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Biodiversity in rubber agroforests, carbon emissions, and rural livelihoods: An agent-based model of land-use dynamics in lowland Sumatra

Grace B. Villamor [a, b, *], Quang Bao Le [c], Utkur Djanibekov [d], Meine van Noordwijk [b], Paul L.G. Vlek [a]

[a] *Department of Ecology and Natural Resources Management, Center for Development Research (ZEF), University of Bonn, Walter-Flex 3, 53113 Bonn, Germany*

[b] *World Agroforestry Centre (ICRAF), Southeast Asia Regional Office, Jl. CIFOR, Situ Gede, Sindang Barang, Bogor 16115, Indonesia*

[c] *Institute for Environmental Decisions, Swiss Federal Institute of Technology Zurich, Universitaetstrasse 22, 8092 Zurich, Switzerland*

[d] *Institute for Food and Resource Economics, University of Bonn, Meckenheimer Allee 174, 53115 Bonn, Germany*

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A B S T R A C T

Rubber agroforests in the mostly deforested lowlands of Sumatra, Indonesia are threatened by conversion into monoculture rubber or oil palm plantations. We applied an agent-based model to explore the potential effectiveness of a payment for ecosystem services (PES) design through a biodiversity rich rubber eco-certification scheme. We integrated conditionality, where compliance with biodiversity performance indicators is prerequisite for awarding incentives. We compared a PES policy scenario to ‘business-as-usual’ and ‘subsidized land use change’ scenarios to explore potential trade-offs between ecosystem services delivery and rural income. Results indicated that a rubber agroforest eco-certification scheme could reduce carbon emissions and species loss better than alternative scenarios. However, the suggested premiums were too low to compete with income from other land uses. Nevertheless, integrating our understanding of household agent behavior through a spatially explicit and agent-specific assessment of the trade-offs can help refine the design of conservation initiatives such as PES.

1. Introduction

Land-use/cover change (LUCC) is a major driver of global environmental change and is accelerating due to continuous growth of the global population and export-oriented agriculture (DeFries et al., 2010; Lambin and Meyfroidt, 2011). Indonesia has been ranked as having the second highest rate of deforestation among tropical countries after Brazil (Margono et al., 2012) due to the rapid replacement of vast areas of primary lowland forests with monoculture plantations of oil palm, rubber and other crops (Broich et al., 2011; Dewi et al., 2013; van Noordwijk et al., 2012). As a result, Indonesia has been identified as one of the main global contributors of greenhouse gasses stemming from deforestation and forest degradation (IPCC, 2007), suffering associated with biodiversity loss, land degradation, and impairment of ecosystem services, along with resulting negative effects on local livelihoods. A recent land-use intensity analysis in Sumatra found that over time, land dynamics have shifted from an overall pattern of primary forest loss in the 20th century to the loss of agroforests during the 21st century (Villamor et al., 2014). Although lowland rubber agroforests (hereafter ‘rubber agroforests’) support relatively higher biodiversity, greater carbon stocks and local livelihoods, this land use is giving way to monoculture oil palm and rubber plantations (Rudel et al., 2009; van Noordwijk et al., 2012). Since very few primary forests remain in Sumatra, conserving rubber agroforests is one of the few options for supporting biodiversity on the island, and incentives to prevent further land cover conversion are an urgent conservation need (Ekadinata and Vincent, 2011; Feintrenie et al., 2010).

Payments for ecosystem services (PES) schemes are one of the policy options being considered to help sustain rubber agroforests in Sumatra. The PES schemes have been implemented in many countries, particularly in agricultural landscapes, to add ecosystem

* Corresponding author. Department of Ecology and Natural Resources Management, Center for Development Research (ZEF), University of Bonn, Walter-Flex 3, 53113 Bonn, Germany. Tel.: +49 228 734947.

E-mail addresses: gracev@uni-bonn.de (G.B. Villamor), quang.le@env.ethz.ch (Q.B. Le), u.djanibekov@ilr.uni-bonn.de (U. Djanibekov), m.vannoordwijk@cgiar.org (M. van Noordwijk), p.vlek@uni-bonn.de (P.L.G. Vlek).

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services (ES) to the portfolio of production choices in a sustainable way (Pagiola et al., 2004). Through PES, landuse decisions that contribute to greater ES provision can be rewarded with modest incentives, as there are land-use options in the mosaic of remaining natural or secondary forests with existing low-to-intermediate intensity agriculture that provide financial returns in addition to environmental benefits. However, there is no clear understanding of how PES schemes affect the synergies and trade-offs among ES or of the factors that contribute to participation in PES schemes. Four design principles have been identified to determine if a PES scheme is effective and fair: realistic objectives or goals, conditionality of benefits, voluntary participation, and pro-poor outcomes (van Noordwijk et al., 2007). Among these four principles, conditionality (i.e., benefits are conditional on achieving performance measures specified in contracts and understood by all relevant stakeholders) distinguishes PES from other conventional forms of incentives such as taxes and subsidies (van Noordwijk and Leimona, 2010). This PES principle establishes the need for performance indicators that can be measured to determine if the scheme is effective. To better understand the impact of PES schemes, including inherent complexities related to the future of rubber agroforests, we developed an agent-based model (ABM) that simulated land-use dynamics named the Lubuk Beringin-Land Use Dynamics Simulator (LB-LUDAS). We selected this modeling approach because it is primarily used for simulating socio-ecological processes to understand the dynamic interactions between the social and natural systems as well as for policy and institutional analysis of these systems (Kelly et al., 2013). Its main strength is that it incorporates the decision-making process of heterogeneous households (Matthews et al., 2007), while capturing feedback effects and nonlinearities from natural system processes. The main focus of ABM is the discovery of emergent behavior, where large-scale outcomes result from simple interactions of heterogeneous household agents. The agents are typically able to react to (locally) perceived changes in their environment through action on the environment or internal adaptation (Kelly et al., 2013). Because of this, many ABM models have been used to simulate LUCC scenarios taking land-use decisions into account (Bousquet and Le Page, 2004; Le et al., 2010, 2008; Villamor et al., 2011b). Recent similar applications include: simulating the effects of social norms on enrollment in a PES program in China (Chen et al., 2012), simulating land-use decision making of the farm households participating in PES schemes of the Sloping Land Conversion Program in China (Sun and Müller, 2013), and assessing changes in household-level inequity associated with the transition from shifting cultivation practices to rubber plantation adoption in Laos (Evans et al., 2011). Most of these applications have strongly emphasized the land-use decision making of households. Though very important, this aspect of PES is limited with respect to revealing the real impacts of these schemes on the provision of ES.

In this research we simultaneously addressed the integration of household decision making regarding PES participation and competing policies, and the potential ES trade-offs or synergies emanating from those decisions. Also, we explicitly integrated conditionality as an innovative aspect of assessing PES schemes using an ABM to assess the effectiveness of the proposed PES design. By coupling the socio-economic and ecological systems of the rubber agroforest landscape, our objectives were: (1) to test the internal consistency of the model as a basis for exploring policy options that extend beyond historical trends; (2) to explore the policy efficiency of environmental programs that provide economic incentives for achieving environmental goals, specifically in the form of eco-certification and price supports for biodiversity-friendly rubber production; and (3) to quantify trade-offs between local livelihoods and ES delivery (i.e., agro-biodiversity conservation, carbon emission reduction, and crop yields) across plausible levels of external investment. Household land-use choices, behavior, and preferences were determined using a combination of methods and translated into decision rules for the LB-LUDAS model.

2. Study area and data

2.1. Study area

The study area includes three villages, Lubuk Beringin, Laman Panjang, and Buat, in the Jambi Province of Indonesia on the island of Sumatra, and the surrounding area of around 15,000 ha (Fig. 1). The area stretches along the foothills of Kerinci Seblat National Park, which is home to endangered species such as the Sumatran tiger. There are four major land-use/cover types in the study area: forest, rubber agroforest, monoculture rubber, and rice field (Table 1). Rubber agroforest was formerly the dominant land use in Jambi Province (van Noordwijk et al., 2012).

Due to the relatively low latex productivity of rubber agroforests, most of the surrounding area has been converted to more profitable land uses such as monoculture rubber and oil palm plantations. Moreover, initial investments for plantation establishment were made through loans from private sector and state-owned companies provided to farmers through credit cooperatives as a form of agricultural support (i.e., low-cost capital with a maximum value of about US$ 5800). Oil palm concessions were planned and licensed by the provincial government for virtually all secondary forests, often including large tracts of rubber agroforest owned and managed by smallholders (Minister degree No. 720/KPTS-II/1989). This effort has been accompanied by a government settlement program to address labor shortages in the provinces. Jambi is one of provinces targeted by the program, in which a large settler workforce, mostly from Java, is allocated to the labor-intensive rubber and oil palm plantations. The settlers are provided with land share certificates for 2 ha parcels for the establishment of monoculture rubber or oil palm plantations (Vermeulen and Goad, 2006).

