Understanding smallholder farmer decision making in forest land restoration using agent-based modeling

Vianny Ahimbisibwe[1,2*], Jürgen Groeneveld[3], Melvin Lippe[1], Susan Balaba Tumwebaze[4], Eckhard Auch[5], Uta Berger[6]

[1] Thünen Institute of International Forestry and Forest Economics, Hamburg, Germany
[2] Ecosystem Dynamics and Forest Management, Technical University of Munich, Freising, Germany
[3] Department of Ecological Modeling, Helmholtz Centre for Environmental Research—UFZ, Leipzig, Germany
[4] School of Forestry, Environmental and Geographical Sciences, Makerere University, Kampala, Uganda
[5] Institute of International Forestry and Forest Products, TU Dresden, Tharandt, Germany
[6] Institute of Forest Growth and Computer Sciences, TU Dresden, Tharandt, Germany

Abstract

Success of forest restoration at farm level depends on the farmer´s decision-making and the constraints to farmers' actions. There is a gap between the intentions and the actual behavior towards restoration in Sub-Saharan Africa and the Global South. To understand this discrepancy, our study uses empirical household survey data to design and parameterize an agent-based model. WEEM (Woodlot Establishment and Expansion Model) has been designed based on household socio-demographics and projects the temporal dynamics of woodlot numbers in Uganda. The study contributes to a mechanistic understanding of what determines the current gap between farmer's intention and actual behavior. Results reveal that an increase in knowledge of the current forest policies laws and regulations (PLRs) from 18% to 50% and to 100% reduces the average number of woodlots by 18% and 79% respectively. Lack of labor reduces the number of woodlots by 80%. Increased labor requirement from 4 to 8 and to 12 man-days, reduces the number of woodlots by 26% and 61% respectively. WEEM indicates that absence of household labor and de facto misconception of PLRs "perceived tenure insecurity" constrains the actual behavior of farmers. We recommend forest PLRs to provide full rights of use and ownership of trees established on private farmland. Tree fund in the case of Uganda should be operationalized to address the transaction costs and to achieve the long-term targets of forest land restoration.

Keywords

Forest restoration; land-use change; agent-based model; decision-making; labor

Code availability

The Woodlot Establishment and Expansion Model (WEEM) is available to download at CoMSES Net (Ahimbisibwe et al. 2021).

Correspondence:
Contact V. Ahimbisibwe at vianny.ahimbisibwe@thuenen.de

Cite this article as:
Ahimbisibwe, V., Groenveld, J., Lippe, M., Tumwebaze, S.B., Auch, E. & Berger, U.
Understanding smallholder farmer decision making in forest land restoration using agent-based modeling
Socio-Environmental Systems Modelling, vol. 3, 18036, 2021, doi:10.18174/sesmo.2021a18036

Socio-Environmental Systems Modelling
An Open-Access Scholarly Journal
http://www.sesmo.org

1. Introduction

Small-scale tree-based land-use intensification (STLI) associated with agroforestry, woodlot mosaics, fruit orchards, home gardens is seen as a pathway for forest land restorations (FLR) (Rudel et al., 2019), and forest product diversification (Rahman et al., 2017). This is supported by numerous governments and other development partners (Cesar & Jessica, 2010). Woodlot mosaics are also regarded as a suitable measure to enhance ecosystem services, and mitigate climate change (Kiyingi et al., 2016; Lienhoop & Brouwer, 2015). STLI is seen as conducive due to the increased occurrence of landscape fragmentation around the globe (Demetriou et al., 2013; Taubert et al., 2018). STLI through woodlot mosaics and boundary planting has historically been witnessed around the globe, particularly in sub-Saharan Africa, where smallholder tree planting has occurred for at least three decades in countries such as Kenya (Holmgren et al., 1994; Tiffen et al., 1994), Ethiopia (Nawir et al., 2007), Madagascar (Kull, 1998), and Uganda (Veljanoska, 2018). Key factors such as the need for consumption and commercial purposes motivated households to extend their available labor to include trees on their agricultural farms (Lambin & Meyfroidt, 2010) which is termed as the STLIs theory of the forest transition (Rudel et al., 2002).

The historical paradigm implies that smallholder farmers have an intention to plant trees, especially through woodlot mosaics. However, the actual behavior "implementation of this intention" may be threatened by perceived control variables such as inadequate enabling de facto policy conditions, especially insecure land and tree tenure. Under the theory of planned behavior (Ajzen, 1991), the perceived control attribute creates a gap between intention and actual behavior towards woodlot establishment.

Farm households are key actors and decision-makers in the transformation of land use towards STLI (McConnell & Dillon, 1997). It is crucial to explore and simulate the gap between intention and actual behavior from the household decision-making perspective. Farm household decision-making is influenced by several interacting factors that are poorly understood (French, 1995; Gebreegziabher et al., 2020; Twongyirwe, 2015; Villamor et al., 2012). Research in the arena of household decision making towards STLI "woodlot establishment" is mainly carried out using econometric and empirical analysis that focus on the determinants to tree adoption (Ashraf et al., 2015; Gebreegziabher et al., 2010; Nigussie et al., 2017; Tefera & Lerra, 2016). With the complexity in understanding the intention and actual behavior of individual households, there is need to advance and analytically expand econometric results. This entails building or developing a computational land use agent-based simulation model based on empirical survey data. Integration of empirical data and results in Agent-Based Models (ABMs), improves our understanding of the gap between the intention and actual behavior of households in STLI. In particular, the knowledge derived from empirical data and household surveys at one point in time can be extrapolated in time using a dynamic ABM by simulating scenario-based projections of woodlot establishment.

Agent-based modeling provides the possibility to better understand the impact of decision making in socio-economic context and environmental scenarios. Although with challenges in modeling Social-Ecological Systems (SES), such as difficulties in integrating both qualitative and quantitative data, and representing human dimensions in SES (Elsawah et al., 2019), agent-based land-use decision models have evolved during the last decade, and have been grounded on empirical data. Groeneveld et al. (2017) reviewed agent-based land-use models and have found that 61% of the studies have been grounded on empirical data. Zhang & Vorobeychik (2019) also highlight that most ABMs are hypothetical and there is more need to ground them on empirical data. This approach is implemented in the current study by using WEEM model to simulate the intention and actual behavior of household decisions towards STLI. ABM is a promising tool to improve our understanding and increase our ability to predict and successfully manage systems (Gilbert & Troitzsch, 2005; Grimm et al., 2005; Squazzoni, 2012). Such models are widely used to represent and analyze land use and land cover changes (Matthews et al., 2007; Parker et al., 2003) and they are significant in policy guidance when based on empirical data (Zhang & Vorobeychik, 2019). The potential of ABMs in policy-related research is well documented and accepted with most focusing on land-use optimization, economics, climate change adaptation, and agronomy (e.g. Andersen et al., 2017; Balmann, 1997; Berger, 2001), with less focus on understanding the gap between intention and the actual behavior of forest land restoration through woodlot establishment. Lempert (2002) suggested the application of ABMs to check the impacts and performance of policies over different features. Yet there persists the gap in using ABMs to solve real-world problems in specific case studies to provide appropriate policy strategies as noticed by Lippe et al. (2019) and Schulze et al. (2017). ABMs could be applied to check the de facto policy impacts, human behavior, and their unintended consequences. As indicated by Lupo (2015), actual behavior is influenced by the type of knowledge and information obtained and interpreted by smallholders. This creates either a favorable or unfavorable perception towards innovations (Lupo, 2015) such as woodlot mosaics.

In Uganda, for example, the National Forestry and Tree planting Act, 2003 aims to sustainably restore and manage forest lands both on public and private land. As a strategy to achieve this aim, local governments are authorized to guide tree farmers on when (not) to harvest trees on their private land based on sustainable forest management principles prescribed in the National Forestry and Tree Planting Regulations, 2016. The Regulations require forest owners to prepare a felling plan before proceeding with timber extraction. The same Act gives sole ownership, decision making, and tree tenure to the forest owner. This mismatch is perceived by the smallholders as a behavioral control, which creates mixed interpretation, conflicts, and challenges in the de facto implementation of the Act. ABM can be used in such a case to highlight the mismatch of policy design and its implementation (de jure vs. de facto), pinpointing to the nexus of land and tree tenure and the unintended consequences of FLR policies by highlighting the gap of intention and the actual behavior of farmers in FLR. Assessing and visualizing the inadvertent consequences of current Policies, Laws, and Regulations (PLR) is a daunting task and crucial for the ongoing FLR initiatives that promote the STLI pathway. Therefore, we hypothesize that current de-facto understanding and knowledge of forest Policies, Laws, and Regulations (KPLR) hinders and threatens forest land restoration in Sub-Saharan Africa (SSA).

Furthermore, since smallholders mainly base their decisions on farm inputs, primarily available household labor (Hoch et al., 2012; Taylor & Charlton, 2019; Tripathi et al., 1992), it is also vital to understand the influence of labor availability on the implementation and expansion of STLI, that in turn affects the success or failure of respective forest initiatives. Based on simulation experiments, we focus in the presented study on extrapolating the farmers' intention and the actual behavior of STLI while, evaluating the influence of KPLR and household labor on the observed household intention in SSA, using a case study in Uganda. In summary, we test the hypotheses that there is a significant gap between intention and the actual behavior of smallholder farmers, and this is influenced by the current situation of de-facto forest PLRs and the absence of labor. These perceived control variables hinder and threaten the observed forest land restoration intention to fully evolve through STLI in the form of woodlot mosaics.

