Biodiversity and Adoption of Small-scale Agroforestry in Rwanda (BASAR):

Overview, Design Concepts and Details + Decision-making protocol

1) Overview:

I.i Purpose: The Biodiversity and Adoption of Small-scale Agroforestry in Rwanda (BASAR) model compares different approaches to represent small-scale farmers' decision-making in the context of agroforestry adoption in rural Rwanda. In particular, it compares random decision-making with perfect rationality (non-discounted and discounted profit maximization), bounded rationality (satisficing heuristic and fast and frugal decision tree heuristic), Theory of Planned Behaviour (TPB) as a psychological theory, and a regression-based approach. The model addresses modelers and users of models, such as policy-makers, to support them in selecting an approach to represent human decision-making in agent-based models (ABMs) of social-ecological systems and to understand the implications of a specific choice. This comparison contributes to improving forecasts of adoption rates and to supporting the development and implementation of policy interventions that aim at raising low adoption rates.

I.ii Entities, state variables, and scales:

The model comprises three different kinds of agents: farming households, links, and landscape patches. The farming households are the main decision-making units in the model and decide about adopting an agroforestry systems with diverse tree species on their land. They are defined by household characteristics such as household size, number of social contacts, labour force, land owned, their agricultural activities, and resulting income, as displayed in table 1. Further household variables describe indicators to calculate farmers' intention, attitude, subjective norm (SN), and perceived behavioural control (PBC) in the context of the TPB.

Table 1: Household agent variables.

Household variables	Description
HHID	Household identifier
Hhsize[a]	Size of the household
Non-workers[a]	Number of non-workers in the household
ilaborforce[a]	Labour force of a household (in work-days per year)
Actuallaborforce	Available labour force of a household (in work-days per year)
Valuebiodi[a]	Valuation of biodiversity (5-point-Likert-scale)

Extensionaccess[a]	Dummy variable indicating access to extension services
Nurseryaccess	Dummy variable indicating access to a tree nursery
Landsize[a]	Land size owned by household (in hectare (ha))
Landquality[a]	Perceived quality of owned land (5-point-Likert-scale)
My-plots	Set of landscape agents owned by household
Friends[a]	Number of social contacts
Attitude[a]	Attitude (TPB construct, estimated via structural equation modelling (SEM))
PBC[a]	Perceived behavioural control (TPB construct, estimated via SEM)
SN[a]	Subjective norm (TPB construct, estimated via SEM)
Intention[a]	Intention (TPB construct, estimated via SEM)
Ctpb[a]	Auxiliary variables capturing individual indicator variables to calculate TPB
Adopter	Dummy variable indicating if household adopted agroforestry
Income	Income generated by household (in Rwandan franc (RWF))
Vali	Validation variables for three years

Note: [a] parameterized according to household survey.

Links, the second agent type in the model, connect farming households and, thus, represent the social network. Through these links the farming households exchange information on who has already established agroforestry. Thereby, the social network constitutes the subjective norm.

Table 2: Landscape agent variables.

Patch variable	Description
Owner	Indicates household owning the plot
Sizeha	Land size (in ha)
Potatowheat	Dummy variable indicating if potatoes and wheat are cultivated
Agroforestry	Dummy variable indicating if agroforestry is cultivated
AFage	Indicates age of agroforestry system

Thirdly, patches represent the models' spatial landscape, e.g. farming plots. Cultivated by the households, they provide ecosystem services including agricultural outputs. They are described by several variables such as owner, size, and land use, as indicated in table 2.

Space is included explicitly in the model. Each patch represents 0.5 ha and corresponds to rounded land sizes as reported in the survey. The model covers a total land area of 800 ha. The model moves in yearly time steps over a period of 30 years, which is sufficiently long to capture the time span until trees mature.

