SAFARI: Simulating Agroforestry Adoption in Rural Indonesia

The description of the agent-based model (ABM) follows the ODD (Overview, Design concepts, Details) protocol (Grimm et al. 2006; 2010; 2020). The model was implemented using NetLogo 6.1.1 (Wilensky, 1999).

Purpose

The Simulating Agroforestry Adoption in Rural Indonesia (SAFARI) model aims at exploring the adoption of illipe rubber agroforestry systems by farming households in the case study region in rural Indonesia. Thereby, the ABM simulates the interdependencies of agroforestry systems and local livelihoods, income, land use, biodiversity, and carbon sequestration. The model contrasts development paths without agroforestry (business as usual (BAU) scenario), corresponding to a scenario where the government promotes rubber monoculture, with the introduction of illipe rubber agroforestry systems (IRA scenario) as an alternative. It aims to support policy-makers to assess the potential of IRA over larger temporal and spatial scales.#

State variables and scales

The SAFARI model comprises two agent types: farming households and landscape patches. The farming households are the primary decision-making units in the model. They are characterized by state variables indicating their location, household size and resulting energy requirement, labor force, and further variables related to their agricultural activities as displayed in table 1. Livelihood indicators show whether the households engaged in rice or rubber farming, agroforestry cultivation, and illipe processing. The variable food-insecure indicates whether a household has failed to meet its minimal energy requirement. Income indicates household's wealth. Decision making follows a bounded rationality approach including a satisficing heuristic based on if-then-else statements.

Variable	Description
HHID	Identifier of household
Initial-laborforce	Initial labor force, based on household size
Available-laborforce	Available labor force after livelihood decision, considers labor input for livelihoods chosen
Farmsize	Total farm size
NumberPlots	Number of plots
My-plots	Set of plots claimed by household
Plots_cultivated	Plots cultivated by household
Fallow_plots	Fallow household plots
Plots_rice	Number of plots with rice
Plots_rubber	Number of plots with rubber monoculture
Plots_AF	Number of plots with agroforestry
RiceFarmer	1 if household cultivates rice, 0 otherwise
RubberFarmer	1 if household cultivates rubber, 0 otherwise
IllipeFarmer	1 if household cultivates illipe, 0 otherwise
Illipeprocessor	1 if household processes illipe nuts, 0 otherwise
Illipeharvest	Illipe nuts harvested (in kg)
iEnergyRequirement	Auxiliary variable to calculate initial energy requirement of household
EnergyRequirement	Energy requirement of household
EnergyConsumption	Expected energy consumption resulting from agriculture cultivated in previous periods and current period
RiceConsumption	Expected energy consumption from rice
RubberIncome	Expected income from rubber monoculture
IllipeAFIncome	Expected income from illipe nuts
RubberAFIncome	Expected income from rubber in agroforestry systems
AFincome	Expected total income from agroforestry
IllipeIncomeProcessed	Expected income from illipe nuts processed

aEnergyConsumption	Actual total energy consumption (total)
aRiceConsumption	Actual energy consumption from rice
aRubberIncome	Actual income from rubber monoculture
aIllipeAFIncome	Actual income from illipe
aRubberAFIncome	Actual income from rubber in agroforestry systems
aAFIncome	Actual total income from agroforestry
aIllipeIncomeProcessed	Actual income from processed illipe
Income	Total income in Mio IDR
Food-insecure	1 if household did not meet energy requirements, 0 otherwise
Deficit	Caloric deficit

Table 1: Farmer variables.

Landscape patches, the other agent type, represent the spatial environment of the model. They describe the land use and resulting vegetation cover as table 2 describes. Based on patch class, vegetation, fallow age, and the resulting fertility are derived. Fertility is used as an input to calculate yields. Associated to the specific uses, patch variables indicate carbon sequestration and biodiversity indicators, namely tree Fisher's alpha, basal area, tree species richness, and tree density as well as bird richness. The agents are parameterized according to survey and GIS data as well as ecological indicators.

One patch agent represents an area of 100x100 meters resulting in a total area of about 28x44km covered.