2. The ABM Woodlot Establishment and Expansion Model (WEEM)

2.1 Model development and implementation

For a better understanding of smallholder decision-making and intentions towards STLI and its adoption trends in forest restoration, we developed a stylized agent-based simulation model experiment called Woodlot Establishment and Expansion Model (WEEM). The model is grounded on survey data collected in 2018. Data were obtained from small scale tree growers around Budongo protected forest reserve in Masindi District, Uganda. It is calibrated based on empirical results and implemented in NetLogo 5.3.1 and updated in 6.2 (Wilenski, 2016). A screen shot of the graphical user interface is provided in Figure 2. For simplicity, understanding and uniformity and to enable reproducibility, the model is presented using an established protocol for describing ABMs, namely the ODD (Overview, Design Concepts, and Details) protocol (Grimm et al., 2006; Grimm et al., 2010). Since the current model involves a concept of human decision-making, its description was further extended to the ODD + Decision (ODD+D) protocol (Müller et al., 2013). The ODD+D is suitable and it allows a clear and comprehensive description of ABMs with an emphasis on human decisions, including appropriate decision sub-model and theoretical foundations (Müller et al., 2013). The model can be downloaded at CoMSES Net (Ahimbisibwe et al., 2021).

2.2 Model overview

2.2.1 Purpose

WEEM model is designed to project woodlot establishment and expansion in space and time based on demographic data and behavioral data from a household survey. The model translates empirically derived stated preferences for woodlot establishment into the cumulative number of established woodlots considering both exogenous constraints, also known as perceived control variables (Ajzen, 1991), such as knowledge and awareness of forest land use PLRs, and endogenous constraints such as demographic changes that affect the availability of household labor. The current model is specifically designed for decision- and policy makers, stakeholders, and practitioners especially those involved in forest land restoration initiatives.

2.2.2 Entities, State variables, parameters, and Scales

Model entities cover both the social and ecological components of the SES. The social entities in the model include households and household members whilst the ecological entities include patches, and the respective trees (Table 1). Patches are characterized by their owner, presence of woodlots which is determined by the number of individual trees of the same species (e.g. *Eucalyptus grandis*) and their respective ages. Woodlots are subjected to harvesting in two phases, <10 years and >10 years of age, assigned with different market prices, that is $tree\text{-}price_1$ and $tree\text{-}price_2$ respectively.

Households are characterized by individual farm households including their household traits, household available labor (l), savings, and food security. Household members are characterized by their home, respective to their household head "decision-maker", and parents both father and mother with their respective gender and age. Household members are further categorized by their level of knowledge on land use PLRs (K_{plr}), willingness to establish woodlots, and the ability to access an extra source of non-farm income. Seasonality is characterized by dry and wet seasons that are defined by the probability of rainfall occurrence. Rainfall dynamics are considered due to their high influence on the chance of tree planting, growth, and yield. In case of labor shortage, a given number of man-days termed as labor-pool are set aside within the community. This enables continual establishment and expansion of woodlots, especially for the households that have enough savings but without household labor.

For the temporal resolution, the model runs on a discrete-time step of 6 months called a season. It runs for a period of 25 years to represent a given generation of a population. Each household is assigned initially with one patch randomly located in the simulation arena. The rest of the empty patches are randomly distributed among households using a tessellation routine such as each patch belong to its nearest household. Each patch represents a woodlot parcel owned by an individual household termed as owner. The initial landscape builds on 84 randomly selected households with 44 having woodlots and 40 with no woodlots. The spatial configuration is currently not based on the real geographical information of the study area which allows for model expansion. Each grid cell represents one patch that is equivalent to one acre (0.4 hectares). The simulations are run on a virtual landscape and its extent is 33 grid cells * 35 grid cells making it a total of 1155 patches i.e. a total area of 1155 * 0.4 ha = 462 ha real-world area represented.

2.2.3 Process overview and scheduling

The model is comprised of various procedures (Figure 1) projected during the time step of 6 months in sequential order. Most important procedures that are repeated are setting up weather that provides the probability of rainfall occurrence, set up and update household structure, update household labor, tree growth and yield, household security, and update plots, land use decision on “woodlot establishment” and tree harvesting.

Table 1: Global and state variables for WEEM Agent-Based Model of trees planting decision making by the household

Variable Name	Description
Global variable	
Season	Defines the particular weather patterns; dry and wet seasons
Weather	Defines the probability of either having a drought or having rains, ranging from 0 to 1
Labor pool	The number of people/man-days within the community that can provide human labor. These can be hired by any household if there is a shortage of household labor.
newwoodlotslowlabour	The accumulated number of woodlots established by household that have not enough family labour to establish a woodlot on their own
newwoodlotshighlabour	The accumulated number of woodlots established by household that have enough family labour to establish a woodlot on their own
State variables	
Patches own	
Owner	Defines the owner of the patches with a respective who number/ household code e.g. from 0 to 85.
Woodlot	A patch that contains a necessary number of trees. Each household has a maximum of 23% fraction of the patches to establish a woodlot.
Woodlot _age	Defined by the age of the trees which increases on an annual basis
Trees own	
Tree_age	Defines the age of trees hence their growth and yield. It also enables to determine the harvesting decision of the tree by the households.
Households own	
Savings	Amount of money in dollars per year a household owns. This contains all income minus the household´s expenditure in terms of the number of members within the household.
Food-security	Calculated from household´s savings and indicates the ability of a household to live either above or below the poverty line.
Family-labor	Amount of people aged between 9 to 65 years who can provide human power to carry out farm activities within a household.
Household-labor	Family labour and potential labor from the labor pool
Members own	
Gender	Defines the gender of household members including parents and children to enable make appropriate decisions during update household sub-model and household heads.
Age (*AH*)	Defines the age of the household members including parents and children to enable make appropriate decisions during updating a household and labor.
Home	It indicates the household the members belong to.
Knowledge	Knowledges indicates whether a member is aware of PLRs (knowledge = 1) or not (knowledge = 0)
Willingness (*W*)	Willingness indicates whether a member is willing to establish a woodlot (*W* = 1) or not (*W*= 0)
Extra-income (*EI*)	*EI* indicates whether the member has access to extra income (*EI* = 1) or not (*EI* = 0)
Selected model parameters	
Likelihood to establish a woodlot "see logit model"	
Con-policy knowledge	log-odds for policy knowledge
Con-extra income	log-odds for access to extra non-farm income
Con-age	log-odds for the age of household head
Con-willingness	log-odds for willingness to change land use activities towards tree planting
Woodlot establishment and harvesting	
Rainfall_drySeason	Absence of rainfall "dry season"
Rainfall_wetSeason	Availability of rainfall "wet season"
Labor-para	Average human labor required to carry out an activity
Tree-price $_2$	The market price of trees harvested at age of < 10 years
Tree-price$_1$	The market price of trees harvested at age of >= 10 years

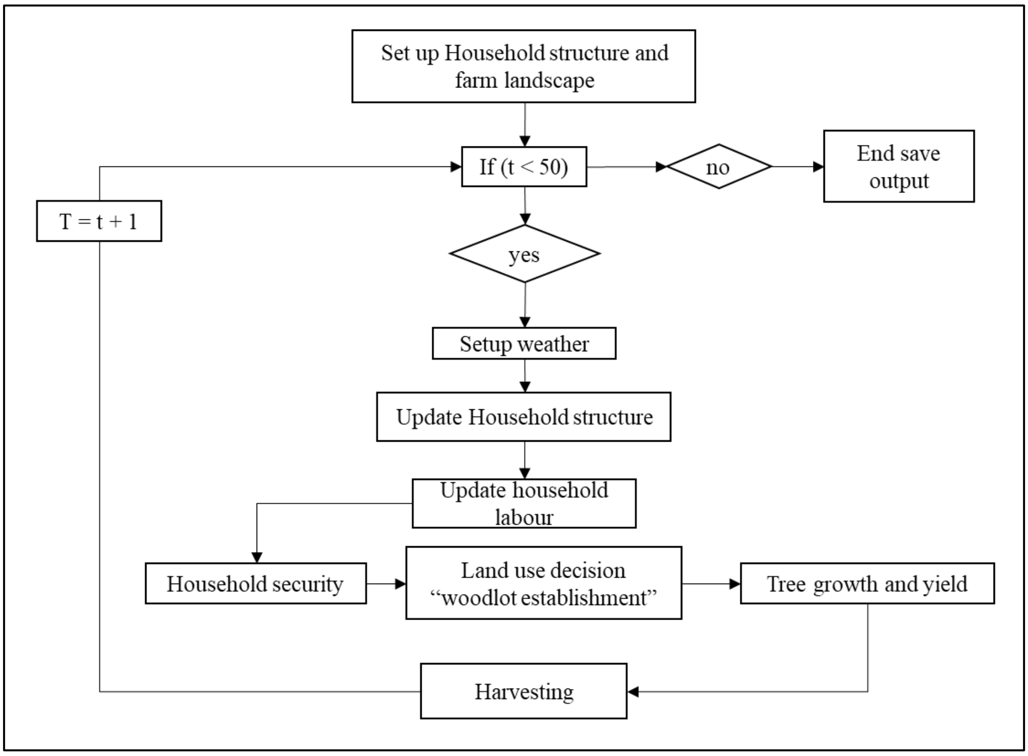

Figure 1: WEEM model process and overview and scheduling (T = time. Each time is 1 season = 6 months)