I.iii Process overview and scheduling

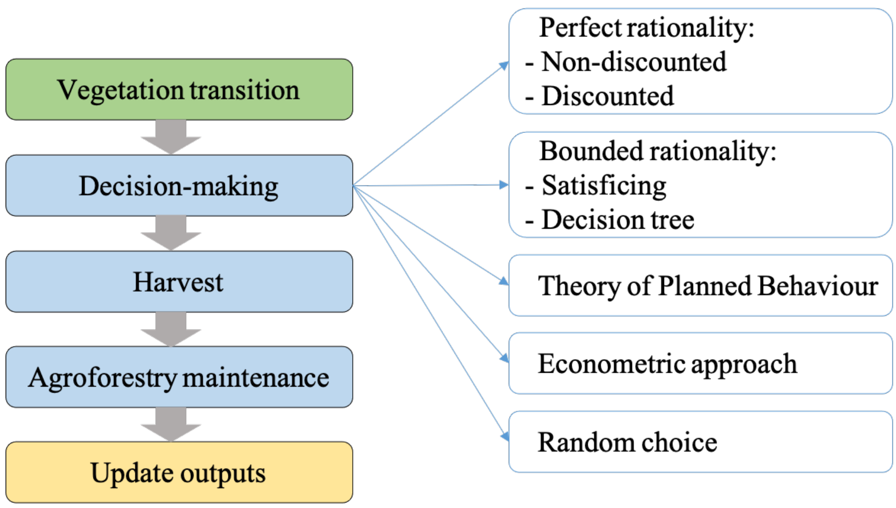

Figure 1: Process overview.
Note: Colors represent agents performing the respective procedure. Green: landscape patches. Blue: Farming households. Yellow: Global observer.

Within each year, the model simulates a sequence of activities in the following order (figure 1): first, the landscape patches undergo vegetation transition. Then, the households decide whether to adopt agroforestry or cultivate potatoes and wheat according to the selected decision-making approach. After deciding about land uses, harvest takes place. Subsequently, the farming households who cultivated on-farm trees maintain their agroforests. In the last step, agent and global variables are updated, and charts as well as further outputs are computed. If a household decides to cultivate potatoes and wheat in a rotational system, they reevaluate this decision in the consecutive year, whereas adopted agroforestry systems remain for twenty years without switching to potato wheat cultivation. During each procedure, the order of agents performing the respective action is random. The number of simulation runs was based on an empirical formula for minimum sample sizes for agent-based simulations (Secchi and Seri, 2017). The minimum sample size was rounded up, leading to 50 simulation runs for each decision-making specification to achieve robust and stable results.

II) Design concepts

II.i Theoretical and empirical background

The BASAR model simulates a social-ecological system in rural Rwanda, based on small-scale farming households as human agents. These farming households have the option to alternate Irish potatoes (*Solanum tuberosum L.*) and wheat (*Triticum aestivum L.)* in line with traditional agricultural production systems or to combine the crops with three tree species, *Grevillea robusta*, *Alnus acuminata* Kunth, and *Markhamia lutea* in an agroforestry hedgerow system. The core of this model lies in the module modelling farmers' decision-making. The model includes several decision-making modules to test different approaches representing farmers' decision-making, which are described below. Livelihood decisions by the farming households determine land use, which in turn impacts the development of land cover and future land use decisions. Landscape dynamics emerge from farming households' decisions and their interactions with each other and the farm patches.

II.ii Individual decision-making

Initially, all households cultivate wheat and potatoes, but they can decide to implement agroforestry over the course of the simulation runs. Decision-making is modelled on the farming household level. Depending on how the different decision-making approaches are implemented in the simulation model explain decision making, farmers' objectives, the role of social norms, and uncertainty may differ. In the following, the alternative decision-making approaches tested in the BASAR model are presxsented in more detail.

Rational choice theory: Rational choice theory assumes that humans are perfectly rational decision-makers who assess all possible alternatives under complete information without succumbing to cognitive biases. In line with their preferences, decision-makers optimize their well-being, which can be expressed through a utility function (Sen, 1994; Simon, 1955, 2007; van Duinen et al., 2016). Because utility is difficult to measure, practical applications frequently replace the utility function with a profit function (Edwards-Jones, 2006), as it is done in this application: the farming households aim to maximize their income. To choose the most profitable option, the households calculate the income for each agricultural activitiy as follows

$$p_i = -C_0 + \sum_{t=1}^{T} \sum_{j=1}^{J} \frac{price_j * output_{jt} - inputcosts_j - laborcosts_{jt}}{(1+\delta)^t} \qquad 1$$

with p_i=profit generated by household i, t=time, j=agricultural activity, and C_0=investment costs in the year of establishment. δ describes the discount factor. It accounts for the fact that humans may discount future cash flows because of their impatience (Schlüter et al., 2017). In the non-discounting scenario, farmers are assumed to have no temporal preference, and δ is set to 0. In the discounting scenario, temporal preferences are accounted for by setting δ=7% (Ministry of Environment – Rwanda, 2020).