A number of studies have described the rich biodiversity and ecosystem functions supported by rubber agroforests (Beukema et al., 2007; Griffith, 2000; Joshi et al., 2003; Rahayu, 2009; Rasnovi, 2006; Schroth et al., 2004; Tata et al., 2007; Tomich et al., 2004, 1998, 2001). To protect the rubber agroforests from conversion to other land uses, conservation agreements were developed under the Rewarding Upland Poor for Environmental Services (RUPES) program of the World Agroforestry Centre (ICRAF). The main purpose of these agreements was to develop and test appropriate schemes for agro-biodiversity conservation for agroforests through an action-research approach. Conservation agreements are the initial step toward institutionalizing payment schemes for agro-biodiversity through eco-certification (Villamor et al., 2011a). Eco-certification efforts target the raw materials from crops produced in biologically diverse transitional systems and verify that producers have used management practices that conserve ecosystem services (Bennett, 2009). In 2009 the Waseda-Bridgestone Initiative of Japan granted financial support to a local NGO, Komunitas Konservasi Indonesia, together with ICRAF for a feasibility study of the eco-certification of rubber in the villages of Lubuk Beringin and Laman Panjang. According to the results of this feasibility study, local agroforest farmers were negotiating for an increase of US$ 1 over the baseline price (a 40% increase) for dry rubber latex (Akiefnawati, personal communication).

2.2. Data

We surveyed 95 households in the study area between February and March 2010 that were randomly selected from a total

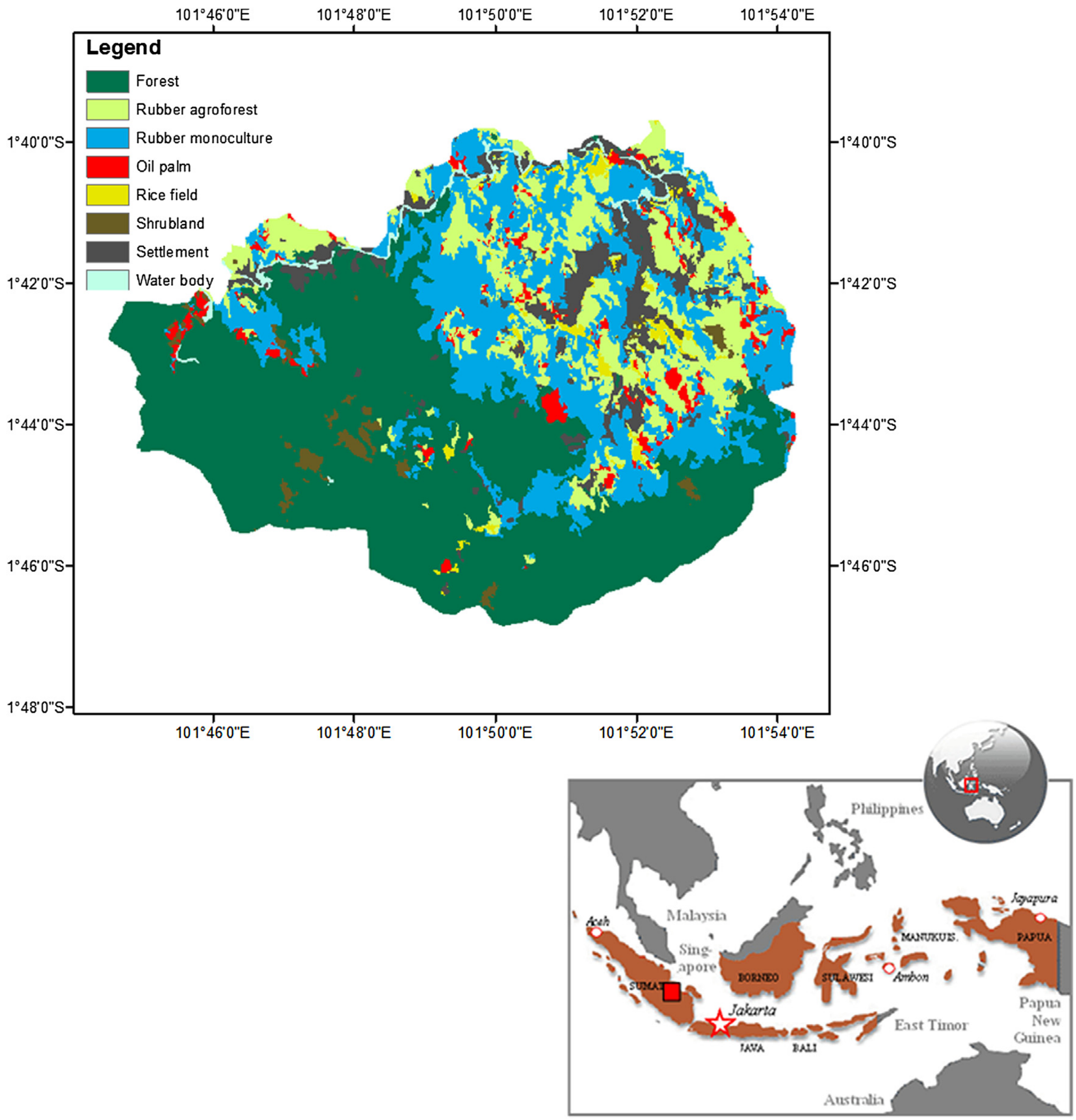

Fig. 1. Map of the study area in the Jambi Province of Indonesia on Sumatra.

Table 1
Dominant land-uses/cover types in the study area.

Land use/cover type
Forest consists of dense canopy cover with variable species composition, structure, age, and history of timber extraction. As of 2002 most remaining forest exists above altitudes of 500 m (asl) and only small forest remnants persist in the lowland peneplains.
Rubber agroforest is dominated by rubber trees along with other tree species and has a structure similar to forest. This is also called 'jungle rubber' because of the presence of native woody species that help protect the rubber trees from weeds (Gouyon et al., 1993). Rubber yields from this cover type range 400–600 kg of dry rubber per ha/yr.
Monoculture rubber refers to intensively managed plantations that consist entirely of rubber trees with other shrub and groundcover species. This cover type includes less intensively managed smallholdings. Rubber yields from this cover type range 1000–1800 kg of dry rubber per ha/yr.
Rice field refers to non-irrigated upland rice production areas.

population of 550 households. The objective of the survey was to elicit data on household characteristics, preferences, and behavior. We used the survey to explore: (1) household profiles and land-use characteristics, and (2) household land-use choices under specific policy scenarios (i.e., PES adoption and willingness if establishment capital or subsidies are provided). We also asked about the justifications behind land-use decisions in order to better understand household motivations and preferences. We applied principal component and cluster analyses to the survey data to characterize the households. Two types of households were identified based on economic status: Type-1 households that were economically 'better-off' and Type-2 households that were 'poor.' The difference between the two household types was due to the variability of income generation from rubber and rice production. Rice income represented a 10% greater share in Type-1 households, while rubber income represented a 10% greater share among Type-2 households.

For each household type, the current and preferred land-use choices were assessed using multinomial logistic regression. We assessed willingness to adopt PES using binary logistic regression

(Villamor, 2012; Villamor et al., 2011a). These land-use choice and willingness to adopt results became the basis of agent decision making for developing three model scenarios; the current or 'business-as-usual' (BAU) scenario, the 'with subsidies' (SUB) scenario, and the 'adopt PES' scenario, which are further described in Sections 3.1.3 and 3.2. Table 2 presents a summary of the choice probabilities under the three scenarios. In addition to the household survey, we employed land-use role playing games (RPG) with the survey respondents to refine the set of decision rules for the ABM (Villamor and van Noordwijk, 2011). The RPG exercise helped reveal close-to-reality behaviors and responses to external actors who are interested in converting the respondents' rubber agroforests (e.g., oil palm and timber companies) and to PES negotiators who are interested in conserving rubber agroforests. Land-use game boards were provided to each village and allowed the players to change land uses according to the outcome of negotiations with external actors. The results of this exercise were also used to validate the ABM results, particularly regarding land-use changes (see Section 2.2).

To make the sample households' farm parcels spatially explicit, plot data were collected through a participatory mapping effort. A parcel map with high resolution and true color images was developed using Google Earth (2003) and geo-referenced with a 700 m eye-view using PCI Geomatica 9.1. A total of 291 parcels managed by the 95 sample households were identified and geo-referenced. The distances from parcels to households, major roads and town centers were derived from this map. A digital elevation map with 30 m resolution was used to derive a wetness index, and aspect and slope values for individual parcels. A validated 2005 land-cover map (30 m resolution) was prepared from Landsat ETM images (Ekadinata and Vincent, 2011). The enrichment factors of different land-uses were also integrated into the model as decision-making variables and processed using Netlogo (Verburg et al., 2004).