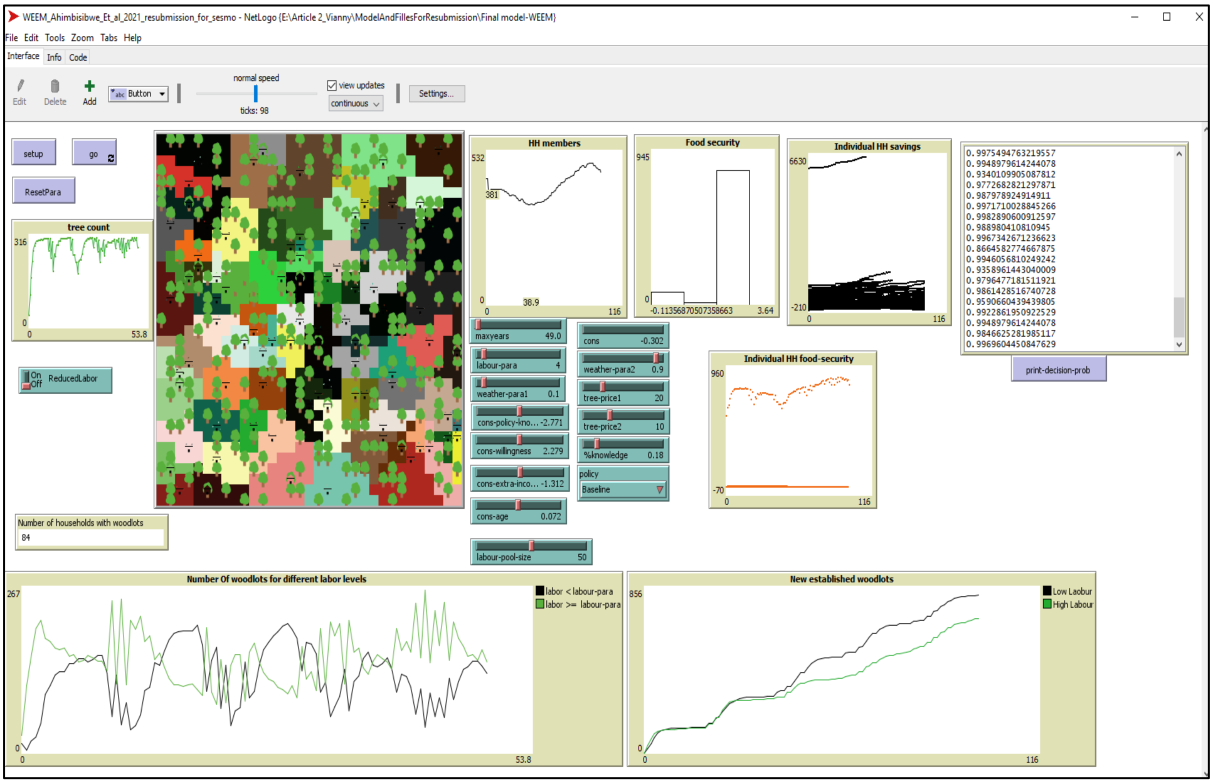

Figure 2: Interface of the agent-based Woodlot Establishment and Expansion Model (WEEM) providing an interactive test and application for users and decision makers. The diagrams indicate results at the end of the 50th season (25 years).

2.3 Model design concepts

Theoretical and Empirical Background

Overall, the model conceptualization is based on the socio-ecological understanding that embeds both social and ecological settings implicitly interacting together (Koontz et al., 2015) within the farm household system. In summary, the model has components such as the biophysical input (e.g. landscape patches) and social actors (e.g. the household agents), the environment (e.g. weather) and institution (e.g. forest policy). The social actors are built on agent traits comprising household assets based on the household livelihood framework as explained in Ahimbisibwe et al. (2019) and exogenous variables such as KPLRs. The biophysical input only considers the farm landscape on which a household under conducive weather environment may establish their woodlots. The components interact with each other, for example, the agent interacts with the biophysical system by causing an effect through the alternation of the land use patch based on his decision to establish a woodlot. On the other hand, the biophysical system (the farm landscape) reciprocates by providing positive feedback as outcomes such as tree products that are converted into household income, which then affects household savings. Other processes such as fertilization, change in landscape status (e.g. soil fertility and water table) are not modelled.

The concepts of forest transition theory are taken into consideration. The theory states the change from net forest loss to net forest gain over time (Farley, 2010; Mather, 1992). We focus on the recovery (forest net gain) phase that is mainly explained by five pathways such as globalization, governance, changes in socio-economic attributes, state forest policy, and smallholder, tree-based land-use intensification (Lambin & Meyfroidt, 2010; Meyfroidt et al., 2018). Herein, we only consider the smallholder, tree-based intensification concept, a significant pathway towards forest restoration in agricultural-forest frontiers. The concept highlights a baseline for farmer's intention to reforest their farmlands as long as the intended action removes costs or promises revenue (Rudel et al., 2002), in the model termed as savings. To understand the gap between intention and actual behavior, the theory of planned behavior (Ajzen, 1991) further helps to understand how household intentions are restricted by the perceived control variables, which links between perceived intention and actual behavior. The probability of establishing a woodlot is based on an empirical preference function that has been derived from an empirical analysis (Ahimbisibwe et al., 2019). Empirical data was obtained from household surveys, which were accompanied with direct observation and key informant interviews.

Level of aggregation

Generally, the model is based on the household member level. Land use decisions are made by the head of the household. Thus, his or her attributes are decisive and not household averages. The initial level of aggregation comprises a total of 84 households among which 44 have woodlots and 40 with no woodlots. However, this categorization changes at a faster rate with the trend moving towards more households establishing woodlots.

Individual decision making

Decision-making is modeled at the individual household level and in particular based on the attributes of the household head. The initial settings are imported into the ABM model from tabulated string files compiled from the empirical data. Newborns inherit the attributes from their mother and if new agents appear in the system their attributes are assigned randomly based on the proportion derived from the household survey. Each household head decides whether or not to establish woodlots and the decision is done once every season (6 months). This decision is constrained by a number of factors such as availability of empty patches, labor and savings to hire external labor. For newly formed households, a new household head will take over an abandoned household.

Usually, the household head (mainly father) decides on woodlot establishment and harvesting and if there is no father, the mother acts as the household head. The decision to establish or expand the woodlot is simulated based on a logit function (equation 1) that provides the probability of either to plant or not to plant trees. The function is denoted by:

$$\log(\frac{p}{1-p}) = -0.302 - 2.771\mathrm{K}_{\mathrm{PLRs}} + 2.279\mathrm{W} - 1.312\mathrm{EI} + 0.072\mathrm{AH} \quad (1)$$

Where K_{PLRS} = Knowledge on forestry PLRs; *EI* = Non-farm income; *W* = Willingness to change land use; *AH* = Age of household head (Ahimbisibwe et al. 2019). Within the model, K_{PLRS}, *EI*, and *W* are between 0 and 1, while *AH* ranges from 22 to 65 years. A combination of these parameters provides the estimated probability (*p*) as a measure of intention to establish woodlots. Whereas *p* at the end of the simulation ranged from 0.18 to 0.99, with a median of 0.98 and mean of 0.92. The lower range closer to 0.18 belongs to relatively young household heads, with limited resources and savings.

However, irrespective of the high probability to plant or expand woodlots, a household head has to check for different constraints such as labor availability and weather before he/she executes a decision. Land availability is attributed to the occurrence of potential empty patches without both woodlots and households. With the availability of empty patches, woodlot establishment and expansion were limited to a mean fraction *f* in equation 2 below. The fraction is given by:

$$\mathrm{f} = {}^{\mathrm{pw}}\!/_{\mathrm{ph}} \tag{2}$$

Whereby *pw* = patches with woodlot and *ph* = total number of household patches. This implies that, if all these constraints are trounced, households start establishing trees every year.

As a result, from the empirical analysis, farmers who own woodlots set aside only a proportion of 23% of all patches for woodlot establishment. Therefore, we set our system limits in the model for woodlot establishment to 23%. This 23% are in line with the advice from the agricultural extension officers to set aside land to fulfill the high demand of both annual and perennial crops for both food consumption and commercial purposes. Additionally, the rule is also used to test and suggest it as minimum standard for tree inclusion on farms in the farm forest policy of Uganda.

Goal orientation
In the model, the goal orientation is represented by the probability to establish a woodlot *p* (equation 1).

Adaptive behavior
Agent's adaptive behavior is then modeled considering various aspects from the real farm household system. Firstly, farm household decision to establish a woodlot is constrained following available household labor, savings, rainfall, and potential patches "land" for woodlot establishment. For example, if a household cannot establish a woodlot when there is no household labor, the head adapts by hiring external labor using available savings. An individual household adapts to drought by delaying tree planting until sufficient rain occurs. This is to avoid losses in time and resources due to expected high tree mortality. Having managed to establish the woodlots, an individual household adapts to the lack of savings and food insecurity by harvesting some of the woodlots to increase his/her income and livelihood security.

Spatial aspects
Although not modeled explicitly, WEEM considers spatial aspects in the decision process, as the number of woodlots cannot exceed 23% of all patches own by a household.

Temporal aspects
Learning, memory, or discounting effects are not considered in the decision-making process, but households cannot commence with tree harvesting unless woodlots are 6 years of age or above.