Bounded rationality: satisficing: The satisficing heuristic, combining “satisfy” and “suffice”, offers one possibility to conceptualize bounded rationality. It is based on the premise that humans’ cognitive capabilities do not always suffice to find the optimal solution for complex problems. Hence, searching for and evaluation possible alternatives can be costly for the non-omniscient decision-maker. As a consequence, the decision-maker settles for a satisfactory rather than optimized solution according to this approach. In particular, the decision-maker sets an aspiration threshold and evaluates possible solutions in a random order until an alternative satisfies, e.g. exceeds, this aspiration threshold. Because decision-makers take shortcuts rather than optimizing their choice, satisficing describes a decision heuristic (Schilirò, 2018; Simon, 1972). In this application, the households apply the same profit function as perfectly rational decision-makers (*equation 1*) to evaluate livelihood options in a random order. They consider a livelihood satisfying if it ensures food security. Thus, the households stop searching once they identified a livelihood that generates an income that secures at least 1830 calories per household member (Roser and Ritchie, 2013). Therefore, households applying this satisficing heuristic might not evaluate all options and not choose the best solution in contrast to perfectly rational decision-makers.

Bounded rationality: decision tree: Bounded rationality can also be conceptualized via a fast and frugal decision tree heuristic. In this case, decision-makers simplify decisions by evaluating specific criteria or cues in a predetermined order until a cue leads a decision. Thus, decision-makers applying this heuristic also take shortcuts and process only certain information (Gigerenzer and Gaissmaier, 2011; Gigerenzer and Goldstein, 1996; Schilirò, 2018). In this application, the households implement a decision tree that accounts for the perceived urgency to adopt agroforestry and whether required inputs are available. As illustrated in figure 2, the decision is initiated if the farming household is concerned with degraded soil on their land, as they indicated in the survey, or if basic needs cannot be met. Basic requirements are assumed to be satisfied if the wheat potato mix as the default option provides enough calories to ensure household food security, i.e. at least 1830 calories per household member (Roser and Ritchie, 2013). In the next step, households check whether they have access to a tree nursery to receive seedlings. If a household can obtain seedlings via a nursery, they evaluate their knowledge on tree management and agroforestry. Their expertise corresponds to their knowledge level as indicated in the survey. If households do not have access to seedlings and knowledge, extension services can provide an alternative to deliver relevant knowledge about tree management, agroforestry, and own seedling production. Consequently, households evaluate whether labour is available. Labour can either be provided by household members or hired. If all input requirements are fulfilled, the households adopt the agroforestry system.