Variable	**Description**
Owner	Identification of household claiming ownership
Plotid	Plot identifier according to survey
Class	Land use class (natural forest, secondary forest, old fallow, young fallow, rice and weeds, rice, rubber monoculture, IRA)
Vegetation	Plot vegetation
Fallowlength	Indicates age of plot laying fallow
Fertility	Auxiliary variable to calculate yield
Yield	Rice yield, depends on fertility
Rubber	Indicates if rubber is planted on patch and age of trees

Illipe	Indicates if illipe nut trees are planted on patch and age of trees
Patch_alpha	Tree Fisher's alpha
Patch_basal	Basal area
Patch_tree_richness	Tree richness
Patch_density	Tree density
Bird_richness	Species richness of birds
Biomass	Above-ground biomass in C Mg / patch
Vegetastipatch	Land cover according to GIS data
River	Indicates location of rivers
River-prox	Indicates patch proximity to a river
Nationalpark	Indicates location of national parks

Table 2: Patch variables.

Process overview and scheduling

The model proceeds in annual time steps, and simulations were run for 60 years. Within each time step, six modules are processed in the order corresponding to figure 1. Within each module, the agents conduct the respective processes in a random order.

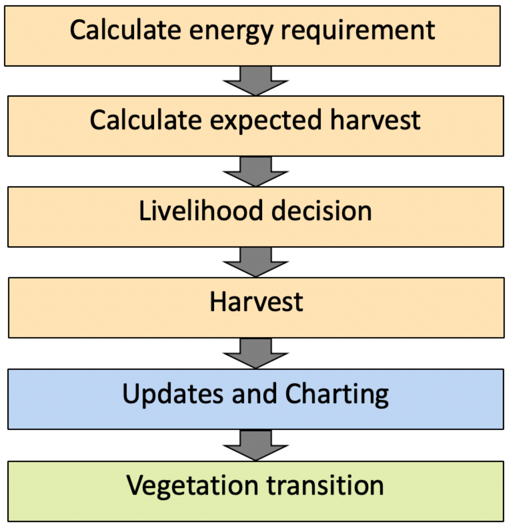

Figure 1: Process overview.

Note: orange: household agent procedures, green: landscape agent procedures, blue: general procedures.

Design concepts

Basic principles: Given the limited cognitive abilities of humans, farming households are assumed to follow a satisficing approach based on the concept of bounded rationality (Gigerenzer and Goldstein, 1996; Robinson et al., 2007; Schreinemachers and Berger, 2006; Simon, 1972). The landscape patches follow transition rules and are impacted by the farmers' land use decisions.

Emergence: Livelihood decisions determine land use, which in turn influences the development of land cover and future livelihood decisions. Thus, landscape dynamics emerge from the interaction between patches and farming households.

Adaptation: Farming households adapt by taking past agricultural decisions and their subsequent situation in the present into account when deciding about livelihoods to fulfill caloric requirements.

Fitness: Fitness-seeking is modelled as the objective to fulfil caloric needs as part of a satisficing procedure. As a secondary objective, households invest the excess labor to generate cash income.

Sensing: Farming households know their own characteristics such as household labor, agricultural activities, etc. Furthermore, they are aware of the land use and which patch has been claimed by a household. Households also know about the labor requirements of each agricultural activity and market prices of the outputs.

Interaction: Interaction between households takes place indirectly through competition for land.

Stochasticity: The order of agents performing the procedures is random. The location of claimed plots contains stochastic elements. The initialization procedure comprises random elements with respect to the location of farms, initial cultivation of rice and rubber, vegetation, fallow length, and hence fertility, whose initialization values are drawn from random distributions.

Observation: The main simulation outcomes computed every time step include livelihood choices, income generation, land cover, carbon sequestration, and biodiversity. Regarding the latter, bird species richness and Fisher's alpha for trees signify the respective biodiversity levels. Additional biodiversity indicators reflecting further aspects of biodiversity include tree density, tree species richness, and basal area.

Initialization

The farming households are initialized according to a household survey. Specifically, their original farm size, number of (cultivated and fallow) plots, labor force, and location are directly derived from the survey data and are thus household-specific. Locations of plots are assigned randomly, but within a certain radius that corresponds to maximum distances between households and plots derived from the survey. Cultivation of rice and rubber is probabilistic with likelihoods corresponding to the share of households engaging as indicated in the survey (23% and 76%, respectively). Other land uses origin from GIS data. The setup of the biodiversity and carbon indicators is based on local data collection (Simamora et al., 2021) as presented in table 3. Fallow length is random and corresponds with vegetation. Fertility equals the fallow age.