3. Methods

3.1. The LB-LUDAS model

The LB-LUDAS model was developed to explore the potential trade offs among ES provided by rubber agroforests. The model framework is based on LUDAS (Le et al., 2008), a multi-agent system model for the spatio-temporal simulation of coupled human–landscape systems. The LB-LUDAS model was described using the ODD (Overview, Design concept, and Details) protocol (Grimm et al., 2006, 2010).

Table 2
Land-use choice probabilities and willingness to adopt PES among Sumatran households, (2010).

Land-use type	Probability (%)			
	BAU (current)	SUB[a]	Adopt PES	
			Yes	No
Type-1 households			81	19
Rubber agroforest	33	87		
Monoculture (rubber or oil palm)	1	13		
Rice field	66	0		
Type-2 households			92	8
Rubber agroforest	99	47		
Monoculture (rubber or oil palm)	1	53		
Rice field	0	0		

[a] Under this scenario land-use choices are supported by financial investments in the next 5–10 years. For the detailed logistic regression results see Villamor (2012).

3.1.1. Overview

3.1.1.1. Purpose. The LUDAS model was primarily designed to consider land-use decisions at forest margins with the following three objectives: (1) to explore the magnitude of possible socio-ecological changes caused by different land-use policy interventions over space and time; (2) to identify the most strongly affected components of the system (what), locations (where), and periods (when) with respect to specific policy interventions; and (3) to highlight policy interventions that are likely to enhance environmental and socio-economic benefits efficiently (Le et al., 2008). Our research had a fourth objective: to explore the potential trade-offs and synergies of policy interventions on the goods and services over space and time.

3.1.1.2. Agents and their state variables and scales. The LB-LUDAS model consists of two types of agents, human and landscape agents, each with several state variables described below.

1) Human agents are representations of individual farm households. The state variables of these agents capture the sustainable livelihood capital of each household. This includes social identity (or identification number), age, group membership, and human resources (i.e., 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 markets and distance to town), and policy access (e.g., participation in a conservation agreement and involvement in related activities). The human agents are also spatially explicit in terms of household location.
2) Landscape agents are congruent land pixels with characteristics 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., distance to nearest road and town center), institutional spatial variables (e.g., parcel owners and zoning restrictions), and household collections of disjointed neighborhood household plots (see *Prediction* in Section 3.1.2).

Each time step represents one year. Each grid cell or pixel represents a 30 m × 30 m area and the model landscape covers 156 km^2. The environmental variables that drive agent behavior in the model are forest protection zoning, market prices, policy interventions (e.g., PES schemes), and neighborhood land-use and livelihood conditions. Similar to the general LUDAS framework, the behavioral strategy of household agents change over time based on annual evaluations of updates in land-use and livelihood structures of the surrounding environment. The parameters determining household behavior were treated as state variables that 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 land-use decisions, and a set of ratios that determine the amount of labor allocated for each aspect of livelihood activities.

3.1.1.3. Process overview and scheduling. The basic LB-LUDAS scenario simulation consisted of 12 main steps (Fig. 2). 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 and landscape agents' actions are synchronized. The LB-LUDAS model was coded using Netlogo version 5.0.5 (Wilensky, 1999).

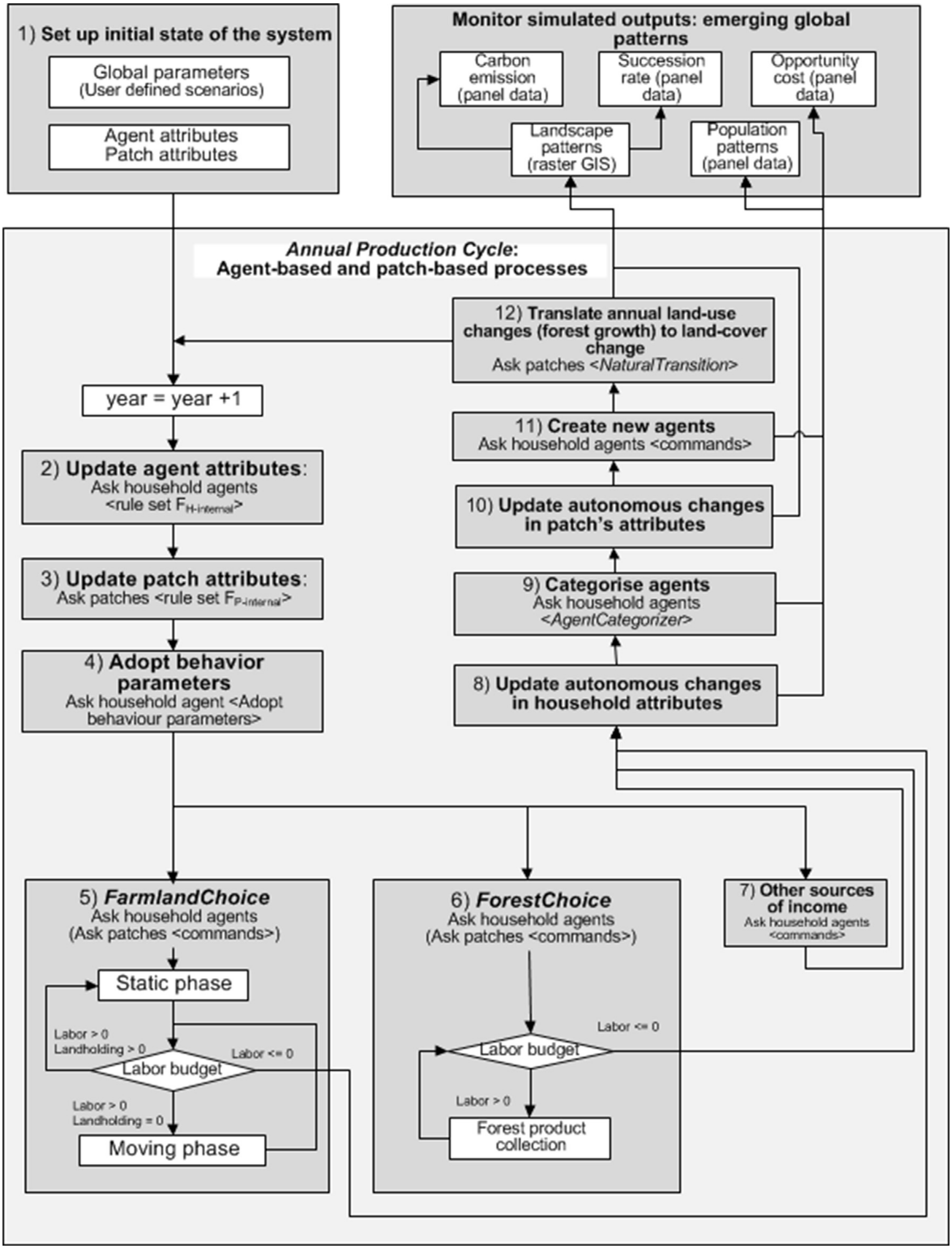

Fig. 2. Flow chart showing main steps of the LB-LUDAS model simulation process (modified from Le et al., 2008), for land use decisions among Sumatran households.

3.1.2. Design concepts

The LB-LUDAS model was designed to address the concepts of heterogeneity, diversity deficits (Villamor et al., 2011b), and the complexity of coupled human–environmental systems in land-use decisions that result in trade-offs. These concepts were taken into account using variables that affect agent decisions and the complex sub-models and processes within agents.

3.1.2.1. Emergence. The LUCC at the landscape level emerge from two micro-processes: (1) land-use change caused by household agents; and (2) natural succession of the vegetation cover. In the LB-LUDAS model the choice of adopting PES (see *Sub-models* Section 3.1.3) is linked with the biodiversity performance (indicator measurement) of a certain land use. This linkage could provide new insights on the potential impacts on the land over space and time.

3.1.2.2. Adaptation/learning. Adaptive traits of each individual agent are explicitly processed, mainly by land-use decisions and changes in behavior (i.e., the preference coefficient of land-use choice function, willingness to adopt policies, and the structure of labor allocation). At first, agents adapt to existing 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 behavioral model may change by imitating the strategy of the household group most similar to it (Le et al., 2010, 2012). In this way, individual agent decision models may change over time and context. Also, a household agent accumulates landscape knowledge by updating past landscape visions (see *Prediction* below) to describe the basic landscape space.

3.1.2.3. Objectives. The model applies a bounded-rational approach for household agent decision making in which household access to information is limited. This approach follows an ordered-choice algorithm (Benenson and Torrens, 2004; Le et al., 2010). In the algorithm, a household calculates the utilities (expressed in probability terms) for all the land uses and locations within its domain and for the policy scenario. The household can choose the option with the highest utility or take risks by selecting other alternatives.