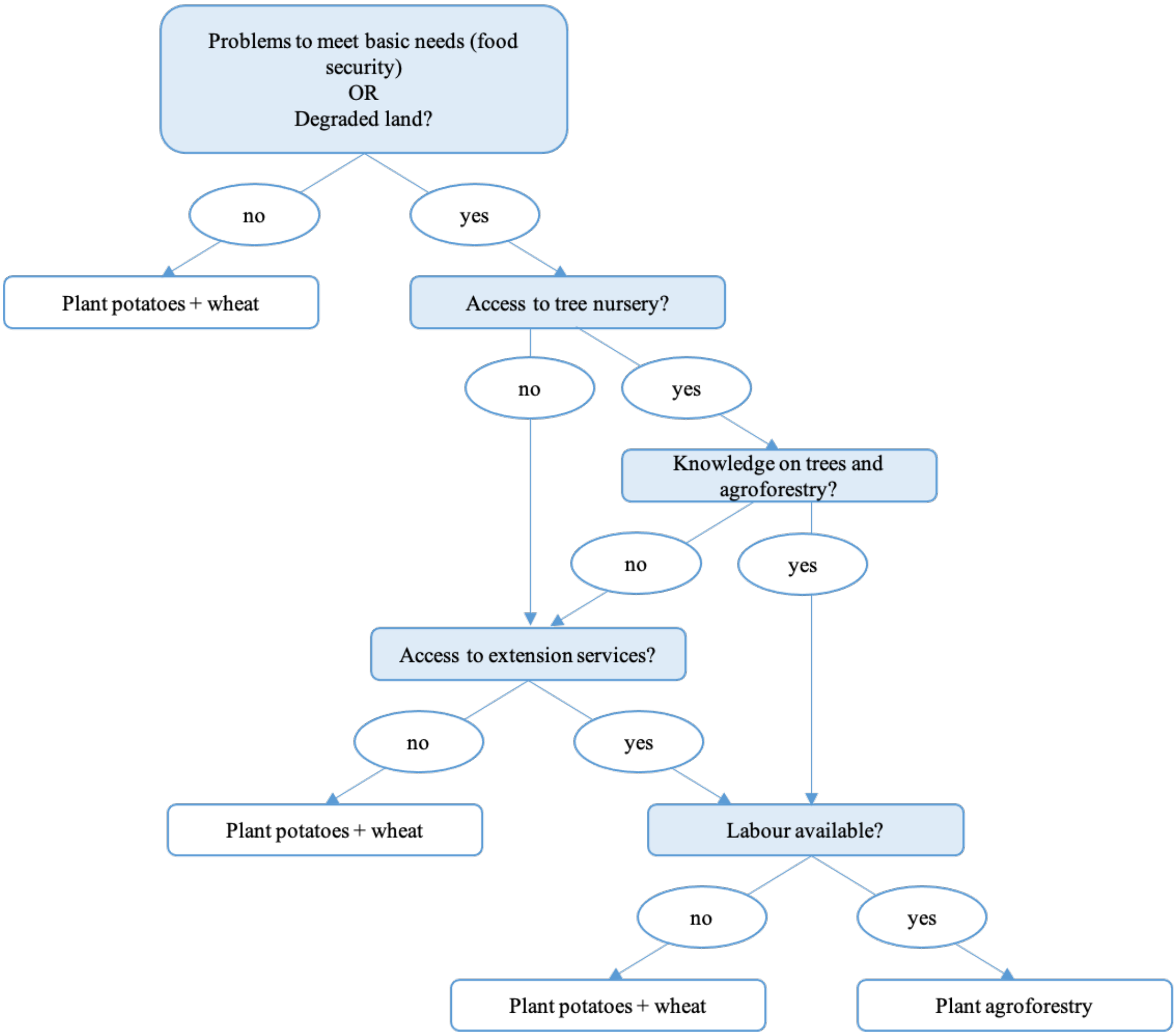

Figure 2: Bounded rationality: decision tree.

Theory of Planned Behaviour: As an extension of the Theory of Reasoned Action, the TPB assumes that deliberative thoughts inform decisions as humans consider the implications of their actions. According to the TPB, attitude, SN, and PBC drive the decision-making process as direct antecedents of behavioural intentions (Ajzen, 1991; Fishbein and Ajzen, 2010; Scalco et al., 2017). In this application, a PLS-SEM is applied to estimate the latent constructs of attitude, SN, PBC, and intention as well as the relationships thereof based on the indicator items from the survey. Details of the PLS-SEM are presented in the supplementary material (Noeldeke et al., submitted). Knowledge is considered as an additional construct. Because it does not exert a significant influence on intention, it is not included as a decision-making determinant in this application.