Sensing
Households are modeled in such a way that they can sense the occurrence and absence of rains. This enables them to make an objective decision of whether to plant trees or not to plant. For example, household agents do not plant trees in dry seasons and only in the wet seasons. Household agents further detect the availability of empty patches which are occupied by newly formed households by male children at the age equal to or greater than 22 years old. The absence of these empty patches leads to no formation of new households. Household information is modeled explicitly based on empirical data.

Level of interaction
There are several feedbacks between social actors and environmental entities since patches are managed by social actors. Households indirectly interact through the labor pool where they compete for extra labor. Only households owning savings are able to participate in the competition for labor from the labor pool.

Heterogeneity
Heterogeneity is expressed as differences in: household traits such as household size, savings and household labor; member's traits such as parents, home (agent location), knowledge, willingness and access to extra income. Heterogeneity is also envisioned in terms of households' decision making caused by the differences in traits and also based on the probability decision function.

Stochasticity
Attributes of family members, apart from aging, are assigned stochastically, i.e. knowledge, willingness to establish a woodlot, and access to extra income are assigned stochastically based on the proportions of the empirical data set from the survey. For example, in the data set 18% of the participants had knowledge. Thus, in the model the probability that a household-member has knowledge is 18%. Some processes are implemented stochastically such as reproduction, initial household patch distribution, and the order of households to access the labor pool. The state of the weather is also determined stochastically.

Observation
The number of established woodlots, household savings, and household food security is collected at the end of each season and year (two seasons).

2.4 Details

2.4.1 Initialization

The model is initialized at time t = 0, with 84 households among which 44 have woodlots and 40 with no woodlots. The initial state of the external labor pool is 50 individuals and is a limit as observed from the empirical data in the case study. Each household is initiated with only one patch and later all other patches are randomly distributed using the minimum distance of the owner to the respective patch. Households also initiate with their respective attributes such as age, number of household members, gender, and woodlot ownership based on the field data. The age of the woodlots is initiated to an age of 2 years as the average age observed during the survey.

2.4.2 Input data

The model uses input files obtained from the field surveys (Ahimbisibwe et al., 2019) and these include gross margin, household size, age and gender status of children, age and gender status of parents, and woodlot ownership. These files are used to build the household structure, allocate woodlots and savings to the respective households.

2.4.3 Sub-models

Update household structure
Within the household, the age of all household members increases annually (Figure 3), and those ≥ 65 years old are eliminated from the system. Choosing 65 years is based on the life expectancy within the study area, which is significantly not different from the average life expectancy at birth of 63.7 years for Uganda at large (Uganda Bureau of Statistics [UBOs], 2019). During the simulations, male offspring with an age of 22 years and above, searches for or inherits an empty patch within the landscape to start up a new household. Lack of any empty patch available eliminates him from the system. After occupying an empty patch, he gets married by finding a spouse within the landscape. The spouse is randomly created from and within the system at an age of 18 to 28 years old. The unmarried offspring are then eliminated from the system at the age of ≥ 22 years. Each woman that lives with a partner and is in a certain age interval (18-35 years) may reproduce with a probability of 0.5 each year.

Update household labor
This sub-model (Figure 4) updates household labor and provides the decision rules towards establishment of woodlots. If planting is true, household head checks for the availability of household labor which is, composed of household members aged between 9 to 65 years old who belong to a specific home and depend on him. The household head compares current labor with that of the labor-para a global variable that act as a perceived constraint. At the farm household in reality, an average of 4 individuals/household members is required to achieve the respective land activities ranging from land clearing to harvesting of tree products. Therefore, labor-

para in our current model is set at four. With a deficit in household-labor, the household head calculates labor needed and obtains the additional labor from the labor pool given sufficient savings.

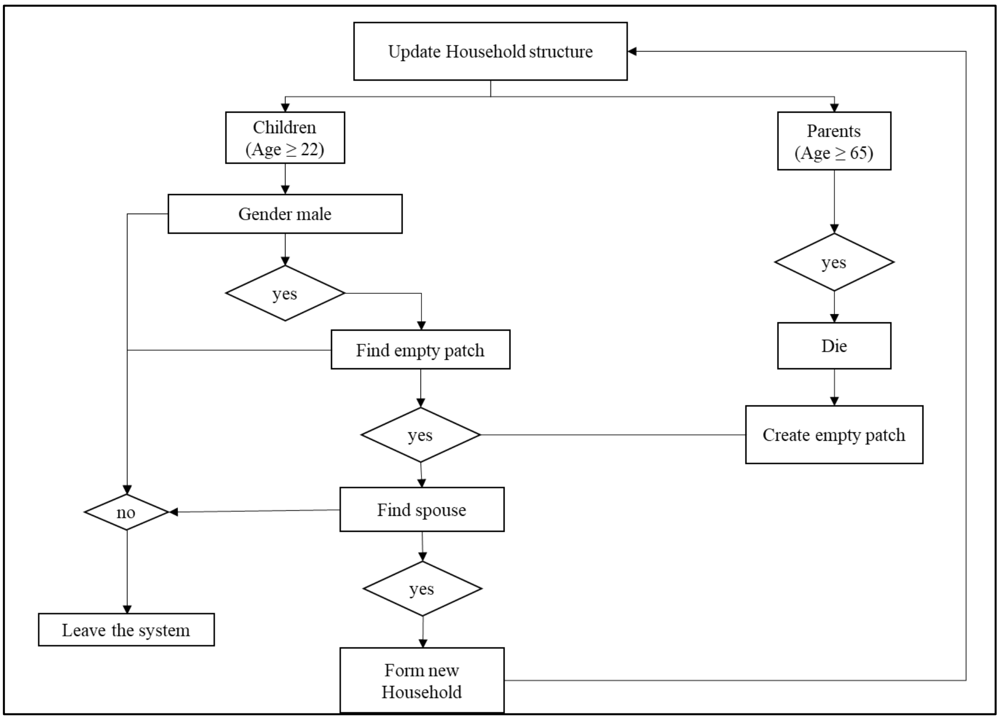

Figure 3: Process for updating household structure sub-model

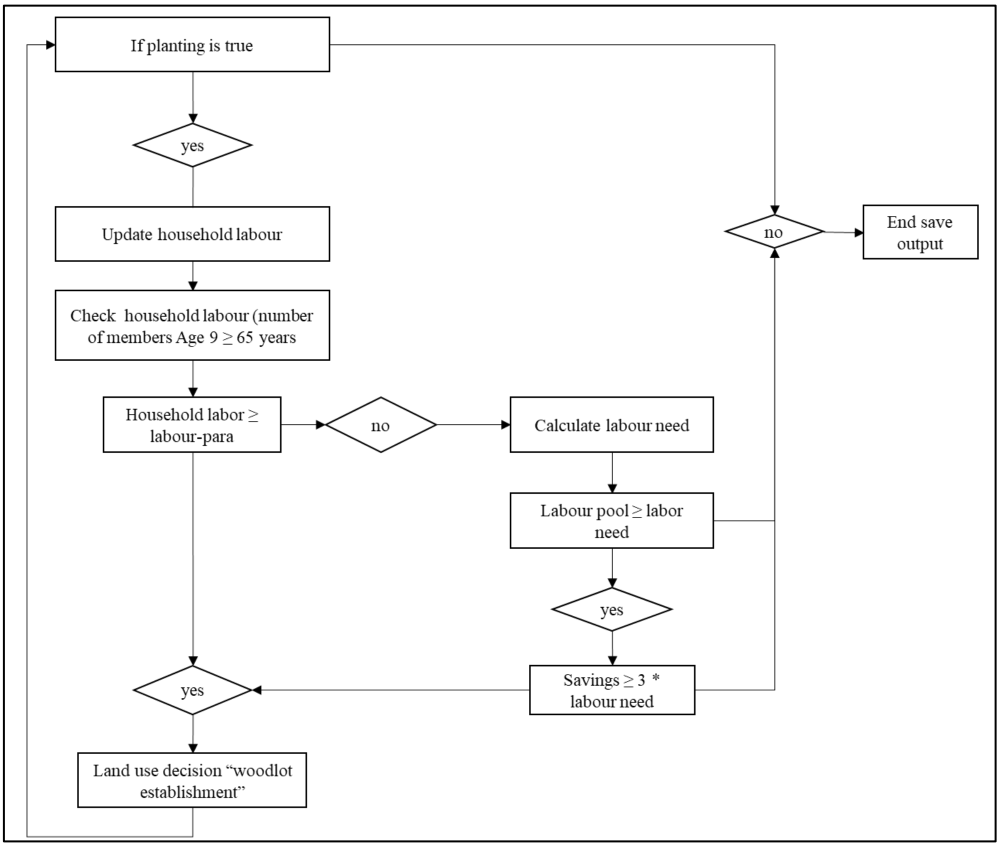

Figure 4: Process for updating household labor sub-model

Tree growth and yield
Tree growth and yield are updated through a simple linear equation: age = current age + 1, updated on an annual basis. Dimensions of tree growth such as height and diameter were not considered in the current version of the model since there are not management activities such as pruning and thinning currently carried out by the households. Additionally, management aspects and productivity are currently not considered because the only focus is on decisions to establish and harvest a woodlot.

Harvesting
Households only harvest trees in their woodlots if the tree age is 10 years and above. Secondly, households harvest trees in case of emergency "savings ≤ 0" provided trees are 6 years and above but below 10 years. Additionally, a tree price of 20 USD (*tree-price*$_1$) and 10 USD (*tree-price*$_2$) is assigned according to the average farm gate market prices of standing trees, for the first and second case respectively. Furthermore, harvesting expenses are not included within the model since households from the study area sell standing trees. Lastly, household income is updated for every tree harvested on an annual basis.