3.1.2.4. Prediction. The LB-LUDAS model has a landscape vision module that stores the spatial information perceived by each household from the landscape, and a program of instructions for generating agent behavior under different circumstances (Le et al., 2008). In this module, household agents recognize spatial information, analyze trade-offs, and optimize spatial land-use choices only within their own parcels.

3.1.2.5. Sensing. In the LB-LUDAS model, household agents are assumed to have perfect knowledge of the landscape characteristics (i.e., through landscape vision) and neighborhood land-use pattern variables (Verburg et al., 2004), which they use for evaluating land-use alternatives.

3.1.2.6. Interaction. Both direct and indirect interactions between agents are assumed in the model. Direct interaction occurs when a household agent transfers information (i.e., state variables) to younger household agents for their own decision-making process, or when two or more household agents find their best land-use alternative in the same location. In this latter situation a random procedure will let the agent(s) leave the location and begin another search. Indirect interaction occurs among household agents when land-use conversion caused by households leads to changes in the decision space of other agents in the following time step.

3.1.2.7. Stochasticity. Stochasticity is incorporated into the LB-LUDAS model through five different processes: (1) initialization of household population; (2) choosing plot locations for the newly created household agents and remaining population generated during 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 that are not affected by agent-based processes (defined by even distribution and pre-defined limits).

3.1.3. Details

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

Step 1: The data of a sample household ($N_s = 95$) are imported, and the user can select the size of the total population ($N_t = 380$, the study area population in 2005). Assuming that the sample (N_s) and the total population (N_t) have the same distributions as the status variables, a household population subset $N_s \times \text{int}(N_t/N_s)$ (i.e., $95 \times 4 = 380$) is generated by multiplying the household sample by the integer component of the ratio N_t/N_s. The generation of the remaining fraction of the total population, $\text{mod}(N_t/N_s)$, is generated by a random selection of households from the sample (N_s). As the $\text{mod}(N_t/N_s)$ component is $\text{mod}(380/95) = 0$, the entire initial household population is a deterministic expansion (four times) of the sampled household set. The 2005 land-cover map is the initial landscape of the model imported as GIS-raster files of landscape variables that are either from secondary data or produced from spatial analyses.

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

3.1.3.2. Sub-models. In the original LUDAS model there are 13 key sub-models and calculation routines (Le et al., 2008). For the LB-LUDAS model we incorporated the following five additional sub-models and calculation routines:

1) The *PES-adoption* sub-model stochastically calculates the probability of whether the household agents adopt the PES scheme or not based on their preference coefficients and the initial conditions at each time step. The preference coefficients were derived from binary logistic regression (Villamor et al., 2011a). This sub-model is integrated into the agent's decision-making process based on two rules: (1) if the household decides to adopt the PES scheme, then do rubber agroforest, and (2) otherwise look for another land-use for current landholdings (Fig. 3a). This sub-model is linked to the *Calculate-species-richness* sub-model, creating an interaction between socio-economic state variables and the bio-physical processes in the systems.

2) The *Calculate-species-richness* sub-model deterministically calculates the estimated species richness in each land-use type (e.g., rubber agroforests). The estimated species richness of rubber agroforest serves as a biodiversity performance indicator measurement for the eco-certification scheme (see Section 3.2). Species richness is estimated using the power function of the species-area relationship (SAR) (Preston, 1960; Rosenzweig, 1995):

$$S = kA \exp z \tag{1}$$

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

Eq. (1) has been used to measure the consequences of changing land use on biodiversity by van Noordwijk (2002), Perreira and Daily (2006), Nelson et al. (2009), and Brady et al. (2012). In this study, we parameterized the SAR for each vegetation class at different successional stages: pioneer (0–5 years), young secondary (5–20 years), late secondary (20–50 years), and forest (>50 years). For each vegetation class, we first depicted the experimental/observed species-area curves using EstimateS software (Colwell, 2009) and plot-based survey data. Then we estimated the k and z parameters in Eq. (1) by fitting a log-linear regression ($\ln S = \ln k + z \ln A$). The results are presented in Table 3. The vegetation class (pioneer, young secondary, late secondary, or forest) is determined by the plot age and the ecological distance from the forest from the *Natural-transition sub-model* (Le et al., 2008).

Once the initial species richness is estimated, the updated species richness over time in response to land-use change is estimated by applying the Tilman and Lehman (1997) equation for species loss, which is formally expressed as:

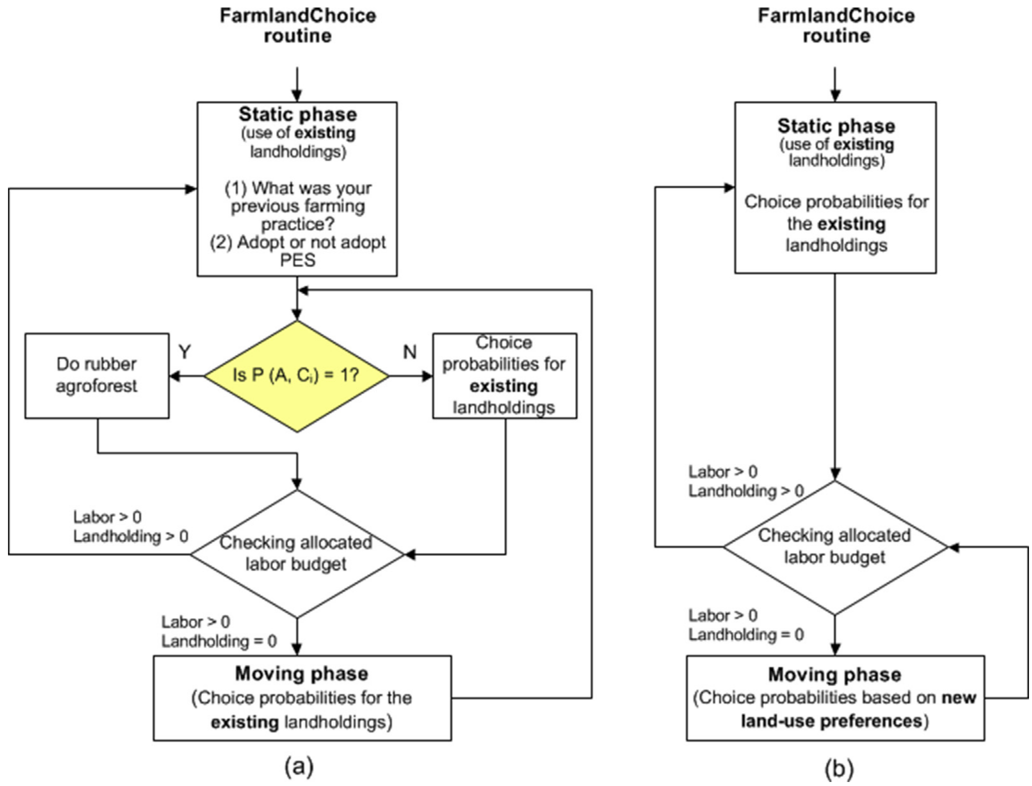

Fig. 3. Flow chart of agent decision-making processes under the (a) adopt PES and (b) with subsidy support scenarios of the LB-LUDAS.

$$S_D = k[(1 - D)A_v]\exp z \tag{5}$$

where S_D is the number of species remaining after the land-use change, D is the proportion of the habitat area destroyed, and A_v is the area of the original habitat. For the k and z parameters, we used the values from Eq. (2). The D variable is sensitive to land-use conversion by household agents.

3) The *Calculate-carbon-stocks* sub-model deterministically calculates the carbon stocks of each land-use type by assigning a time averaged carbon density. The output is used to estimate the possible carbon emissions from land-use changes under different scenarios. In estimating the carbon-stock dynamics, we followed the Intergovernmental Panel on Climate Change (IPCC) approach to measure the emissions from LUCC using stock differences (IPCC, 2006). Accordingly, the carbon stock changes were measured at two points in time using two factors: activity data and an emission factor. The activity data are expressed in terms of the area of land use or land-use change, while the emission factor is the annual carbon-stock difference between two types of land-use systems per unit area (IPCC, 2006). To determine the net carbon release (emissions) or net carbon sequestration (stocks) in the study area, the activity data (which are derived from the simulated land-cover changes) are multiplied by the changes in time-averaged carbon stocks (Mg/ha) with each pairwise land-use type.
4) The *Preferred-land-use* sub-model is integrated into a decision-making routine called the *FarmlandChoice* module (Le et al., 2008). This sub-model calculates the probability that the household agents choose their preferred land use under the condition of 'if supported by financial investment or subsidies' with a time element of five to ten years. These preference coefficients were derived from multi-logistic regression and integrated in the moving phase (when the agent is ready to convert to a new land use) as shown in Fig. 3b.
5) The *Financial-return* sub-model estimates the annual financial return to household agents from different land uses. The yields generated from the *crop-production* sub-model (i.e., for rubber and rice) are captured by this sub-model (Table 4), where all crop production costs (e.g., labor and agro-chemical inputs) are deducted from annual revenues. At the end of the simulation, the results are used to estimate the net present value (NPV) of the different land uses, which serves as an indicator for the livelihood options of the household agents in each scenario.