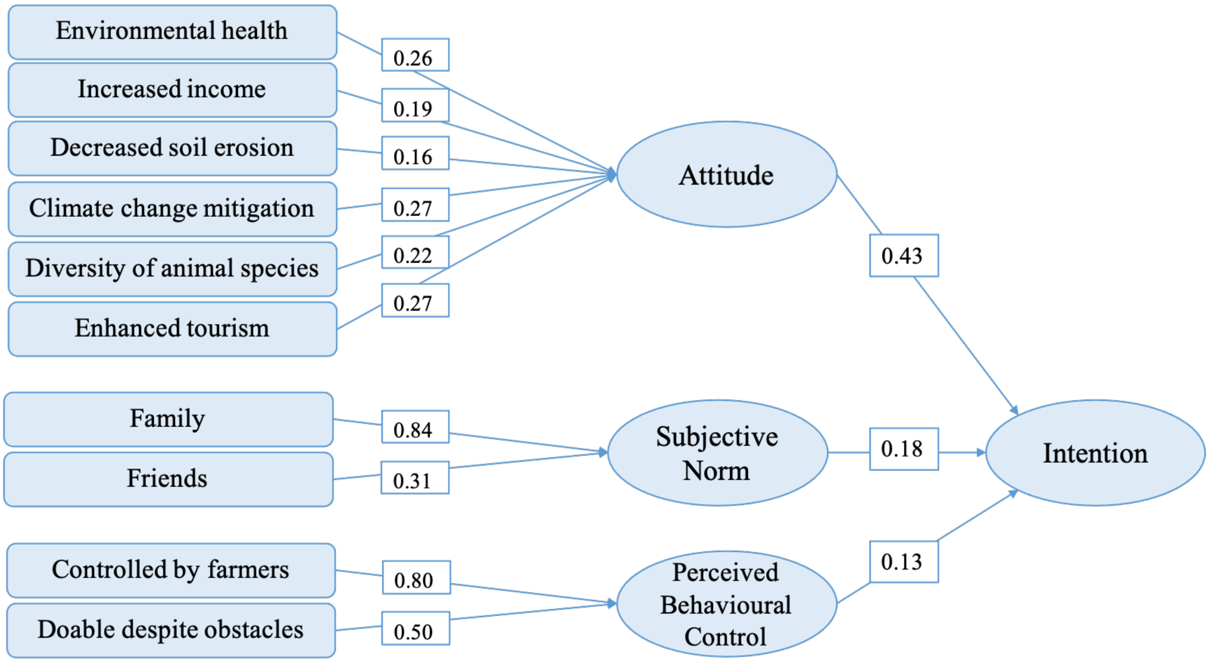

Figure 3: Results: TPB.
Note: All path coefficients and weights are significant at α=5%.

As depicted in figure 3, the PLS-SEM demonstrates that attitude is the strongest predictor for intention, but also SN and PBC significantly affect farmers' intentions to adopt agroforestry. Attitude itself is formed by financial motives (increased income due to agroforestry), decreased soil erosion, protection of environmental health, climate change mitigation, increased animal species diversity, and improved tourism. SN is constituted by the farmers' families and friends. PBC is influenced by farmers' perception that cultivating trees is controlled by themselves and doable despite possible obstacles such a such as extreme weather events, lack of institutional support, insufficient knowledge, lack of land, and unavailability of seedlings. In the model, each household i computes their individual intention to adopt agroforestry with diverse tree species according to the following equation

$$Intention_i = 0.43 * Attitude_i + 0.18 * SN_i + 0.13 * PBC_i \qquad 2$$

with the factors according to the results of the PLS-SEM. The constructs are calculated for each household based on PLS-SEM results and the survey data. For SN, the share of adopters in the social network is additionally considered: if a household is connected to a high share of adopters, the SN intensifies proportional to this share. Intention is rescaled to lie between 1 and 100 and implemented as the adoption probability.

Econometric: This approach applies statistical methods to empirical data to estimate relationships between variables based on their correlations (Gebru et al., 2019; Sanou et al., 2019; Sood and Mitchell, 2009). For investigating the binary decision of adopting agroforestry systems with diverse tree species, we estimate a logistic regression model as follows

$$P(Y = 1|X = x_i) = \frac{1}{1 + e^{-x_i^T \beta}} \qquad 3$$

with β=coefficients and x_i=vector of regressors for household *i* (Stock and Watson, 2015). The regressors displayed in table 3 significantly influence the adoption of agroforestry systems according to the backwards stepwise regression.

Table 3: Results of the logistic regression model

Agroforestry adoption	Coef.	St.Err.	t-value	p-value	[95% Conf Interval]	
Land size (in ha)	2.737	0.899	3.04	0.002***	0.975	4.500
Household size	0.829	0.267	3.11	0.002***	0.307	1.352
Land quality	-1.491	0.450	-3.31	0.001***	-2.372	-0.609
Value biodiversity	0.930	0.390	2.38	0.017**	0.166	1.695
Non-workers in household	-0.615	0.274	-2.25	0.025**	-1.151	-0.079
Constant	-1.724	2.019	-0.85	0.393	-5.681	2.233

Mean dependent var	0.841	SD dependent var	0.367
Pseudo R^2	0.343	Number of obs.	145
χ^2	43.482	Prob > χ^2	0.000

*Note: *** p<.01, ** p<.05, * p<.1.*

In the ABM, these results are used to compute adoption probabilities for each household based on the heterogeneous characteristics derived from the survey and the estimated coefficients.

Random choice: Random (non-rational) choice as the baseline scenario is compared to the decision-making approaches described above. In this scenario, the households do not follow any explicit or implicit goals and randomly decide about adopting agroforestry with a likelihood of 50%.

II.iii Learning

Households pursue the same strategy and do not change their decision-making over time. The model does not include collective learning.

II.iv Individual sensing

The farming households know their own state variables and which of the other households they are connected to have adopted agroforestry. Furthermore, they are aware of the correct inputs and outputs of the agricultural activities, prices, and what they have planted on their own plots.

II.v Individual prediction

The farming households predict conditions such as prices, livelihood inputs, and outputs. They correctly assume that these parameters remain stable over time.

II.vi Interaction

The households interact via a social network to transfer information about adoption. If a household is connected to a high share of adopters, the SN according to the TPB intensifies.

II.vii Collectives

The agents do not belong to or form any collectives.

