process of change: 1) *Speed of change*: The interval 1993-2005 has the fastest overall annual rate of land-cover change. Historical accounts support this, since during this period there was an interplay of many factors of land-use change (i.e., increase in the pressure of production on resources, changing market opportunities, and outside policy) (Lambin 2003). 2) *Active land-cover types for change*: The three main land-cover types that changed during 1993-2005 are rubber agroforest, monoculture rubber and shrubland. Forest cover was found to be dormant in this period. New land-cover types such as oil palm and rice fields emerged rapidly, though the areas were comparatively small compared to rubber agroforests or monoculture rubber. 3) *Targeted land-cover types*: Rubber agroforest was the most highly targeted land-cover type for monoculture rubber, rice and settlement areas during the interval 1993-2005.

Since Jambi province is aiming to pioneer the reduction of emissions from deforestation and degradation (REDD scheme, information on the dynamics and process of land-cover change particularly between 1993 and 2005 is crucial. Without consideration of this information, the implementation of the scheme will fail (van Noordwijk and Minang 2009).

Varying trends of transition show that the land-cover change in the study area from 1973 to 2005 was highly dynamic. Monoculture rubber initially replaced forest but now replaces agroforests. Rubber agroforest has a high conservation value for conservation organizations due to its functions that resemble those of primary forest especially for climate mitigation and biodiversity conservation, and at the same time contribute to the socio-economic welfare of the villagers. Conversion from rubber agroforests to monoculture crops leads to environmental trade-offs.

The change or transition in the Jambi rubber-agroforest landscape is a highly complex phenomenon, and we need to know and understand if the decision making of the land managers is influenced by the changing socio-economic and socio-political factors. Thus, the question is: "*How do farmers decide which land-cover type to choose and what factors affect their choice?*" (see Chapter 3).

10.2 Appendix 2: Species richness estimators[16]

The following are the species richness estimator equations used for expected species accumulation curve.

1. Mao Tau (S_{obs}) - number of species expected in the pooled *Qd* (Quadrats) samples, given the empirical data (Colwell et al. 2004). It is expressed as:

$$S_{obs} = \sum_{j=1}^{H} S_j \qquad (10.10)$$

where S_j stands for the number of species found in exactly j samples of the empirical set, which has a total of H samples.

2. Chao 1 (Chao 1984) – is a simple estimator of the true number of species in an assemblage based on the number of rare species in the sample, and is expressed as (Colwell and Coddington 1995):

$$S_1^* = S_{obs} + \left(\frac{a^2}{2b}\right) \qquad (10.11)$$

where a is the number of observed species that represented by only single individual in sample (i.e., the number of singletons), and b is the number of observed species represented by exactly two individuals in the sample (i.e., the number of doubletons).

3. Jackknife 1 – first-order jackknife estimator of species richness (incidence-based) (Burnham and Overton 1978; 1979) which might be used to reduce the bias of estimates (Miller 1964). It is based on the number of species that occur in only one sample (L) and expressed as:

$$S_{jack1} = S_{obs} + L\left(\frac{n-1}{n}\right) \qquad (10.12)$$

where n is the number of samples.

[16] www.viceroy.eeb.uconn.edu

10.3 Appendix 3: Model fitting, sources of variability and sensitivity analysis

Model validity could be measured in terms of goodness of fit to the characters of the model's referent (Moss et al. 1997). The following are the example tests results to address the sources of variability in the LB-LUDAS model generated from STATA (version 11):

10.3.1 Correlation matrix of the whole area

Table 10.8: Type 1 households' correlation matrix

	H_AGE	H_SIZE	H_EDU	H_ACT	H_DEP	H_GINCPE	P_USE
H_AGE	1.0000						
H_SIZE	0.1495	1.0000					
H_EDU	0.0000	0.1976	1.0000				
H_ACT	-0.0633	-0.2844	0.1999	1.0000			
H_DEP	-0.4855	0.4044	0.0781	0.1999	1.0000		
H_GINCPE	-0.5401	-0.1775	0.1399	0.2842	0.3598	1.0000	
P_USE	-0.0352	-0.1001	0.2614	0.1852	0.1345	0.1737	1.0000
P_WETNES	0.0668	0.2208	0.2302	0.0563	0.1811	0.1639	-0.4364
P_F45_05	-0.2492	-0.1297	-0.3017	0.0454	0.0694	0.1851	0.2507
P_F8_0	-0.020	-0.0413	0.1714	-0.0253	0.0319	-0.1032	0.061