3. Model application and scenario analysis

3.1 Model sensitivity analysis

Both global and local sensitivity analysis was used to analyze the model. This aided us to integrate potential changes and errors plus their impacts on the model output (Pannell, 1997; Railsback & Grimm, 2012). Sensitivity analysis included testing the effect of five model input parameters, *labor-para*, *rainfall_wetSeason*, *rainfall_drySeason*, *tree-price*$_1$, and *tree-price*$_2$ on the cumulative number of established woodlots. Model parameters in local sensitivity analysis were altered one at a time [one-factor-at-time approach (OAT)] (Bar Massada & Carmel, 2008; Broeke et al., 2016). Here, we calculated elasticities since the units of measure of the parameters are not comparable. This also provides a good indication of the parameters to which the cumulative number of established woodlots is most sensitive. The input parameter was varied on a small range using the standard deviation for *labor-para* and a ± 10% range above (X_{max}) and below (X_{min}), and the reference value (X_{ref}) for the rest of the parameters (*rainfall_wetSeason*, *rainfall_drySeason*, *tree-price*$_1$, and *tree-price*$_2$). The sensitivity of the model to changes in input parameters was measured as the relative change in the established number of woodlots at above (Y_{max}), low (Y_{min}), and reference level (Y_{ref}) per model input.

Model elasticities were calculated using:

$$E = \frac{Y_{max} - Y_{min}}{Y_{ref}} * \frac{X_{ref}}{X_{max} - X_{min}} \quad \text{(e.g. in Groeneveld et al., 2002; Pannell, 1997).} \qquad (3)$$

Where Y_{max}, Y_{min}, Y_{ref}, and X_{max}, X_{min}, X_{ref} are the maximum, minimum, and reference mean values of the model output(Y) and input (X) parameters respectively.

Since local sensitivity analysis does not consider the interaction effect between input parameters, we implemented a global sensitivity analysis (Saltelli, 2008). This was done by varying input parameters simultaneously to evaluate not only the effect of one factor at a time but also the interaction between input factors using a full factorial experimental design (Thiele et al., 2014). The input parameters are included using the minimum, mean and maximum values. Data output from the global sensitivity analysis was further statistically analyzed using general linear regression models and analysis of variance tests. The results indicated relationships between the input factors, and the model output parameter, including their interaction effects.

3.2 Model experiment (Scenarios)

3.2.1 Effect of knowledge of Policy Law Regulations (K_{plr}) on tree planting

Despite an abundance of policy instruments and guidelines for afforestation and reforestation, the success rate of these efforts to enhance forest cover is limited in many countries (Lienhoop and Brouwer 2015). As an example of Uganda, we assessed farmer's percentage in awareness of PLRs related to tree planting and harvesting (tree tenure and security) on their land. To observe and understand the role of policy on established woodlots at the landscape level, we ran policy scenarios while other decision-making constraints such as *EI, W* and *AH* are set to zero. The scenarios are divided into 3, namely scenario one (K_{plr} 0%), scenario two (K_{plr} 50%), and scenario three (K_{plr} 100%), which represents percentage awareness of forest policies at 0%, 50%, and 100% respectively (Table 2). From the survey data, only 18% of the respondents knew about PLRs, while 50% and 100% are hypothetical scenarios. Therefore, we set our baseline at K_{plr} = 18%. The results obtained from scenario one to three are compared within and between the scenarios at selected point of analysis using error bars.

Table 2: Scenario settings for the effect of PLRs on woodlot establishment. All other scenarios are based on a reduced decision model (see text for details).

Scenario	Designated name	Description
Baseline K_{plr}	K_{plr} 18%	18% of the household are aware of the forest policy, laws, and regulations and this acts as a baseline situation.
Scenario one (SC_1 K_{plr})	K_{plr} 0%	None of the households are aware of the forest use policies, laws, and regulations most especially concerning tree planting and harvesting. While keeping other decision-making variables to zero.
Scenario two (SC_2 K_{plr})	K_{plr} 50%	Half of the households are aware of the forest use policies, laws, and regulations most especially concerning tree planting and harvesting. While keeping other decision-making variables to zero.
Scenario three (SC_3 K_{plr})	K_{plr} 100%	All households are aware of the forest policies, laws, and regulations most especially concerning tree planting and harvesting. While keeping other decision-making variables to zero.

3.2.2 Effect of household labor availability on tree planting

The effect of household labor on woodlot establishment was evaluated using a global variable called *labor-para* and *labor-pool*. As stated earlier, *labor-para* acts as a perceived control variable for the households' decision-making. It creates the sense of feasibility for a household (not) to establish a woodlot. On the other hand, *labor-pool* is the number of man-days available in the labor market and can be hired by households with enough savings to establish woodlots. The evaluation was conducted in two ways. First, we ran the model at the normal parameter levels to obtain the number of newly established woodlots for two household categories those with high and low family labor.

Secondly, we assumed that the increase in the commitment to restore more forest lands would require more labor input, herein restricting the *labor-para* to 4, 8 and 12-man days. Using these limits, we created 3 scenarios with *labor-para* at zero, 8 and 12 man-days while keeping the baseline at 4 man-days and *labor-pool* at 50 man-days for all scenarios. Scenario one indicates no constraints in terms of labor whereas scenario two and three indicates that 8 and 12 man-days are required to establish woodlots.

Table 3: Scenario settings for the effect and importance of household labor on woodlot establishment

Scenario	Designated name	Description
Baseline	labor-para = 4 man-days	Woodlot establishment and expansion requires more or equal to 4 man-days of household labor
Scenario one (SC_1_L)	labor-para = 0 man-days	Woodlot establishment and expansion does not have a restriction on the number of required man-days of household labor
Scenario two (SC_2_L)	labor-para = 8 man-days	Woodlot establishment and expansion requires more or equal to 8 man-days of household labor
Scenario three (SC_3_L)	labor-para = 12 man-days	Woodlot establishment and expansion requires more or equal to 12 man-days of household labor

4. Results

4.1 Changes in the number of woodlots (intention of woodlot establishment and expansion)

Generally, the model simulates a high rate of increase in the number of established woodlots with increased time until the 20th to 23rd season and then 38th to 45th seasons (Figure 5). Woodlot expansion ceases to happen with the maximum number of established woodlots being attained at 38th season. The downward trends from 18th to 23rd and from 38th to 45th season indicate tree harvesting while upward trends from 23rd to 38th and 45th to 50th season indicate re-establishment and expansion. The trends in household savings increases at the commencement of woodlot harvesting especially from t >= 20 seasons (10 year). Overall the graph indicates that local households have a high intention to establish and expand the number of woodlots. It additionally suggests that STLI is a potential pathway to FLR in fragmented landscapes.

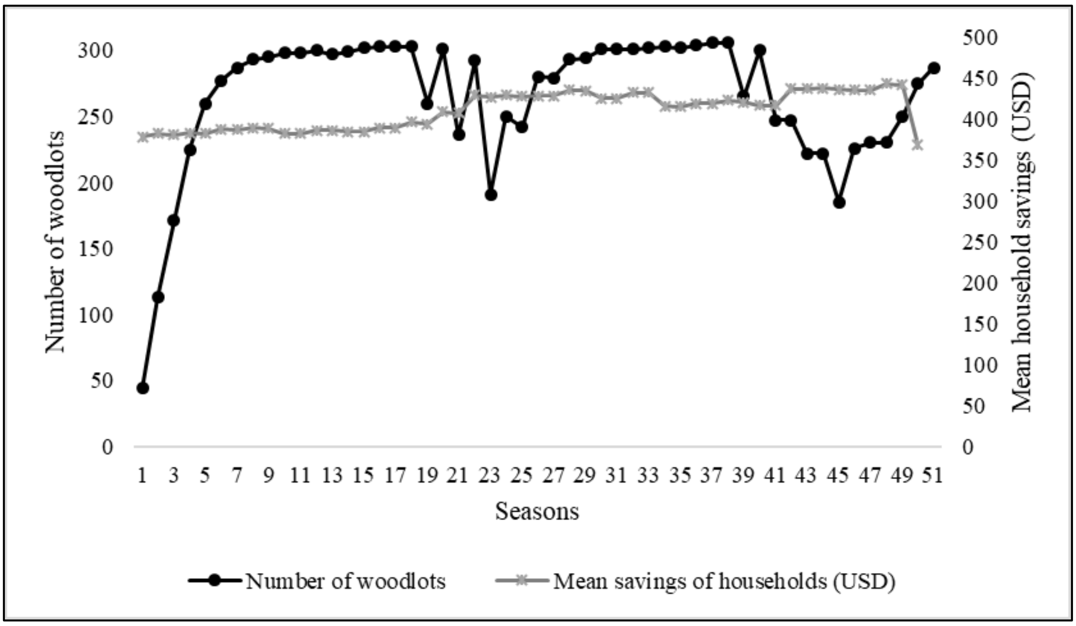

Figure 5: Trend of woodlot establishment and expansion concerning changes in mean savings of households (USD). The simulation runs at a seasonal time step (2 seasons = 1 year).