II.viii Heterogeneity:

The agents differ with respect to their state variables, for example household size, attitude, satisficing threshold, or income. Once a decision-making module was chosen by the modeler, all household agents follow the same approach.

II.ix Stochasticity

The initialization procedure comprises random elements with respect to location of households and their farming plots, access to tree nurseries, and establishment of the social network. The agents perform the procedures in a random order. In the random decision-making module, the adoption decision is random. Also, the TPB and econometric decision approaches generate probabilities. During the satisificing heuristic, households evaluate livelihoods in a random order.

II.x Observation

Livelihood choices (agroforestry adoption rate), income generation, and land cover are the main simulation outcomes, which are computed every time step.

III) Details

III.i Implementation details

The model was implemented in NetLogo 6.1.1 (Wilensky, 1999).

III.ii Initialization

Initialization of the farming households was based on a household survey. Household-specific variables such as farm and household size, land quality, and indicators related to the calculation of attitude, SN, and PBC are directly derived from the survey data. Location of the farming households and their plots within a certain distance from the household are assigned randomly. With an assumed probability of 10%, households are initialized to have access to a tree nursery. Initially, all households practice traditional wheat potato cultivation. Based on the number of contacts, with whom the farmer generally discusses agricultural decisions, as reported in the survey, random links are created between the households to establish the social network. Global variables such as prices, outputs, and parameters specific to the decision-making procedures are set up.

III.iii Input Data

A household survey provides data for the parametrization of the farming households (see tables 1-2). Further input data used during the simulations refer to costs and outcomes of the livelihood activities. Costs include inputs such as labour for preparation, management, and harvesting, as well as farming inputs such as seeds, pesticides, and fertilizers (ESoko, 2021; Franzel, 2004; Ministry of Environment – Rwanda, 2020; Mugabo et al., 2007; Nduwamungu, 2011). Agricultural outputs for wheat and potatoes are based on official agricultural reports (NISR, 2020a, 2020b). As trees are assumed to positively impact crop growth, potato and wheat yields in the agroforestry system are adjusted according to calculated yield gaps (Ministry of Environment – Rwanda, 2020). Timber provision of the different trees are calculated based on reported growth rates (Kalinganire, 1996; Maroyi, 2012; Ministry of Environment – Rwanda, 2020; Nduwamungu, 2011). In terms of caloric outputs, potatoes provide 670 kcal/kg and wheat 3340 kcal/kg (FAO, 2001). Daily calorie requirement is assumed to be 1830 kcal per capita (Roser and Ritchie, 2013). Hiring labour is assumed to cost 800 RWF per day (Maniriho, 2016). The market prices for potatoes are 300 RWF, 700 RWF for wheat (ESoko, 2021), and the domestic timber price 115,000 RWF/m^3 (GIZ et al., 2019). Further details regarding the agricultural activities are contained in tables 4-7.

Table 4: Potato wheat cropping: inputs.

Input	Unit	Quantity/cost	Reference
Labour	Work days/ha/season	110.5	(Ministry of Environment – Rwanda, 2020)
Seeds (potato)	RWF/Ha	217528	(Mugabo et al., 2007)
Seeds (wheat)	RWF/Ha	17500	(ESoko, 2021; Ministry of Environment – Rwanda, 2020)
Fertilizer (DAP)	100 Kg/Ha	48000	(Ministry of Environment – Rwanda, 2020), (ESoko, 2021) 480RWF
Fertilizer (NPK)	300 KG/Ha	180900	Quantity from (Ministry of Environment – Rwanda, 2020), price from (ESoko, 2021) 603RWF
Pesticides	RWF/Ha	17059	(Mugabo et al., 2007)

Table 5: Potato wheat cropping: outputs.

Output	Unit	Quantity/cost	Reference
Potato quantity	Kg/Ha	10986.5[1]	(NISR, 2020a)
Wheat quantity	Kg/Ha	1221	(NISR, 2020b)
Potato price	RWF/Kg	300	(ESoko, 2021)
Wheat price	RWF/Kg	700	(ESoko, 2021)

Note: [1] District average.

Table 6: Agroforestry system: tree inputs.

Input	Unit	Quantity/cost	Time	Reference
Seedlings		Freely distributed during annual tree-planting week or own production	Year 0	(Nduwamungu, 2011)
Labour preparation and planting	Work days / ha	14.6+7.1	Year 0	(Franzel, 2004)
Labour weeding	Work days/ ha	16	Year 1,2	(Franzel, 2004; Nduwamungu, 2011)
Labour pruning	Work days/ ha	8.8	Years 3,7,10	(Franzel, 2004; Nduwamungu, 2011)
Labour harvesting (wood cutting and chopping)	Work days/ ha	36.5+121.9	Year 20	(Franzel, 2004)

Note: Costs additional to potato wheat cropping.