	P_WETNES	P_F45_05	P_F8_05
P_WETNES	1.0000		
P_F45_05	-0.1975	1.0000	
P_F8_05	0.0047	-0.6948	1.0000

Table 10.9: Type 1 households' covariance matrix

	H_AGE	H_EDU	H_SIZE	H_DEP	H_GINCPE	H_ACT	P_WETNES
H_AGE	110.12						
H_EDU	0	.258065					
H_SIZE	2.01714	.129032	1.65222				
H_DEP	-4.14012	.032258	.422379	.660282			
H_GINCPE	-13758.7	172.542	-553.917	709.693	5.9e+06		
H_ACT	-3.79637	.580645	-2.09073	.449597	3945.04	32.7056	
P_WETNES	2.19587	.366145	.888704	.460751	1245.63	1.00869	9.80306
P_F45_05	-193.432	79.9954	-48.7258	23.7843	-230160	-132.992	13.6127
P_F8_0	-583.752	-34.2178	-37.2142	12.5928	100308	57.8993	-138.049

	P_F45_05	P_F8_05
P_F45_05	844160	
P_F8_05	-142511	49838.3

10.3.2 Collinearity using variance inflation factor (VIF)

In this analysis, the question of interest is "how much is being inflated by standard error (SE)?"

Table 10.10: Example of the household type 1 VIF

Variable	VIF	1/VIF
P_F45_05	2.57	0.388756
P_F8_05	2.27	0.439699
H_DEP	2.22	0.449934
H_AGE	2.12	0.472784
H_SIZE	2.03	0.492330
H_GINCPE	1.77	0.564299
H_ACT	1.35	0.741258
H_EDU	1.32	0.757269
P_WETNES	1.23	0.814142

Table 10.11: Example of the household type 1 collinearity

Variable	VIF	Square VIF	Tolerance	R-squared
P_USE	2.61	1.61	0.3838	0.6162
H_AGE	2.72	1.65	0.3683	0.6317
H_SIZE	2.09	1.45	0.4782	0.5218
H_EDU	1.89	1.37	0.5294	0.4706
H_ACT	1.35	1.16	0.7412	0.2588
H_DEP	2.54	1.59	0.3943	0.6057
H_GINCPE	1.91	1.38	0.5224	0.4776
P_WETNES	1.94	1.39	0.5157	0.4843
P_F45_05	3.58	1.89	0.2794	0.7206
P_F8_05	2.76	1.66	0.3622	0.6378
Mean VIF	2.34			

Variable	Eigenval	Cond Index
1	8.3133	1.0000
2	0.8380	3.1497
3	0.6315	3.6283
4	0.4668	4.2203
5	0.3101	5.1776
6	0.1861	6.6835
7	0.1271	8.0884
8	0.0661	11.2140
9	0.0354	15.3309
10	0.0219	19.4874
11	0.0037	47.2250
Mean VIF		

Condition Number: 47.2250; & Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
Det(correlation matrix): 0.0272

10.4 Appendix 4: Recommended cause-effect decision-making sub-model

Rothman et al. (2008) define confounder as the factors (e.g., exposures, interventions, treatment, etc.) that explain or produce all or parts of the difference between the measure of association and the measure of effect that would be obtained with counterfactual ideals. In other words, confounders are known or unknown variables that correlate with both the dependent and the independent variables. The methodologies of scientific studies therefore need to control these factors to avoid a false positive (Type 1) error or an erroneous conclusion that the dependent variables are in a causal relationship with the independent variable. Thus, confounding is a major threat to the validity of inferences made about cause and effect, as the observed effects should be attributed to the independent variable rather than to the confounder. One of the fundamental adjustment methods relies on the notion of stratification on known confounders. Greenland and Robins (1987) clarified the role of confounding and confounders by examining risks measures under a simple potential-outcome model for cohort individuals.