Table 3
Species richness estimator equations of the LB-LUDAS.

Vegetation class	Equation	
Young secondary (5–20 years)	$S_e = 1.60A^{0.440}$	(2)
Late secondary (20–50 years)	$S_e = 5.84A^{0.202}$	(3)
Forest (>50years)	$S_e = 1.66A^{0.424}$	(4)

Note: Data for the pioneer class was not available.

To investigate the financial returns of land-uses (e.g., monoculture rubber, rubber agroforest, and rice field), we calculated their NPV:

$$NPV^L = \sum_{t=0}^{T} \frac{P_t^L Y_t^L - C_t^L t}{(1+r)^t} \tag{6}$$

where superscript L stands for land-use activity; P_t is the farm-gate price per unit of harvested product; Y_t is the harvested yield of rice and rubber (kg/ha); C_t^L is the labor and input costs of the land use activity (US$/ha); t is the length of the simulation period in years (0, 1, 2, … t), with t being equal to 20 years; and r is the real interest rate of 20% (Wibawa et al., 2005). Rice was valued at US$ 1/kg and dry rubber was US$ 2.5/kg. The variable costs of each crop were derived from Wulan et al. (2008) and labor costs were set at US$ 2/day. We assumed that farmers practice conventional land uses, thus there are no costs for rice cultivation in $t = 0$. For presentation consistence of NPV of rice and perennial crops, the discounted cost and revenue values of perennial crops during the establishment period (i.e., $t = 0$) and first year (i.e., $t = 1$) were summed up and presented as in first year. We also assumed that an additional US$ 70/ha/yr is generated beginning at year eight from intercropping fruit trees within rubber agroforests, which is a practice observed during the field survey.

Table 4 presents a summary of the key parameters and data sources for the other sub-models of LB-LUDAS including appropriate evaluation tests (Bennett et al., 2013). A total of six simulation runs were performed to compute the average and the standard error values of each indicator.

3.2. Scenarios

To investigate the trade-offs associated with rubber agroforests, three main scenarios were developed and their parameters are summarized in Table 5. The scenarios are primarily based on household land-use decision making under different policy contexts. A forest protection zoning is set at 70% under all scenarios, suggesting that 30% of the forest near the household agent can be utilized for household consumption.

1) Business-as-usual (BAU) scenario—under this scenario, agents operate on the premise that there is no policy intervention involved. We observed agent land-use choices for their initial landholdings and simulated continuously until year 20 using the current land-use choice probabilities (Table 2) integrated into agent decision making as biophysical conditions change dynamically and populations increase.
2) Subsidies (SUB) scenario—this scenario operates on the premise that agents are offered initial financial support. Using the current land-use practices (i.e., by running the current land-use choices), the agent assesses if there is enough labor. If sufficient labor is available the *Preferred-land-use* sub-model (see *Sub-models*) will be run to convert land to a new land-use type (Fig. 3b). For the biophysical context, cloned-rubber seedlings are used if the land-use choice is monoculture rubber.
3) PES scenario—in this scenario agents operate on the premise that a conditional eco-certification scheme is offered. First, the

Table 4
Sub-models and parameters in the LB-LUDAS.

Sub-model	Brief description	Explanatory variable		Parameter	
		Variable	Initial value	Parameter	Default value
Calculate-species-richness	A function calculates species richness using the power function of the species-area relationship (Preston, 1960; Rosenzweig, 1995)	Area of a continuous parcel of a vegetation cover type (m^2)	900 m^2 of rubber agroforest extracted from ICRAF land-cover data 2005	Coefficient k: Young secondary, Late secondary, and Forest Coefficient z: Young secondary, Late secondary, and Forest	 1.60[a] 5.84[a] 1.66[a] 0.440[a] 0.202[a] 0.424[a]
Forest-growth-response	A function predicts the basal area of rubber agroforests (Le et al., 2008; Villamor, 2012)	Previous basal area (m^2/ha)	Data from Rahayu (2009) and Rasnovi (2006)	Rubber agroforest basal area at the equilibrium state (m^2/ha)	41[b]
Yield-mono-rubber	Yield of mono-culture rubber plantation (dry kg/ha/yr)	–	–	Steady average yield (dry kg/ha/yr)	1800[c]
Yield-rice	Extended Cobb–Douglas yield function of rice field (dry kg/ha/yr) (Villamor, 2012)	Labor input (days/ha/yr) Agro-chemical input (g/ha/yr) Wetness index Farm plot area (m^2)	Field survey (2012) Field survey (2012) Topographic-driven (GIS) Field survey (2012)	Elastic coefficient Elastic coefficient Elastic coefficient Elastic coefficient	1.063[d] 0.093[d] −0.031[d] 0.201[d]
Yield-rubber-agroforest	Extended Cobb–Douglas yield function of rubber agroforest (dry kg/ha/yr) (Villamor, 2012)	Labor input (days/ha/yr) Wetness index Number of mature rubber trees Number of seedlings planted	Field survey (2012) Topographic-driven (GIS) Field survey (2012) Field survey (2012)	Elastic coefficient Elastic coefficient Elastic coefficient Elastic coefficient	0.954[d] −0.750[d] 0.368[d] −0.096[d]
Calculate-carbon-stocks	A look-up procedure calculates carbon stock (Mg) for each patch based on the average carbon density of each land cover type	Land use/cover	ICRAF land-cover data 2006	Average carbon density (Mg/ha) of: Rubber agroforest Monoculture rubber Oil palm Rice field	 62[e] 46[e] 31[e] 1[e]
Preferred-land-use	Multi-nominal logistic functions calculate the probability that the household agents choose their preferred land use under particular circumstances	Characteristics of household agent (e.g., age, educational status, income); natural land attributes (e.g., wetness index, slope); neighborhood characteristics of land use (e.g., enrichment factor of land-use types)	Field survey 2012	List of preference coefficients of the explanatory variables	Villamor (2012)
PES-adoption	Binary logistic function calculates the probability of whether the household agents adopt PES schemes or not based on particular circumstances.	Characteristics of household agent (e.g., age, educational status, income, etc.); access to conservation policies	Field survey 2012	List of preference coefficients of the explanatory variables	Villamor (2012)

[a] Estimated using regression of species data from Rahayu (2009).
[b] Data from Rahayu (2009) and Rasnovi (2006).
[c] ICRAF data (2009–2010).
[d] Estimated by log-linear regression analysis of 2012 field survey data.
[e] Tomich et al. (1998, 2004).

Table 5
Scenarios and assumed parameters in the LB-LUDAS.

Parameter	Scenario		
	Business-as-usual (BAU)	SUB (with subsidies)	PES (eco-certification)
Decision-making on farm choice routine	Current land-use choice routine	Current land-use choice routine and preferred future land use	Current land-use choices routine and PES adoption
Rubber price (per kg of dry rubber)[c]	US$ 2.5	US$ 2.5	1) US$ 0.50, or 2) US$ 1 *if compliant with the biodiversity performance indicators*
Rubber trees	From existing trees	Cloned rubber seedling	From existing trees
Initial households	1500 individuals or 380 households	1500 individuals or 380 households	1500 individuals or 380 households
Forest protection zoning restriction[a]	70%	70%	70%
Population annual growth rate	1.14%[b]	1.14%[b]	1.14%[b]

[a] Based on the Ministry of Forestry No. P.49/Menhut-II/2008 of August 25, 2008.
[b] Statistical Record 2003.
[c] Rubber price was derived Leimona and Joshi (2010) and the 2010 list of rubber prices for the area.

agent assesses the initial land-use. Then, agents assess whether to adopt PES or not through the *PES-adoption* sub-model (see *Sub-models*). If an agent adopts PES, the following biodiversity performance indicators are measured to determine whether the agent is in compliance (Tata et al., 2007). These performance indicator measures are generated by two sub-models (e.g., *Calculate-species-richness* (see Sub-models), and *Forest-Growth-Response*) (Le et al., 2008):

- at least four different trees species (>10 cm diameter at breast height or DBH) within a circle with an 8 m radius around a random starting point within the parcel (with an average of five observations per parcel);
- if the number of species is less than six, the relative basal area of the rubber trees is determined, with 2/3 as a threshold; and
- at least one tree with a DBH >40 cm within a 25 m radius (based on an average of five observations).