Vegetation class	Setup
Natural forest	Vegetation: uniformly distributed between 20 and 40 Basal area: 3.75 Tree Fisher's alpha: 50.487 Tree density: 81 Tree richness: 91 Biomass: 36.7 Bird richness: 81a
Secondary forest	Vegetation: uniformly distributed between 20 and 40 Basal area: 3.53 Tree Fisher's alpha: 35.3 Tree density: 96 Tree richness: 85 Biomass: 7.4335 Bird richness: 68
Old fallow	Vegetation: uniformly distributed between 10 and 20 Basal area: 0.75 Tree Fisher's alpha: 18.38 Tree density: 67.5 Tree richness: 39 Biomass: 0.8119 Bird richness: 69
Young fallow	Vegetation: uniformly distributed between 2 and 10 Basal area: 0.25 Tree Fisher's alpha: 10.91 Tree density: 48.5 Tree richness: 25 Biomass: 0.2

	Bird richness: 57
Rice + weeds	Vegetation: 1 Basal area: 0 Tree Fisher's alpha: 0 Tree density: 0 Tree richness: 0 Biomass: 0 Bird richness: 1
Rice	Vegetation: 0 Basal area: 0 Tree Fisher's alpha: 0 Tree density: 0 Tree richness: 0 Biomass: 0 Bird richness: 1
Rubber monoculture	Basal area: 2 Tree Fisher's alpha: 25.48 Tree density: 54.7 Tree richness: 69 Biomass: 9.8 Bird richness: 49
Illipe rubber agroforestry	Basal area: 2.7 Tree Fisher's alpha: 39.74 Tree density: 132 Tree richness 60 Biomass: 13 Bird richness: 60

Table 3: Landscape agents' setup.

Input

Data input is used for the initialization of the model: household survey data indicates household composition and energy requirements as described in table 1. GIS data provide information to setup the landscape agents (Laumonier et al., 2020a). The input for the biodiversity indicators and carbon sequestration origins from data collection on site (Simamora et al., 2021). Further inputs used include costs and benefits of the livelihood activities. The labor inputs origin from Suyanto et al. (2009). Labor inputs for trees are adjusted to account for the duration until trees reach maturity: accordingly, rubber is assumed to require 52 labor days per person per hectare in the first year, 26 in the years 2-5, and 99 afterwards as input (Suyanto et al., 2009). Illipe nut trees are assumed to require the same amount of labor input as rubber trees. However, after illipe nut trees mature at the age of eight, 99 labor days per person per hectare are only required every four years, when the illipe nut trees can be harvested. In the other years, 26 labor days per person per hectare are assumed to be required for maintenance. 20 labor days per person are assumed as input for illipe nuts processing. Whereas for rice a yield function following Jepsen et al. (2006) is used, annual outputs for rubber and illipe rubber system follow Winarni et al. (2017) and Wulan et al. (2006). Furthermore, rice is assumed to provide 1,650 kcal per kg. 1 kg rice costs 10,000 IDR, and the price for rubber is 6,500 IDR per kg according to the survey and Winarni et al. (2017). Illipe nuts cost 7,000 IDR per kg (Riko and Wardenaar, 2013; Winarni et al., 2017). Regarding processing, about 5 kg of raw illipe nuts yield up to 1 kg fat, which can be sold for about 100,000 IDR (Maharani et al., 2016).

Submodels

Calculate energy requirements

As the first step of each simulation run, the households calculate their energy requirements based on the household size in adult equivalents (Chiputwa et al., 2015). For every adult equivalent, a minimum consumption corresponding to the average caloric consumption (1935 kcal per person per day) from Kalimantan in 2015 (Indonesian Statistics Publications, 2020) as the aspired consumption threshold is assumed. During the same step, variables such as energy consumption are reset to zero.