4.2 Sensitivity analysis

In table 4, the average number of established woodlots is highly sensitive to *labor_para* and *rainfall_wetseason* with an elasticity of 0.33 and 0.19 respectively. Additionally, the factorial analysis in Table 5 confirms a strong significant effect, degree of freedom (df) = 196798, standard error (se) = 44.5, adj. R^2 = 0.53, p-value ≤ 0.001, of *labor-para, tree price*$_2$*, rainfall_wetSeason* and *rainfall_drySeason* on the number of established woodlots. Other factors such as *tree price*$_1$ show no effect on the number of established woodlots (p-value = 0.3472). The results further indicate a significant (p-value ≤ 0.001) profound interaction effect of weather and labor on the changes in the number of woodlots. This further confirms the importance of weather and labor availability towards FLR.

4.3 Effect of PLRs on woodlot establishment and expansion (intention and actual behavior)

Overall, the cumulative number of established woodlots increased throughout the simulation and stabilizes after the 25th year (Figure 6). The rate of woodlot establishment in all scenarios (SC_1 K_{plr}, SC_2 K_{plr}, and SC_3 K_{plr}) reaches maximum at the year of 8.5. This thereafter fluctuates indicating woodlot re-establishment and harvesting. However, the rates occur at different levels with SC_3 K_{plr} having the lowest number of established woodlots. This indicates an inverse trend respective to the increase in knowledge on forest PLRs. This further suggests that farmers especially in SC_3 K_{plr} that previously owned woodlots became hesitant to re-plant trees with increased awareness of forest policy and regulations. Empirically, the cumulative number of established woodlots reduced by an average of 16% and 79% from the baseline to SC_2 K_{plr} and SC_3 K_{plr} respectively. On the other hand, reduction in the number of people with Knowledge on PLR to zero, slightly increased the number of established woodlots by 9%.

Table 4: Local sensitivity analysis of the model for the 5 input variables. Where Xmin, Xref, and Xmax indicate minimum, mean (reference), and maximum values per variable.

Model parameters Process and parameter	Meaning of parameter	Xmin	Xref	Xmax	Elasticity on the number of established woodlots
Woodlot establishment and harvesting					
labor-para	Average human labor required to carry out an activity	0.91	4	7.81	0.33
rainfall_wetSeason	Availability of rainfall	0.81	0.9	0.99	0.19
tree price$_2$	The market price of trees harvested at age of < 10 years	9	10	11	0.10
tree price$_1$	The market price of trees harvested at age of >= 10 years	18	20	22	0.04
rainfall_drySeason	Absence of rainfall "dry season"	0.09	0.1	0.11	-0.01

Table 5: Results of a general linear regression and analysis of variance. Names in the first column are the input factors, lone names are the main effects, and combined with a colon are interaction effects. The estimate variable is the number of established woodlots at the end of the simulation.

Input parameters	Estimate	Std. Error	t value	Pr(>|t|)	Sig. level
(Intercept)	1.03E+02	3.03E+00	33.908	0.000	***
tree-price$_1$	9.01E-02	9.58E-02	0.94	0.347	
tree-price$_2$	1.61E+00	2.29E-01	7.029	0.000	***
rainfall_wetSeason	3.20E+01	3.66E+00	8.764	0.000	***
rainfall_drySeason	7.38E+01	1.03E+01	7.17	0.000	***
Labor-para	3.64E+00	4.15E-01	8.777	0.000	***
tree-price$_2$: rainfall_wetSeason	-1.28E+00	2.76E-01	-4.627	0.000	***
tree-price$_2$: rainfall_drySeason	-2.10E+00	7.78E-01	-2.699	0.006954	**
rainfall_wetSeason: rainfall_drySeason	-4.55E+01	1.24E+01	-3.666	0.000	***
tree-price$_1$: labor	3.00E-02	1.31E-02	2.286	0.022257	*
tree-price$_2$: labor	2.72E-01	3.14E-02	8.674	0.000	***
rainfall_wetSeason: labor	4.72E+00	5.01E-01	9.43	0.000	***
rainfall_drySeason: labor	9.64E+00	1.41E+00	6.844	0.000	***

Note: Significant. Codes: * = p < .05, *** = p < .01 , *** = p < .001

Consistent with the previous results, Figure 7 indicates similar results but only at selected points of analysis i.e. at 6, 10, 12, 18, 20 and 24 years. The error bars indicate an overall similarity in number of woodlots for the Baseline K_{plr} and SC_1K_{plr} at all points of analysis. It also indicates a significant low number of established woodlots especially in SC_3K_{plr} compared to the Baseline K_{plr} and SC_1K_{plr} at all points of analysis. This emphasizes that an increase in PLR knowledge reduces the probability of forest restoration at the landscape level. This further confirms the assumption that the current K_{plr} inhibits the establishment and expansion of small-scale tree-based land use in smallholder farms.

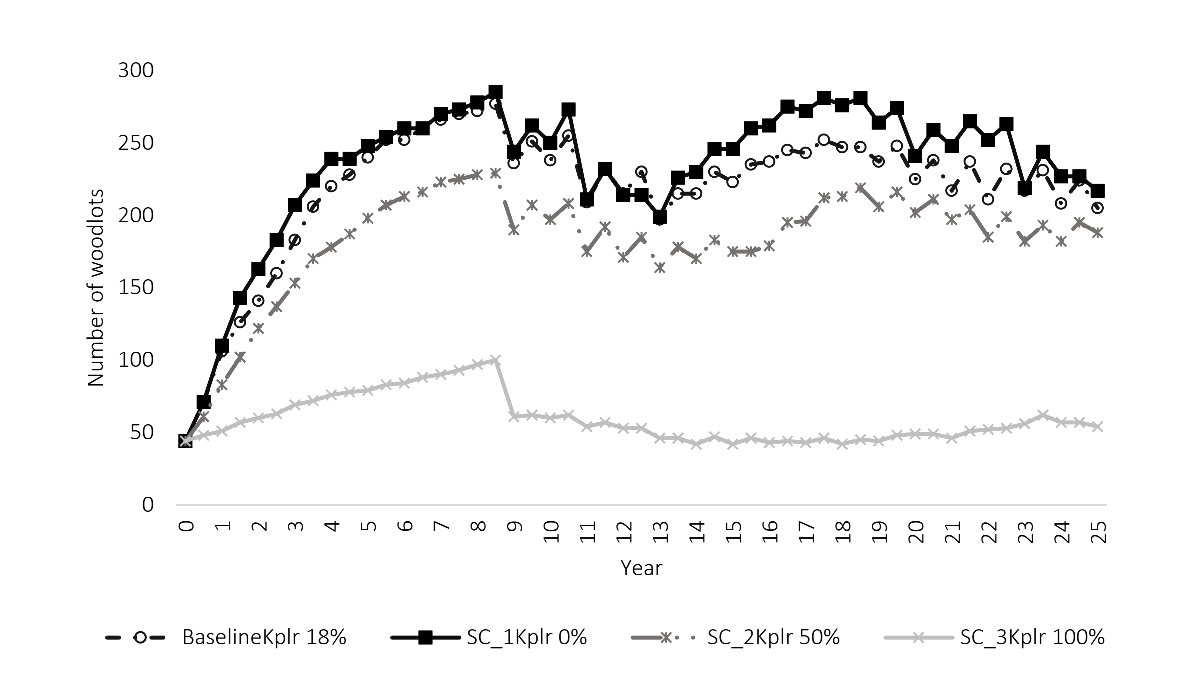

Figure 6: Changes in the number of woodlots due to the changes in PLRs awareness.

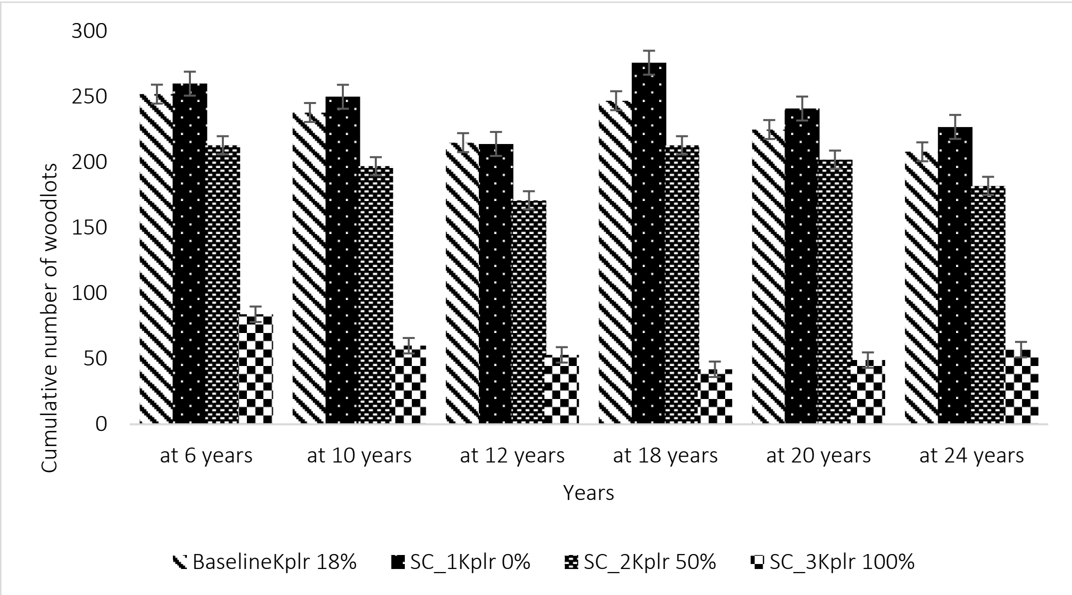

Figure 7: Change in number of woodlots in relation to the level of knowledge on PLR at different points of analysis. Error bars with no intersection indicate significant differences in the number of woodlots.