A price premium is awarded to agents that meet all of these conditions. If one of these measures is not met, agents do not qualify for the price premium. Two PES sub-scenarios were used according to the prices:

a) An increase of US$ 0.50/kg of dry rubber produced; and
b) An increase of US$ 1/kg of dry rubber produced.

As the objective of the paper is on exploring efficiency of environmental programs and the resulting trade-offs from them, and not on the identification of PES values the sensitivity analysis with different PES values were not conducted (for model output with different PES values see Villamor et al. (2013a)).

3.3. Validation

We applied two validation techniques for the LB-LUDAS model: (1) the indirect calibration (IC) technique (Windrum et al., 2007) and (2) social validation using the land-use RPG results (Villamor and van Noordwijk, 2011). The IC technique focused on the parameters (i.e., specific to agent decision model) drawn from stylized facts and empirical datasets using the following steps:

Step 1: Identify a set of stylized facts that the modeler is interested in reproducing;
Step 2: Develop a model based on the empirical evidence regarding the agents and rules;
Step 3: Use the empirical evidence regarding stylized facts to restrict the space of parameters and test the statistical regularities; and
Step 4: Identify the causal mechanisms that underlie the stylized facts.

Following these steps, the stylized facts (i.e., current land-use choice probabilities) derived from the empirical data (step 1 from Table 2) constituted the current land-use choice sub-models. In this stage we applied steps for characterizing and evaluating model performance (Bennett et al., 2013). The (current) land-use choice, mathematically stated in a multinomial logistic form, is integrated in both the static and moving phases of the *FarmlandChoice* routine (Le et al., 2008) (step 2 from Table 2). To simulate the SUB and PES scenarios, we used the stylized facts associated with land-use choice under the conditions 'if supported by financial investments or subsidies in the next 5–10 years' and 'willingness to adopt PES,' respectively (step 3 from Table 2). In this way causal mechanisms (i.e., time element and decision-making process for PES adoption) are embedded explicitly. We therefore reconstructed new decision algorithms that incorporate other stylized facts (see Table 2 and Fig. 3). Hence, if the *FarmlandChoice* model is simulated independently, we can expect that each household type would behave differently. For example, under the scenario of the current land-use choices, 99% of the Type-2 households may choose rubber agroforest. If offered financial subsidies in the future, the probability that Type-2 households will choose rubber agroforest decreases by 50%.

The second approach is a form of social validation, where real-life farmers (who were also the survey respondents) participated in a land-use RPG exercise (Villamor and van Noordwijk, 2011) with settings and roles matching the LB-LUDAS model. The RPG exercise was conducted to deepen our understanding of the system properties and dynamics that had not been communicated through interviews and surveys, and to validate the ABM (Castella et al., 2005; Guyot and Honiden, 2006). Three land-use game boards were used to represent each of the target villages and allowed players to make direct changes to land-use/cover according to their negotiations with actors promoting either conversion or conservation of rubber agroforests. The validation process is two-fold: (1) the decision rules of the LB-LUDAS model were refined according to the observed behavior of the RPG exercise participants, and (2) the simulated land-use change pattern generated from the LB-LUDAS model was validated using the land-use change pattern generated from the RPG (see Section 5.4).

4. Results

We compared the simulation results of the three scenarios according to: (1) land-use change, (2) key ES indicators (e.g., species

Table 6
Simulated results in the three LB-LUDAS model scenarios based on key indicators.

Indicators	Scenarios			
	BAU	SUB	PES (a)	PES (b)
Biodiversity				
a) Species richness	75%	86%	95%	96%
b) Species loss	25%	14%	5%	4%
Carbon emissions (Mg/ha/yr)	0.5	0.33	0.2	0.1
Agronomic yield				
a) Rice field (kg/ha/yr)	426 ± 69	398 ± 81	224 ± 33	227 ± 32
b) Rubber agroforest (kg/ha/yr)	224 ± 37	378 ± 81	314 ± 69	320 ± 51
c) Monoculture rubber (kg/ha/yr)	640 ± 220	1120 ± 104	763 ± 20	791 ± 30
PES-adopters	0	0	16%	32%

Note: PES (a) with increase of US$ 0.50; PES (b) with increase of US$ 1.

richness, carbon emissions, and crop production), and (3) PES adoption and impact on land value. Table 6 presents an overall summary of the observed key ES indicators.

4.1. Land-use change trends

The main trends observed in the simulations for the three main land-use types are summarized in Fig. 4. For monoculture rubber there was an increasing trend under the BAU and SUB scenarios, and decreasing trend under the PES scenarios. For rice field there was an increasing trend under the PES and SUB scenarios, particularly after year 20. Under the BAU scenario rice field area increased after year 10, but then declined to the initial area after year 20. For rubber agroforest there was an increasing trend until year 10 under both the BAU and SUB scenarios, but this trend reversed after year 10. This reduction may be due to low rubber yields for this cover type (Table 6). Agents subsequently converted to monoculture rubber or rice field, especially under the SUB scenario. Another reason might be that simulated new households (which are explorative) preferred monoculture rubber since age is one of the factors affecting the land-use choice (Table 4). Under the PES scenario with a US$ 0.50 per unit increase, there was a decreasing trend in rubber agroforest area after year 10, whereas under the PES scenario with a US$ 1 per unit increase the trend was decreasing until year 10, and maintained thereafter.

Under the BAU scenario rubber agroforest had the largest area during the initial year followed by rice, which matches the land choice probabilities in Table 2, particularly the baseline scenario. Likewise, during the initial year under the SUB scenario both rubber agroforest and monoculture rubber area increased as predicted in Table 2. Land choice probabilities under the PES scenario were not possible to determine since decision making is also dependent on the current land-use and other factors such as access to conservation interventions (Table 4).

4.2. ES indicators

Our model results found that under the PES scenario, 9% more tree species could be conserved in rubber agroforests relative to the SUB scenario and 20% more than the BAU scenario (Table 6). Species loss could be attributed to the reduction of rubber agroforest area under the BAU and SUB scenarios (Fig. 4(1) and (2)). Comparing the SUB and BAU scenarios, around 11% more of local tree species could be maintained under SUB scenario. Meanwhile, there was an increase in species richness from the slight increase of rubber agroforests under the PES scenarios.

In terms of carbon emissions from projected land-use changes, the lowest annual emissions of about 0.1 Mg/ha/yr were observed under the PES scenario, particularly with a US$1 per unit increase (Table 6). This is due to the slight decrease in rubber agroforest compared to the BAU and SUB scenarios (Fig. 4(3)). Carbon emissions were highest under the BAU scenario.

With regard to crop yields, the average simulated yields for the three major crops are summarized in Table 6. The average rice yield under the BAU scenario (426 kg/ha) is substantially higher than under the PES (224 and 227 kg/ha) and SUB (349 kg/ha) scenarios. These rice yields are of rain-fed upland rice production in the area, which is only for household consumption. For yields from rubber agroforests, the highest average yield was under the SUB scenario (378 kg dry rubber/ha), while the lowest was under the BAU scenario (224 kg dry rubber/ha). The average yield from monoculture rubber plantations under the SUB scenario was highest (1120 kg dry rubber/ha), compared to the PES and BAU scenarios. This is likely attributable to the use of commercial variety cloned seedlings in

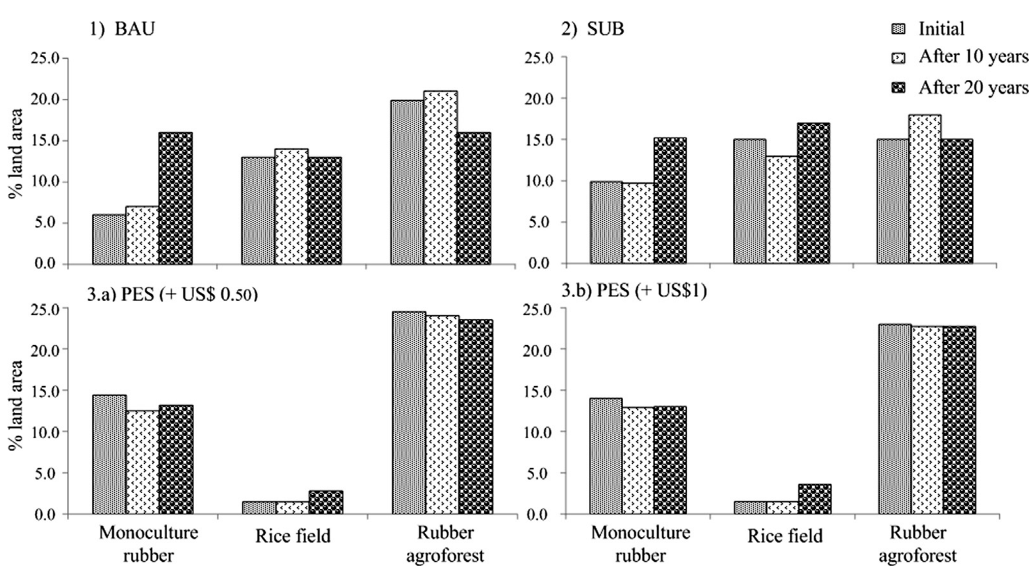

Fig. 4. Simulated trends of key land-use changes among the LB-LUDAS Sumatran land-use dynamics model results.

monoculture rubber that have higher productivity than the rubber varieties in rubber agroforests. The average yields from monoculture rubber under the PES scenarios were over 100 kg greater than under the BAU scenario.