Other ways to explore confounders as suggested by Greenland et al. (2008) are causal diagrams (graphical models), which provide visual models for distinguishing causation from association and thus for defining and detecting confounding. Potential-outcome models which use structural equations to detect and control confounders are also suggested (Greenland et al. 1999a; Pearl 2000; Greenland and Brumback 2002).

For MAS/LUCC modeling, the following methods are recommended to control confounders:

1. Multiple-choice modeling as the best approach for the agent’s decision-making (Kloos 2011),
2. The process-based decision making sub-model (see section 6.3) applied in this study with similarities to the simple potential-outcome model (Greenland and Robins 1987), and
3. Evolutionary programming by Manson (2006).

10.5 Appendix 5: Uncertainty of yield prediction: random-bounded yield function

There are various sources of uncertainty in predicting crop yields. In the LUDAS model, Le (2005) addressed two main sources accounted for in the model:

1. Uncertainty due to either limitation of conceptual model, limited size of dataset, or errors in data collection and conversion; and
2. Unpredictable factors that occur stochastically by nature, e.g., drought, incidence of plant pest and disease, etc.

These uncertainties were expressed in the model in the form of random-bounded functions computed as follows (Le 2005):

$$predicted \ln P_{a-yield} \in \left\lfloor \ln P_{a-yield} - CI_{0.05}, \ln P_{a-yield} + CI_{0.05} \right\rfloor \qquad (10.13)$$

or

$$predicted \ln P_{a-yield} = \left\lfloor \ln P_{a-yield} - CI_{0.05} + random(2CI_{0.05}) \right\rfloor \qquad (10.14)$$

where $\ln P_{a\text{-}yield}$ is the deterministic log-yield estimated by equation 5.9 and 5.10 (see Chapter 5), $CI_{0.05}$ is the confidence interval at 95% of the estimated log-yield, and random ($2CI_{0.05}$) generate a random number within the bounds [0, $2CI_{0.05}$] following a uniform distribution. The $CI_{0.05}$ is calculated as: $CI_{0.05} = t_{0.25}$ x s = 1.96 x s, where s is the standard error of the estimate.

According to Le (2005), in cases where there is a good estimation of yield, e.g., high R^2 and low s, the uncertainty range becomes narrow, and the predicted yield is more deterministic, otherwise there would be high stochastic predictions of crop yield.

10.6 Appendix 6: Simulated major land-cover changes

The following are simulation results of major land-cover changes for three scenarios:

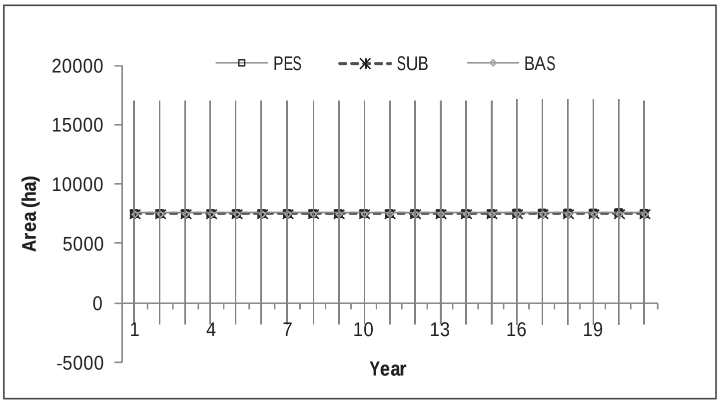

Figure 10.6 Comparison of simulated changes in forest (ha) under three scenarios. Note: vertical segments are the confidence interval (95%) of the means

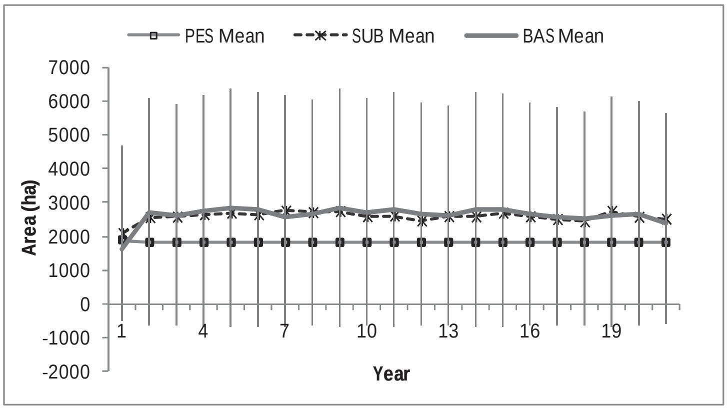

Figure 10.7 Comparison of simulated changes in rubber agroforest (ha) under three scenarios. Note: vertical segments are the confidence interval (95%) of the means