Calculate expected harvest

Then, households estimate their expected harvest. Households may have engaged in agricultural cultivation in previous seasons and take the expected yields into consideration for their livelihood decision in the current year. This includes rice from swidden fields in the second year as well as rubber and illipe nut yields. Thereby, mature illipe nut trees can be harvested only every four years, whereas rubber in the agroforestry systems can be harvested every year once the trees matured. Rice yields are calculated following a yield function of Jepsen et al. (2006) calibrated to the study region

$$y = \frac{a}{1 + b * \exp{(-c * x)}}$$

with a =783.7, b = 8.07, c= 0.52, and x = *fertility*. During the second year of swidden agriculture, the rice yield is assumed to be 50% of first-year-yields. Because the farmers anticipate these yields, they plan accordingly and allocate labor to the respective harvesting activities, which is thus subtracted from the available labor force.

Livelihood decisions

Based on expected harvest, households decide about additional livelihood activities in the current period. Given the cost of searching and comparing alternative actions combined with limited cognitive and computational abilities of humans, a bounded rationality approach including a satisficing heuristic was applied to simulate farmer decision making (Gigerenzer and Goldstein, 1996; Robinson et al., 2007; Simon, 1972). A decision tree represents decision making as a series of if-then-else statements as illustrated in figure 2. The baseline scenario considers rice and rubber, which are the main livelihood activities in the study area. The respective decisions depend on caloric needs and resource availability. Farming household prioritize to fulfill their caloric needs, which represents the aspiration threshold, through rice planting before engaging in market production of rubber (Magliocca et al., 2013; Wangpakapattanawong et al., 2017). If the households have claimed available plots, they choose to plant rice on the plot with the longest fallow age, which represents a preference for clearing secondary fallow over primary forest (Sorensen, 1996). Only if no such plot exists, the household decides to clear an unclaimed plot, located within a radius of six kilometers maximum, through slash and burning to plant rice there. The households continue planting rice until they expect their caloric needs satisfied. The maximum area for clearing unclaimed areas is set to four hectares per period. Once harvest meets the caloric needs, the households check whether they have more labor available. If that is the case, they engage in rubber tapping and maintenance. If still more labor is available, they decide to plant additional rubber monoculture as a cash crop. The maximum amount of rubber is restricted to 1.2 ha in line with survey results.

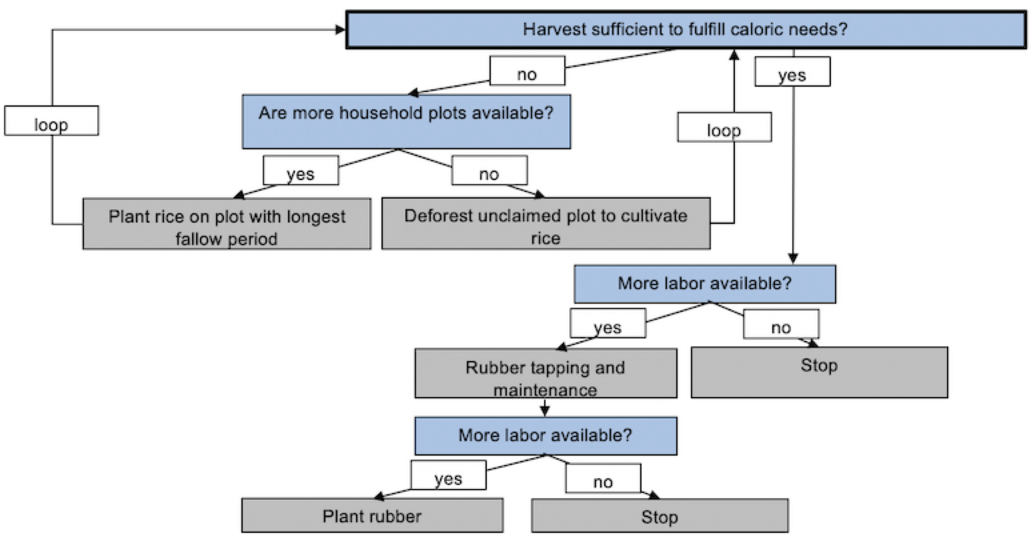

Figure 2: Livelihood decision: Baseline scenario.