4.3. PES adoption and impact on land value

Under the PES scenario the estimated mean portion of households that adopted the PES scheme was between 16% and 30% of the total simulated population (Table 6). This suggests that the adoption of PES depends on the price premium amount. The US$0.50 per unit or 20% increase to the base price was less attractive. This may be why rice field area increased (Fig. 4). Some research efforts in the same study area have found that when the price of rubber is low, farmers shifted to rice cultivation and harvesting non-timber forest products from rubber agroforest (e.g., durian, petai) (van Noordwijk et al., 2012).

Based on the different agent land-use decision-making processes, the potential impacts on the average returns on land investments for each scenario are summarized in Table 7. Most investments in monoculture rubber were required during the first five years, whereas for rubber agroforest they were required during the first eight years. Afterwards, both of these land-use types started generating revenue for the households. Under the BAU scenario the highest discounted net return was estimated for rice field (US$ 1441/ha) and the lowest was estimated for rubber agroforest (US$ 190/ha). Under the SUB scenario the highest discounted net return was estimated for monoculture rubber (US$ 4050/ha) and the lowest was for rubber agroforest (US$ 289/ha). For rubber agroforest the highest discounted net return was under the PES scenario with a US$ 1 increase (US$ 477/ha). This suggests that the price premium of US$ 1 per unit or 40% price increase will not surpass the net return from monoculture rubber. This may explain the slight change in monoculture rubber observed under the PES scenarios as shown in Fig. 4, where farmers maintained monoculture rubber. Rice field area increased under both BAU and SUB scenarios because the net return from rubber agroforest was very low as supported by the mean production yields presented in Table 6.

5. Discussion

5.1. Multi-dimensional effects of PES

Attempts to decelerate the rate of land conversion in Indonesia through PES schemes are a big step, however, further assessment of the dimensional effects would contribute to the policy efficiency of the environmental program. By linking the financial returns from the major land-use types to ecosystem services provision and biodiversity, we could assess the trade-offs. Over a 20-year period the financial returns from rubber agroforest under the PES scenario were more competitive than under the BAU and SUB scenarios. In terms of carbon emission reduction and species richness, the PES scenarios performed very well relative to the other scenarios.

Our model results explicitly depict the multi-faceted nature of PES schemes with respect to agro-biodiversity conservation, carbon emission reduction, and opportunity costs based on local practices (or livelihoods). Through the eco-certification scheme the opportunity cost of rubber agroforest becomes competitive with the other scenarios. Nonetheless, the financial returns from rubber agroforest under the PES schemes could not compete with other land uses such as monoculture rubber. Based on the simulation results, the price premiums were insufficient to match those land uses. Thus, a low PES adoption proportion (32%) resulted along with continuously decreasing rubber agroforest area (Fig. 4).

While various ecosystem services are not completely defined or understood due to the limitations of current scientific knowledge, PES schemes are usually implemented without previously establishing the causal relationships between land uses and ecosystem enhancement (Muñoz-Piña et al., 2008). Nevertheless, the long-term viability of PES schemes may depend on techniques that estimate ES performance from observable ecosystem properties (Jack et al., 2008). Establishing the biodiversity performance criteria (see Section 2.2) could ensure that biodiversity changes are evaluated

Table 7
Discounted net returns over 20 years under the BAU, SUB and PES scenarios for rubber monoculture, rubber agroforests, and rice field land-uses (US$/ha) of the LB-LUDAS model.

Years	Rice (US$/ha)				Monoculture rubber (US$/ha)				Rubber agroforest (US$/ha)			
	BAU	SUB	PES		BAU	SUB	PES		BAU	SUB	PES	
			a	b			a	b			a	b
1	115	5	19	−18	−764	−764	−764	−764	−316	−316	−316	−316
2	181	157	17	36	−241	−241	−241	−241	−100	−100	−100	−100
3	114	68	54	66	−167	−167	−167	−167	−69	−69	−69	−69
4	150	103	29	58	−116	−116	−116	−116	−48	−48	−48	−48
5	132	103	44	42	−81	−81	−81	−81	−33	−33	−33	−33
6	149	94	62	34	521	826	575	563	−23	−23	−23	−23
7	96	52	32	40	299	749	474	493	−16	−16	−16	−16
8	91	67	36	43	346	660	401	421	−11	−11	−11	−11
9	87	64	40	40	234	638	370	333	75	210	126	153
10	62	63	37	20	333	544	298	291	51	84	153	135
11	48	45	24	24	245	447	242	240	59	106	150	237
12	44	51	20	21	99	330	209	197	50	111	113	150
13	36	31	21	21	180	257	182	169	29	83	79	92
14	37	28	18	18	63	252	146	138	36	85	77	78
15	22	27	12	10	141	161	132	114	28	38	79	52
16	17	17	8	10	46	162	107	102	23	43	46	49
17	19	18	12	8	112	120	83	83	20	56	50	56
18	11	10	8	8	35	114	78	69	23	41	33	39
19	14	13	7	8	64	86	62	59	14	25	29	26
20	15	8	5	7	35	77	49	49	19	23	21	27
Total	1441	1026	504	497	1382	4052	2039	1951	−190	289	339	477

Note: PES (a) with increase of US$ 0.50; PES (b) with increase of US$ 1.

meaningfully. In our model, the indicators are based on species richness and basal area (calibrated using plot-based and age-specific inventories) of existing rubber agroforest in the study area (as simple proxies). These 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 a price premium.

Furthermore, engagement with the households could link on-the-ground practices with the quantification and valuation of ES, thus reducing uncertainty related to individual land-management decisions (Villamor and van Noordwijk, 2011). The results also suggest that the conditional eco-certification scheme, based on the proposed design (i.e., biodiversity performance targets) is appropriate for the rubber agroforest landscape context. However, the market for eco-certified rubber latex is still immature and eco-certification for rubber latex needs to be recognized and promoted by the certification bodies (Bennett, 2009).

5.2. Social–ecological interactions and adaptation

One of the main challenges to the assessment of ES trade-offs lies in the complexity of ecosystem dynamics where human and natural processes are coupled (Cumming, 2011). In our model, we show that socio-economic factors influencing the land-use preferences and agent behavioral schema interact in the ecological system and would later affect the environmental dynamics in a collateral way (Scholz, 2011). Though there are few models that explicitly show feedback loops operating in socio-ecological systems (Le et al., 2012), in the context of the PES scheme we could clearly differentiate the primary and secondary feedback loops operating in the simulation model (Fig. 5). In socio-ecological systems primary feedback loops involve human agent activities in response to environmental conditions, with a retroactive effect on agent decisions in a regular short-term manner. This form of feedback updates the decision variables, but does not alter the agent decision schema. The secondary feedback loops are defined by human-driven cumulative changes in the socio-ecological conditions on greater spatial and temporal scales (unintentionally or intentionally), leading to the reframing of the agent behavioral schema, which often occurs over a delayed term (e.g., some operate over decades). This refers to profound co-adaptations in socio-ecological systems (Le et al., 2012; Liu, 2007; Scholz, 2011).

In our simulations, the primary feedback loops are direct actions made by household agents to their landscape (i.e., harvesting rubber latex or rice) and the annually updated environmental impacts (inner cycle between actors/agents and land-use/cover change, represented by the dark gray arrow in Fig. 5). There are two secondary feedback loop pathways. The first pathway, which our model inherited from the mechanism encoded in the existing LUDAS framework, captures the cumulative effects of annual human-induced socio-ecological changes on household decision-making mechanisms. This long-term rebound effect is likely inherent to the framework (Le et al., 2012). The second pathway is formed by the PES and conditional ES reward (B2 demonstrating the inner cycle in Fig. 5). Under the PES scenario, an additional sub-model was added to the *FarmlandChoice* routine, in which agents will decide whether to adopt PES or not (Fig. 3a). In the simulation, not all of those agents adopted PES initially, with some agents requiring a few more years to adopt. PES participants maintained rubber agroforests, which in turn affected the perception of neighboring agents through the neighboring effect brought about by the increasing local enrichment factor of rubber agroforest (Verburg et al., 2004).