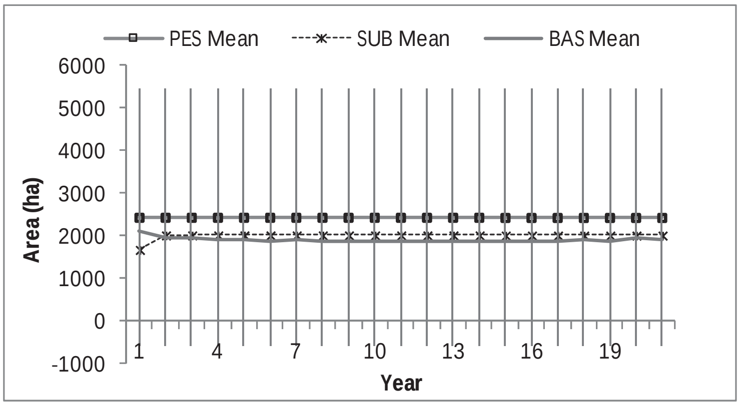

Figure 10.8 Comparison of simulated changes in rubber monoculture (ha) under three scenarios. Note: vertical segments are the confidence interval (95%) of the means

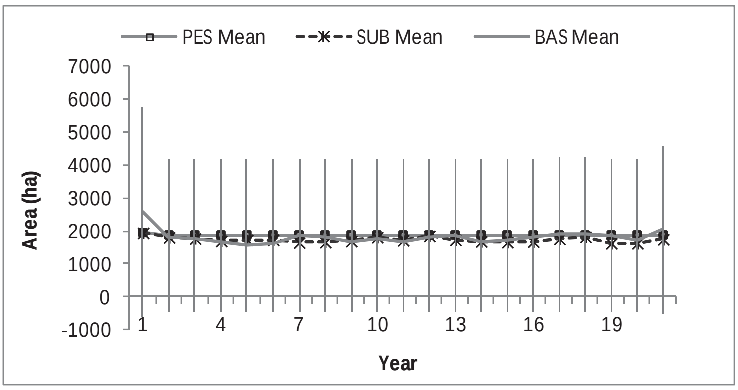

Figure 10.9 Comparison of simulated changes in rice (ha) under three scenarios. Note: vertical segments are the confidence interval (95%) of the means

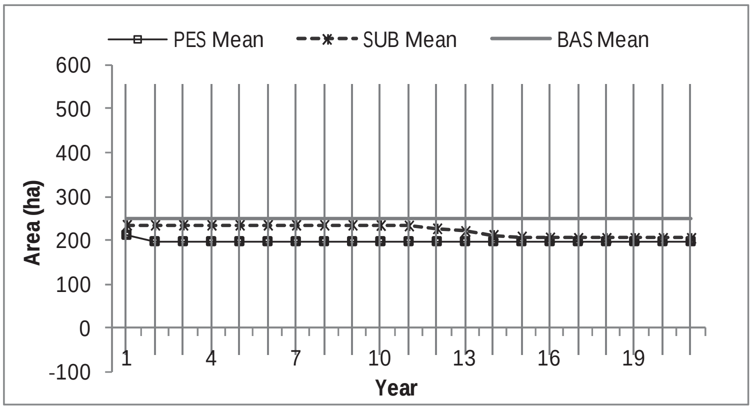

Figure 10.10 Comparison of simulated changes shrubland (ha) under three scenarios. Note: vertical segments are the confidence interval (95%) of the means

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For any errors or inadequacies that may remain in this work, of course, the responsibility is entirely my own.

"Focus on the journey, not the destination. Joy is found not in finishing an activity but in doing it."
(Greg Anderson)