Table 7: Agroforestry system: outputs.

Output	**Unit**	**Price**	**Reference**
Firewood	RWF/m^3	115,000	(GIZ et al., 2019)
Potatoes under AF	RWF/Ha	10250100	(Ministry of Environment – Rwanda, 2020), calculated based on reported yield gap Price according to (ESoko, 2021): 300RWF
Wheat under AF	RWF/Ha	1231148	(Ministry of Environment – Rwanda, 2020), calculated based on reported yield gap Price according to (ESoko, 2021): 700RWF
Wood *grevillea robusta*	m^3	94.392	(Kalinganire, 1996; Ministry of Environment – Rwanda, 2020; Orwa et al., 2009)
Wood *alnus acuminata*	m^3	200	(Bosch, 2009; Ministry of Environment – Rwanda, 2020)
Wood *Markhamia lutea*	m^3	434	(Maroyi, 2012)

Note: Outputs additional to potato wheat cropping.

III.iv Submodels

The following section describes the submodels which are performed during each step as illustrated in figure 1.

Vegetation transition

In the first step, the landscape agents conduct a vegetation transition. This means that the trees grow over time and the age of the agroforestry system is increased by one every year.

Decision-making

The BASAR model tests alternative decision-making modules. Section II.ii “Individual decision-making” provides a detailed description of the distinct modules.

Harvest

During the harvest procedure, the farming households generate income by selling their agricultural outputs. Potatoes and wheat as annual crops generate yields every year. In the agroforestry systems, potatoes and wheat can also be harvested annually. In contrast, cutting down the trees produces timber only after 20 years.

Maintenance

In the two years following establishment of the agroforestry system, farmers engage in weeding. In years 3,7, and 10 pruning takes place.

Update outputs

In the last step, agent and global variables are updated, and charts as well as further outputs are computed.

References

Ajzen, I., 1991. The Theory of Planned Behavior. Organizational Behavior and Human Decision Processes 50, 179–211.

Bosch, C.H., 2009. Alnus acuminata Kunth, in: Lemmens, R.H.M.J., Louppe, D., Oteng-Amoako, A.A. (Eds.), PROTA (Plant Resources of Tropical Africa / Ressources Végétales de l'Afrique Tropicale). Wageningen.

Edwards-Jones, G., 2006. Modelling farmer decision-making: Concepts, progress and challenges. Animal Science 82, 783–790. https://doi.org/10.1017/ASC2006112

ESoko, 2021. Esoko [WWW Document]. Rwanda. URL http://www.esoko.gov.rw (accessed 8.3.21).

FAO, 2001. Food Balance Sheets. A handbook. FAO, Rome,.

Fishbein, M., Ajzen, I., 2010. Predicting and changing behaviour: The reasoned action approach. Psychology Press, New York.

Franzel, S., 2004. Financial Analysis of Agroforestry Practices, in: Valuing Agroforestry Systems. Advances in Agroforestry. Springer, Dordrecht. https://doi.org/https://doi.org/10.1007/1-4020-2413-4_2

Gebru, B.M., Wang, S.W., Kim, S.J., Lee, W.K., 2019. Socio-ecological niche and factors affecting agroforestry practice adoption in different agroecologies of southern Tigray, Ethiopia. Sustainability (Switzerland) 11, 1–19. https://doi.org/10.3390/su11133729

Gigerenzer, G., Gaissmaier, W., 2011. Heuristic decision making. Annual Review of Psychology 62, 451–482. https://doi.org/10.1146/annurev-psych-120709-145346

Gigerenzer, G., Goldstein, D.G., 1996. Reasoning the Fast and Frugal Way: Models of Bounded Rationality. Psychological Review 103, 650–669. https://doi.org/10.1093/acprof:oso/9780199744282.003.0002

GIZ, MINICOM, Rwanda Water & Forestry Authority, CIFOR, 2019. Wood Supply Chain in Rwanda Wood Supply Chain in Rwanda.

Kalinganire, A., 1996. Performance of Grevillea robusta in plantations and on farms under varying environmental conditions in Rwanda. Forest Ecology and Management 80, 279–285. https://doi.org/10.1016/0378-1127(95)03613-x

Maniriho, L., 2016. Assessment of the Role of Trees on Farmland in Soil Conservation and Household Welfare in Rwanda. American Scientific Research Journal for Engineering, Technology, and Sciences (ASRJETS).