Extending the baseline scenario (figure 3), farmers have the option to additionally plant illipe tree mixed with rubber agroforestry on their plots in riverbanks as an option to generate cash income. First, they harvest illipe nuts if it is possible in that season. Then, also in the agroforestry scenario, households aim to fulfill caloric requirements through swidden agriculture on already claimed or newly cleared plots. When the expected yields suffice to ensure food security, rubber has been tapped, and more labor is available, the households check whether they have fallow plots in proximity to a river available. If they do not, they plant rubber on another plot. If they do, they cultivate IRA on that plot. If still more labor is available to the household during an illipe nut harvesting season, they process the illipe nuts into fat.

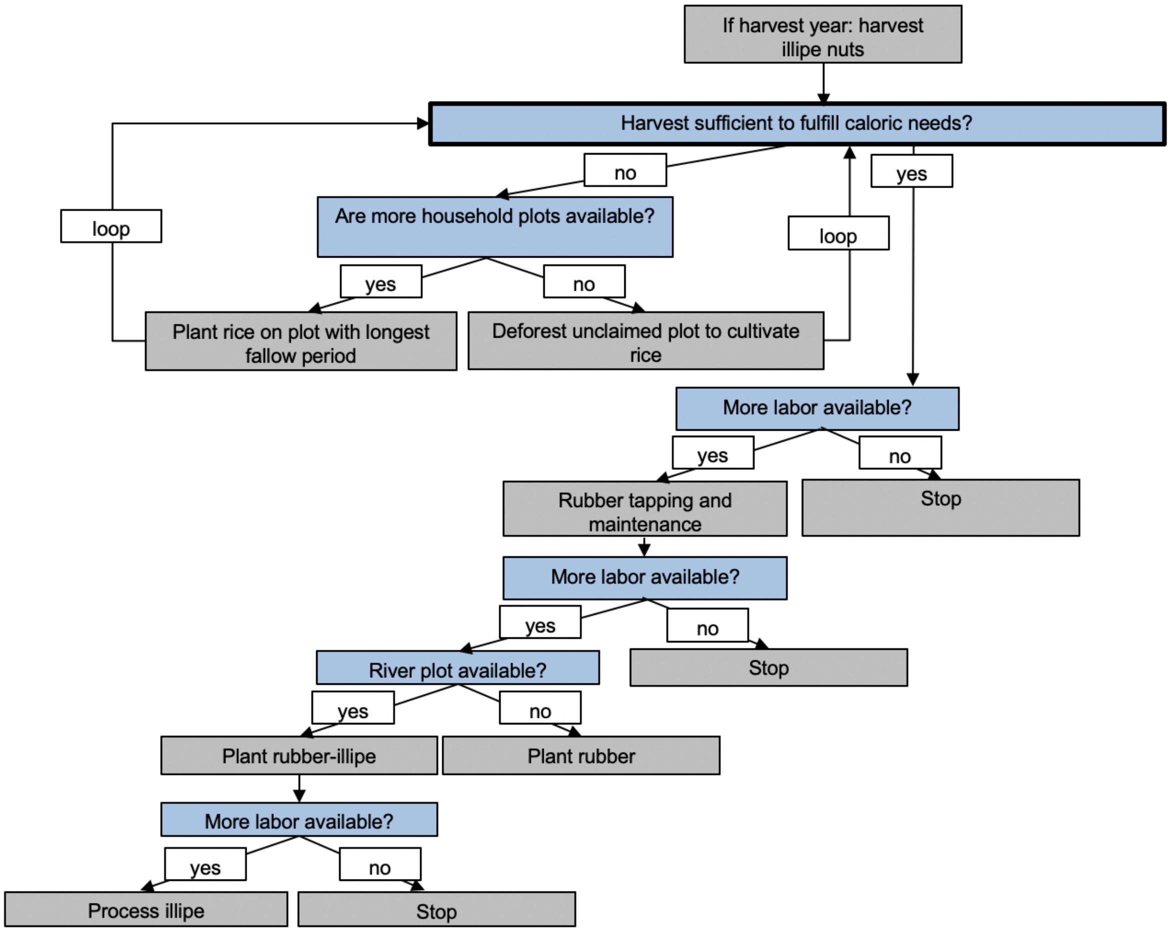

Figure 3: Livelihood decision: Agroforestry scenario.