Given the introduced PES policy, household agents tended to maintain rubber agroforest in order to receive higher payments, resulting in profits or improvement of their socio-economic status (Fig. 5), while also enhancing biodiversity and carbon sequestration. This policy-induced secondary feedback loop should provide the basis to proactively regulate the long-term adaptive management of agroforest landscapes with the objective of mitigating climate change.

In the light of environmental literacy, this policy-induced secondary feedback loop could relate to a secondary feedback loop, which involves learning: "*One is called secondary feedback loop learning: changing the internal model because of an awareness of the changing feedback characteristic of the environment … A special case of learning is when the change of the environment at time* $t_0 + T$ *is caused by human system at time* t *…*" (Scholz, 2011, p. 434). In the case of the PES scenario, households did not cut down forest or establish new farming areas. A contributing factor to the conservation of rubber agroforest in the area is the local labor shortage (Gouyon et al., 1993). Adding incentives to existing land uses for the benefit of biodiversity conservation and carbon sequestration would require a shift in household perceptions and goals, which involves learning and greater conservation awareness.

When using a modeling framework like ABM to better understand dynamic socio-ecological systems, the observed land-use change trends simulated may not reflect the observed land-use choice probabilities (as generated by household survey). The reason behind this is that multitude of the social and ecological variables or factors and processes affecting and interacting on the landscape scale. For others this may be a surprise, but this is a characteristic of socio-ecological system interactions—the

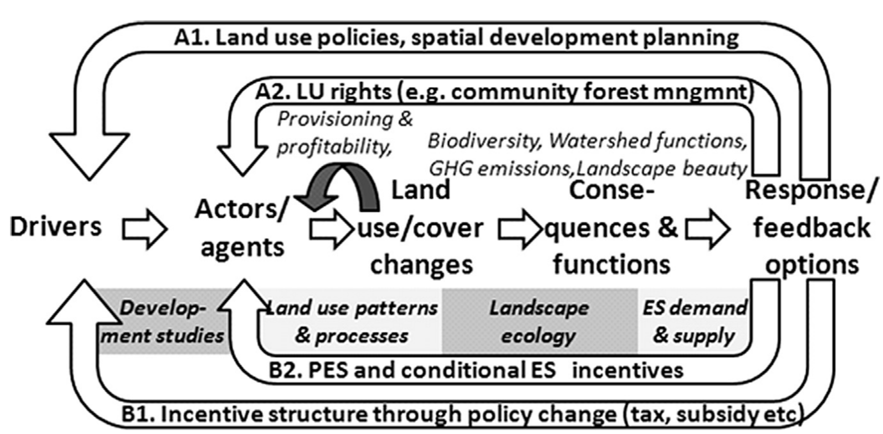

Fig. 5. The primary feedback loop is described by the inner cycle between the actors/agents and land-use/cover changes (dark arrow) and the outer secondary feedback loop through the PES and conditional ES incentives (B2) (modified from van Noordwijk et al., 2011).

emergent property or phenomenon (Section 3.1.2). Emergence is not the sum of the many factors and processes affecting the system, but rather it is a product of the interactions. As a consequence, it is hard to track the process in detail. Thus in this study the use of other tools such as participatory mapping and RPG were essential to justify and support the emergent property resulting from the simulation. A similar observation was made by Washington-Ottombre et al. (2010) when using both RPG and ABM.

5.3. Policy implications and model application

Based on the above observation, PES could contribute to sustainable development policy design before markets appear or are created that place value on environmental considerations (Stenger et al., 2009). The social welfare value of policy intervention is reduced if households fail to adopt practices that generate greater benefits than costs. PES could be evaluated based on the type of payments provided by the schemes (Engel et al., 2008). In the simulation a price premium was assigned to PES adopters that met the biodiversity criteria. However, the level of adoption was low. There are three possible reasons for the observed low adoption levels: (1) the yields from rubber agroforest are already low, (2) the income generated by the price premiums was lower than the other land uses, and (3) the proposed biodiversity performance indicators are hard to meet. The first two of these reasons are addressed in this paper, that due to low yields from rubber agroforest eco-certification schemes for conserving rubber agroforest be evaluated. To address the third reason there is a need to establish biodiversity performance indicators that are both meaningful and that are understood and achievable by participating communities. According to Jack et al. (2008), the overall viability of PES schemes is determined by the preferences of all relevant stakeholders. Thus, proposals for scaling up PES schemes should consider the factors affecting the decision to adopt or participate in PES schemes (e.g., price premium). With the current interest in Reducing Emissions from Deforestation and Degradation plus (REDD+) schemes to achieve emission reduction along with biodiversity conservation (Minang and van Noordwijk, 2012) and high carbon-stock development pathways (Minang et al., 2012), the predicted effectiveness of an eco-certification scheme for biodiversity-friendly rubber production is noteworthy.

Comparing the simulated yields to those in the literature, the rice yield was far below commonly reported yields, however, most available literature describes irrigated rice production. In our model rice production was parameterized based on the native (rain-fed) rice cultivar in the area, which is typically cultivated with only limited or without agro-chemical inputs. For rubber production the simulated yields are in conformity with those reported in the literature (Gouyon et al., 1993). In terms of yields from monoculture rubber, there are literature examples with better productivity and profitability under ideal conditions, however, in reality production often fails to achieve predicted yields due to the inability to achieve ideal field conditions, which can also be captured in the model simulation.

We applied a multi-agent simulation model (LB-LUDAS) to answer the question "*How would land-use change based on household preferences, behaviors, and land-use decisions and what would be the subsequent impacts on the provision of ecosystem services?*" However, we only partially addressed this question due to limitations of the study such as: (1) estimation of species richness was limited to the rubber agroforest land-use type to reduce the run time of the simulation; and (2) because of the slow simulation run we had to limit some functions such as connectivity and species richness calculations for other land-use types.

Integrating the human-agent preferences and land-use decisions heterogeneously (beyond economic rationality assumption) has been accomplished in several ABM applications that explored the impacts of PES schemes on land-use change (Murray-Rust et al., 2011; Sun and Müller, 2013). However, understanding of the ES trade-offs from land-use decisions as emergent property is not well represented. A similar work has been done using an agent-based model (AgriPolis) to assess the impacts of agricultural policy on land use and biodiversity (Brady et al., 2012). Though both studies share similar features (i.e., over-all research objective and the use of the species-area relationship as a biodiversity indicator), the distinctive aspects presented in this work are: (1) our application of bounded rationality for better representing household agent decision making, (2) our calibration of the SAR parameters using a standard experimental approach with field-sourced data (i.e., EstimateS; Colwell, 2009), (3) the explicit representation of ES tradeoffs, and (4) validation.

5.4. Land-use RPG: social validation

The RPG approach has been widely combined with ABM model development (Barreteau et al., 2001; Castella et al., 2005; Etienne, 2003). The strength of combining RPG is to refine evidence-driven ABMs by providing realistic descriptive specifications of individual behavior and social interactions (Le Page et al., 2012; Moss, 2008). We compared the land-use results from the game exercise with survey respondents to the simulated land-use outcomes from the LB-LUDAS model. From the RPG, there was a positive response to the PES negotiator, thus the players maintained their rubber agroforest and forest patches, and there was almost no conversion to monoculture rubber and oil palm. All of the financial bids by external agents to establish oil palm cultivation in the village were rejected despite indications of declining income (Villamor and van Noordwijk, 2011). Based on this observed game behavior, we believe that the land-use change pattern simulated by the LB-LUDAS model (Fig. 4(3)) is consistent with the land-use pattern resulting from the RPG exercise (Villamor et al., 2013b; Villamor and van Noordwijk, 2011), which suggests convergent validity between the two models (Yu, 2003).

6. Conclusions

The use of the ABM framework (LB-LUDAS model) was found to be suitable for exploring and better understanding ES trade-offs. This is necessary for assessing conservation policies such as PES schemes that have multiple objectives, while integrating the decision-making processes and preferences of household agents. The simulation results demonstrate that land-use practices such as rubber agroforests, if coupled with appropriate management regimes or policies like PES, could synergize ES while supporting household livelihoods. The challenge is to search for sustainable land-use practices and appropriate strategies or designs that better support synergy among ES.

However, there are limitations in the study that we wish to address in future efforts, such as the inclusion of other pertinent ES (e.g., water quantity and soil fertility) and agent behavior reflecting rural interdependencies. Some other emergent properties (i.e., learning and adaptation) emanating from the interaction of the social and biophysical systems also need further analysis. It is also important to further investigate appropriate PES modalities that would increase farmers' adoption for environmentally friendly land-use practices.

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