Maroyi, A., 2012. Markhamia lutea (Benth.) K.Schum., in: Lemmens, R.H.M.J., Louppe, D., Oteng-Amoako, A.A. (Eds.), PROTA (Plant Resources of Tropical Africa / Ressources Végétales de l'Afrique Tropicale). Wageningen.

Ministry of Environment – Rwanda, 2020. Forest Landscape Restoration Technical Packages for Rwanda.

Mugabo, R.J., Mushabizi, D., Gagishi, M., 2007. Economic analysis of improved potato technologies in Rwanda. African Crop Science Conference Proceedings 8, 1243–1247. https://doi.org/10.1007/978-90-481-2543-2

Nduwamungu, J., 2011. Forest Plantations and Woodlots in Rwanda, African Forest Forum Working Paper Series. https://doi.org/10.13140/RG.2.1.1360.4724

NISR, 2020a. SEASONAL AGRICULTURAL SURVEY 2020 SEASON A REPORT. Kigali.

NISR, 2020b. SEASONAL AGRICULTURAL SURVEY 2020 SEASON B REPORT. Kigali.

Orwa, C., Mutua, A., Kindt, R., Jamnadass, R., Anthony, S., 2009. Agroforestree Database:a tree reference and selection guide version 4.0 [WWW Document]. URL https://www.worldagroforestry.org/sites/treedbs/treedatabases.asp

Roser, M., Ritchie, H., 2013. Food Supply [WWW Document]. OurWorldInData.org. URL https://ourworldindata.org/food-supply
Sanou, L., Savadogo, P., Ezebilo, E.E., Thiombiano, A., 2019. Drivers of farmers' decisions to adopt agroforestry: Evidence from the Sudanian savanna zone, Burkina Faso. Renewable Agriculture and Food Systems 34, 116–133. https://doi.org/10.1017/S1742170517000369
Scalco, A., Noventa, S., Sartori, R., Ceschi, A., 2017. Predicting organic food consumption: A meta-analytic structural equation model based on the theory of planned behavior. Appetite 112, 235–248. https://doi.org/10.1016/j.appet.2017.02.007
Schilirò, D., 2018. Economic Decisions and Simon's Notion of Bounded Rationality. International Business Research 11, 64. https://doi.org/10.5539/ibr.v11n7p64
Schlüter, M., Baeza, A., Dressler, G., Frank, K., Groeneveld, J., Jager, W., Janssen, M.A., McAllister, R.R.J., Müller, B., Orach, K., Schwarz, N., Wijermans, N., 2017. A framework for mapping and comparing behavioural theories in models of social-ecological systems. Ecological Economics 131, 21–35. https://doi.org/10.1016/j.ecolecon.2016.08.008
Secchi, D., Seri, R., 2017. Controlling for false negatives in agent-based models: a review of power analysis in organizational research. Computational and Mathematical Organization Theory 23, 94–121. https://doi.org/10.1007/s10588-016-9218-0
Sen, A., 1994. The Formulation of Rational Choice. The American Economic Review 84, 385–390.
Simon, H., 1955. A Behavioral Model of Rational Choice Author (s): Herbert A . Simon Stable URL : https://www.jstor.org/stable/1884852 69, 99–118.
Simon, H.A., 2007. Rationality as Process and as Product of Thought. The American Economic Review 68, 1–16.
Simon, H.A., 1972. Theories of Bounded Rationality, in: McGuire, C.B., Radner, R. (Eds.), Decision and Organization. Elsevier, Amsterdam, pp. 161–176.
Sood, K.K., Mitchell, C.P., 2009. Identifying important biophysical and social determinants of on-farm tree growing in subsistence-based traditional agroforestry systems. Agroforestry Systems 75, 175–187. https://doi.org/10.1007/s10457-008-9180-z
Stock, J.H., Watson, M.W., 2015. Introduction to Econometrics, 3rd ed. Pearson, Edinburgh.
van Duinen, R., Filatova, T., Jager, W., van der Veen, A., 2016. Going beyond perfect rationality: drought risk, economic choices and the influence of social networks. Annals of Regional Science 57, 335–369. https://doi.org/10.1007/s00168-015-0699-4
Wilensky, U., 1999. NetLogo. http://ccl.northwestern.edu/netlogo/. Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, USA.