4.4 Effect of household labor availability on woodlot establishment (intention and actual behavior)

Effect of labor-pool

The cumulated number of established woodlots increases with time (Figure 8a) but the rate of increase is lower with low household labor as compared high household labor. As seen in Figure 8b, the results indicate that there is a significant gap at all points of analysis i.e. at 1st, 10th, 24th and 50th season in the number of newly established woodlots between households with high and low labor. This is evidenced with the low number of newly established woodlots for households with low labor in relation to those with high labor. On average, the number of established woodlots is 67% lower if households have low labor compared to when households have high labor input. Therefore, lack of access to labor pool (absence of external source of labor) restricts the expansion and establishment of new woodlots, especially for those with low household labor. This clearly shows the importance of the role of household labor in woodlot establishment and forest restoration as only those with family labor could establish more woodlots when external labor force cannot be accessed.

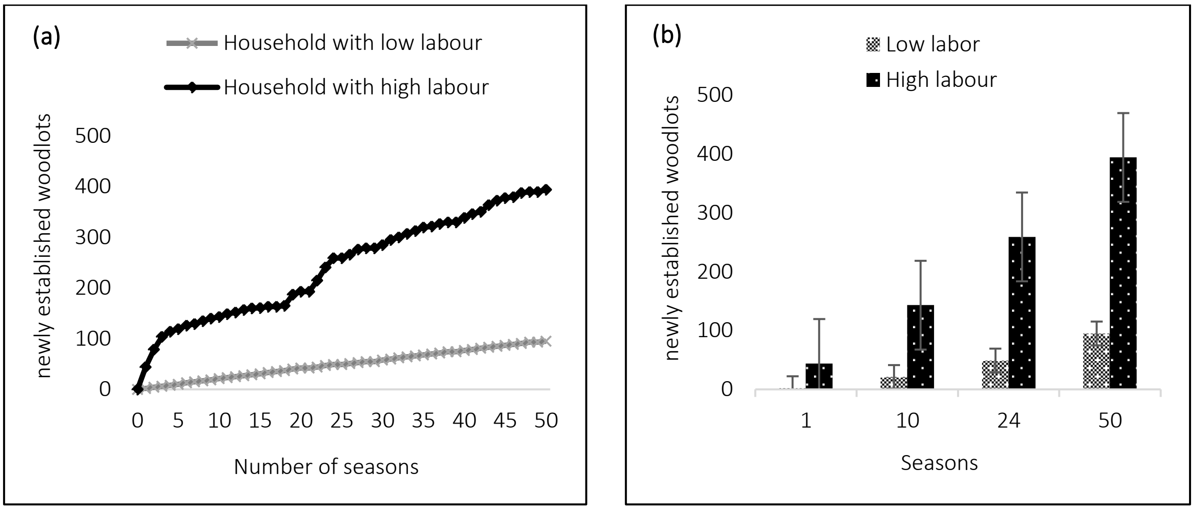

Figure 8: (a) indicates the trend in the number of newly established woodlots for households with low and high labor. (b) further highlights the number of woodlots at the point of analysis (at 1st, 10th, 24th and 50th season). Note: Each season indicates a half a year. Error bars with no intersection indicate significant different between household categories at different seasons in time. For this simulation we have used a reduced labor pool of 4. Also we used a *labor-para* as the threshold to split the groups into high or low labor.

Effect of the amount of labor that is needed to establish a woodlot

The parameter *labor-para* constrains the rate of woodlot establishment as observed with the slow and lower increase in scenario two and three compared to baseline and scenario 1 (Figure 9). Increase in restriction from 4 to 8 to 12 man-days indicates that households with no 8 or 12 man-days and above would not establish woodlots unless they have enough savings to hire external labor. Therefore, the smaller number of woodlots witnessed in SC_2_L and SC_3_L could be established using external labor force.

Empirically, the cumulative number of established woodlots reduced by an average of 26% and 61% in SC_2_L and SC_3_L respectively compared to the baseline. On the other hand, removal of the restriction in number of man-days slightly increased the number of established woodlots by 4%.

Figure 10 indicates similar results but only at selected points of analysis. The error bars indicate an overall similarity in number of woodlots for the baseline and SC_1_L at all points of analysis i.e. at 6, 10, 12, 18 and 20 years. It also indicates a significant reduction in number of established woodlots with increase in *labor-para* to 8 and 12 as noticed in SC_2_L and SC_3_L respective to the baseline. The results provide evidence that woodlot establishment at household level could be successful with labor demand 0-4 man-days. Therefore, the lesser number of woodlots observed in SC_2_L and SC_3_L indicates that household labor has significant importance, and current restoration projects that would require an optimal of 4 or less man-days could be successful compared to those that need more than 4 man-days of household labor.

This highlights that with the increased commitment and pledges to forest restoration, requirement for more labor would pose a significant barrier towards realizing the restoration goal at the landscape level. In such instances, results further indicate the need to incentivize households to enable access to external labor from the labor-pool or to compensate for their free leisure time in case of forest restoration and woodlot expansion.

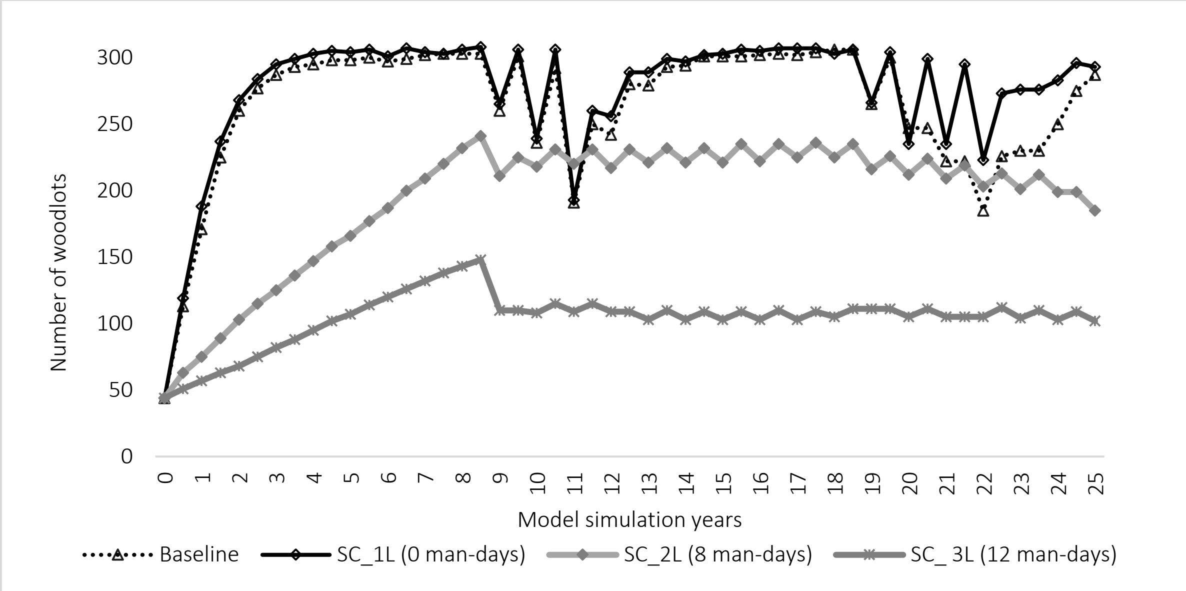

Figure 9: Changes in the number of woodlots due to the changes in household labor.

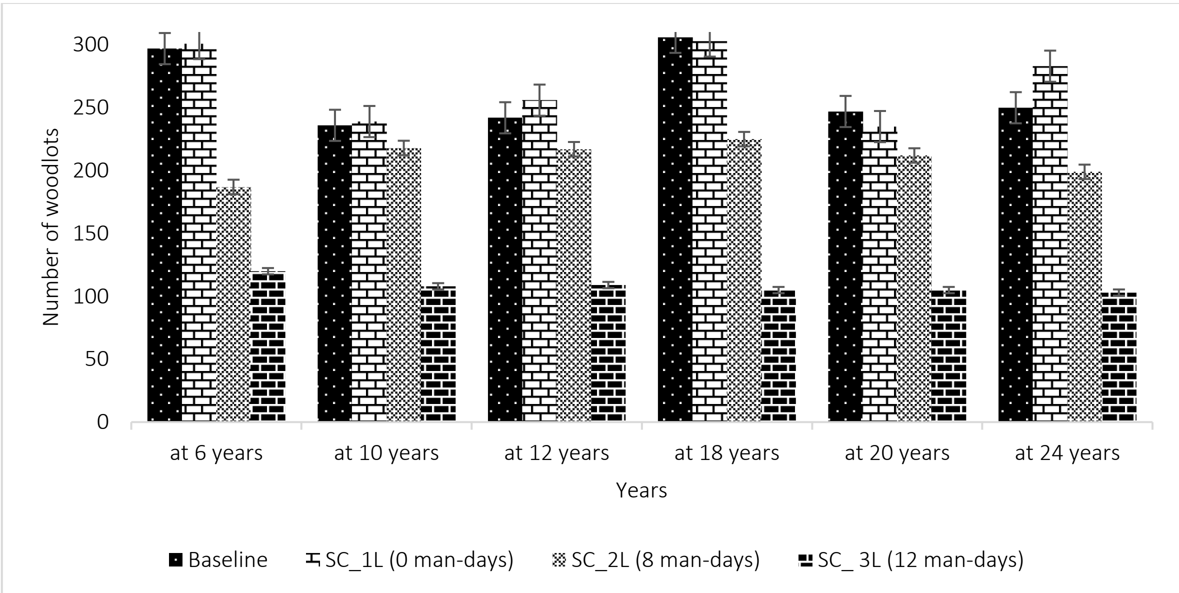

Figure 10: Number of established woodlots in relation to the number of required man-days for woodlot establishment at different point of analysis. Error bars with no intersection indicate significant different in the number of woodlots.