Harvest

After household decisions are made, the households harvest their plots. As the illipe nut tree produces yield approximately every four years depending on weather conditions, illipe nut harvest is assumed to occur every four years for all trees simultaneously (Heri et al., 2020). In contrast, rubber (monoculture or as part of IRA) can be harvested every year. The households accumulate the calories and cash income generated from their livelihood activities. If a household is not able to produce the required calories, it is marked as food insecure.

Update of variables and charting

Update of the farmers includes the number of farmers who chose the respective livelihoods, mean caloric consumptions, and income. Furthermore, number of plots claimed, plots laying fallow and plots cultivated, total farm size, and the share of plots with agroforestry are updated. Besides, number of landscape agents with the various vegetation classes, mean biodiversity indicators of the patches, and carbon sequestered according to the land use are calculated.

Vegetation transition

As the last step of the modelling cycle, the vegetation classes undergo transition dependent on their fallow age and use according to the swidden agriculture cycle (Figure 4).

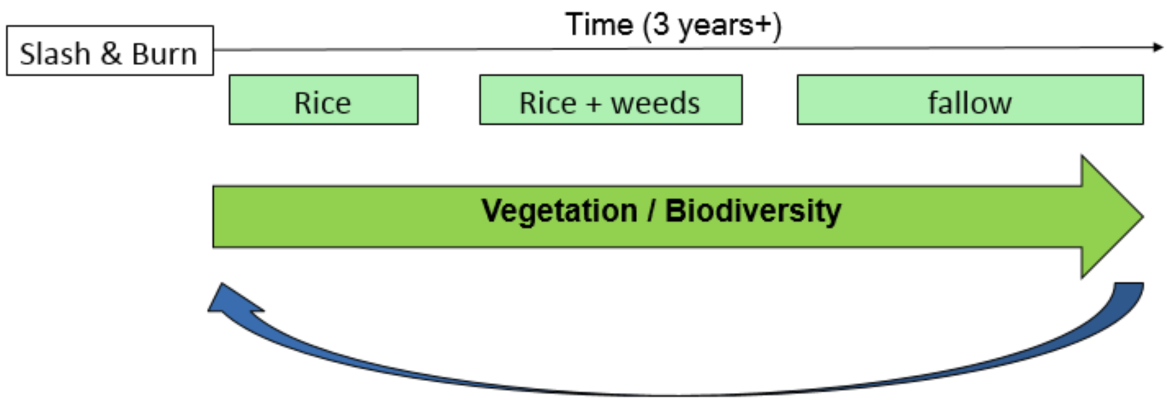

Figure 4: Cycle of swidden agriculture.

Before farmers can cultivate plots, they need to clear them through slash and burn activities. Rice planted on cleared (swidden) fields also provides yield in the second year after planting, when weeds grow on the fields as well. In the consecutive periods, the fields lay fallow to regenerate their fertility until the farmers decide to clear and cultivate them again. During that fallow period, plots transition from young fallow to old fallow to secondary forest unless they are cleared (table 4). Also patches with forest vegetation can be cleared for rice cultivation through slash-and-burning.

To represent the fertility and vegetation on the swidden fields, fallow age, vegetation, and fertility increase by one during every time step except when the plot is cleared. In that case, fallow age and vegetation are reset to zero. Only fertility, whose maximum value is restricted to 12, is not reset until the harvest is completed because it is needed to calculate the yield since fertility improves yield. For vegetation, a maximum of 30 is assumed. With increasing fallow length and change in vegetation, also the biodiversity indicators are modified, corresponding to the respective land use as indicated in table 3. Lastly, rubber trees exceeding the age of 25 are assumed to die and be replaced. Illipe trees can reach the age of 99 years, which is longer than the simulated time span and thus is not considered in this context.

Vegetation class	**Transition into**
Rice	Rice + weeds
Rice + weeds	Young fallow (up to 10 years)
Young fallow	Old fallow (11-20 years)
Old fallow	Secondary forest (> 20 years)

Table 4: Transition of vegetation classes.

Climate change scenario

Extending the model, a climate change scenario (CCS) simulates rice yield reductions as a result of rising temperatures. Thereby, rises in temperature of 1.5° Celsius are simulated (IPCC, 2018) that lead to relative decreases in rice yields of 12.6% (Yuliawan and Handoko, 2016).

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