5. Discussion

5.1 The intention of woodlot establishment and expansion

The model simulates a higher rate of woodlot establishment in comparison to reality. This shows that there is a difference between intention and the actual behavior of households. The model suggests the number of woodlots that would be established if no constraints would hinder the actors from following their intention. Nevertheless, WEEM simulations indicate the possibility and potential of small-scale tree-based land use towards forest land restoration especially for smallholder farmers with an area of less than a hectare. The limitation of woodlot establishment to 23% of the total number of patches allows farmers to utilize the remaining 77% for agriculture (food production). Irrespective of this limitation, the model shows the feasibility of restoring forest lands in small-scale farms as also observed in Tanzania (Kimambo et al., 2020). As a rule, we recommend that the National Forestry and Tree Planting Act of Uganda, 2003, should create a provision for maintaining 23% tree cover on agricultural land. A 10% rule already exists in the farm forestry rules 2009 of Kenya (The Agriculture (Farm Forestry) Rules, 2009). Likewise, farmers with land parcels smaller than one hectare could be considered in farm forest projects, which has not been the case in FLR initiatives in Uganda. The proposed tree cover could be implemented not only in the form of woodlot mosaics but also through a combination of fruit trees mixed with crops, shade trees, and boundary planting.

5.2 Impact of land-use related PLRs on woodlot establishment

As observed, the model simulates a reduction in woodlot establishment with an increase in KPLRs awareness. The negative trend in woodlot establishment could be attributed to the past experiences and de facto interpretation of PLR. The requirement by the National Forestry and Tree Planting Act, 2003 and the regulations of 2016 for any tree harvesting to be permitted by the District Forestry officer through issuance of several permits involving payments is a disincentive for establishment of woodlots. This perceived behavioral control creates insecurity in the certainty of gaining from the long-term woodlot investments, hence acting as a constraint towards FLR. This is in agreement with numerous FLR reports as identified by McLain et al. (2018) that highlight land and tree tenure issues as a major challenge to the success of forest land restoration. Moreover, according to the PLR households are required to develop a management plan that has to be approved by government officials and also prove ownership through payment of several dues. This increases transaction costs, which demotivates the local farmers, especially, towards engaging in tree planting initiatives and projects.

With the role invested into local forest officials, PLRs formulation and implementation are based on a top-down approach without adequate consideration of the farm household needs, ideas, and aspirations. A similar situation was also observed in Vietnam by Salvini et al. (2016). With the current policy situation, farmers feel they have no full tenure rights to their trees hence reducing the chances in woodlot establishment. Accordingly, active participation of smallholders could ensure farmer's security of tree rights, thereby increasing the likelihood for and effectiveness of forest PLRs. With the continued inflexible PLRs, the success of landscape forest restoration is threatened (Lienhoop & Brouwer, 2015). This confirms the notion that smallholder farmers are more likely to plant trees when they have full rights with secure tenure on land and over the trees they cultivate (e.g. Newby et al., 2012; Treue, 2001). We recommend amendments in the legal framework governing privately owned woodlots/forests to avoid misinterpretation of PLRs that the framers envisioned would facilitate sustainable forest management among private tree farmers but are instead disincentivizing participation in woodlot establishment. The PLRs need to be amended to clearly clarify the roles between District and National forestry officials and tree farmers in relation to utilization of trees on privately owned land.

There is also need for investment in policy awareness at the local level which could differentiate between delayed harvest and denial to harvest woodlots, hence avoiding the unintended consequences of PLRs. Moreover, the Ugandan government needs to formulate guidelines that will be used in the preparation of management plans for all categories of forests that are sensitive to the inherent inequities and challenges of small-holder farmers that are involved in woodlot establishment. The country does not have guidelines for preparation of management plans for small-holder farmers that are investing in woodlots or forests yet the law requires farmers to have them. The National Forestry and Tree Planting Act, 2003 needs to be amended to create more positions in the District Forestry Services so that at least every sub-county which is the lowest unit of local governance in Uganda, to have a forest officer who among the several extension services they offer is supporting tree farmers with the preparation of management plans at subsidized rates. It will also be useful to create and operationalize policy incentives that encourage small-holder farmers to establish woodlots. We argue that if this is not considered, the overarching goal of Uganda's Forestry Policy of 2001, which states inter alia "to develop an integrated forest sector that achieves sustainable increases in the economic, social and environmental benefits from forests and trees by all the people of Uganda, especially the poor and vulnerable" may not be achieved.

5.3 Impact of labor changes on the rate of woodlot establishment

WEEM indicates reduction in the cumulative number of established woodlots with low household labor, lack of labor pool and increased number of required man-days. This approves the importance of household labor in driving the changes in farm management as also observed in agricultural production (Dahlin & Rusinamhodzi, 2019; Ellis, 1993; Nyberg et al., 2020).

It also indicates the role played by household savings in woodlot establishment, as observed in the limited number of woodlots in scenario 2 and 3. This is because, the low number of woodlots are established by households that can afford to hire an external labor force using extra savings. Thus, enabling them to implement their intended behavior. In summary, it indicates that households with no labor and savings may hardly engage in small-scale tree growing unless when supported externally as shown by a case in the Amazonia (Hoch et al., 2012).

As observed in real-world case studies, household labor for tree planting is often unavailable because households prefer to use it for intensive agricultural-crop production, and off (non) farm activities. This may also be attributed to the high interest and demand from the household dependents that lead to the allocation of more labor to short-term food crops for feeding and quick returns. Additionally, if the household's portfolio of activities does not contain enough short-term profit, households would integrate profitable but long-term investments like the establishment of woodlots due to the future return on land. On the other hand, the current investment in woodlots would be explained by the expected future returns on investment as highlighted by the increment on household savings in Figure 5. This hence shows the positive contribution of woodlot on household savings (Kiyingi et al., 2016). As a recommendation, showing households a piece of the evidence-based and economic contribution of woodlots to their livelihood would influence them to implement their intentions into actual behavior. Nevertheless, this further proves the dependence and importance of household labor in smallholder farms as noted by Ellis (1993) and Vicente & Pérez (2008), and that labor scarcity acts as a control variable to the implementation of the intended behavior especially in tree planting initiatives.

With the current requirement of 4 man-days per established woodlot relatively similar to the 5 man-days as observed by Hoch et al. (2012), and in Teak plantations by Newby et al. (2012; 2014), it confirms that tree cultivation in small-scale tree-based land-use intensification systems (woodlot establishment) is less intensive and requires less labor as compared to pure agricultural land-use systems (FAO, 1989; Nyberg et al., 2020). This is because woodlots require less attention with only either twice or once per year in comparison to crop production (Nyberg et al., 2020). Hence, it provides more profitable tangible and intangible benefits to the farmers as labor returns on investment. In contrast, this only applies to woodlots but not to other tree-based systems such as agroforestry (Foster & Neufeldt, 2014) and high tree density diverse systems (Nyberg et al., 2020). Therefore, caution should be taken on the type of STLI initiated for the respective forest restoration projects.

Consequently, due to increased pledges of FLR, more man-days would be required for households to expand and re-establish and restore their farm lands. This poses a challenge as observed that increase in the required number of man-days to 8 and 12 drastically reduces the chance to establish woodlots. Therefore, it is crucial to estimate the labor required and available at the farm level before the implementation of FLR initiatives to avoid failure. In cases of labor scarcity, support in form of incentives, could be focused on addressing the trade-offs, opportunity costs, and transaction costs of household labor, and on helping farmers access external labor where necessary. These could be, for example, support in terms of access to low-interest loans based on business plans, compensation payments for labor, performance-based payment, effective training, and advice from forest officials on post-planting silviculture operations, payment for ecosystem service, and provision of alternative sources of livelihood and fuelwood.

In summary, WEEM indicated an aspect of the importance of household labor and external labor which could not be observed in the empirical economic analysis (Ahimbisibwe et al., 2019), hence highlighting the significance of combining empirical data and ABM approaches. Therefore, it confirms the hypothesis that household labor has a significant effect and importance in the STLI system especially on the number of established woodlots. Additionally, it advances research on household labor and its necessity in forest land restoration.

5.4 Policy implication

The results show that WEEM can be used to understand different policy scenarios and labor requirements for individual farm households as a starting point towards FLR. There is a great need in developing models that not only integrate social and ecological systems but also consider the social behavior in the restoration interventions. Approaches such as WEEM can further play an important role in achieving the goals of the Africanled initiative of the 'Great Green Wall' (AFR100) which aims to restore 100 million ha of currently degraded land across the continent. It complements socio-economic farm models (Kremmydas et al., 2018) and contributes to the gap of applying ABMs to solving real-world problems such as unintended de facto consequences of PLR. This is relevant for decision support and policy advice of initiatives such as AFR100 and the currently declared decade (2021-2030) of ecological restoration by the United Nations.

Our findings also provide more insights for countries such as Uganda for the need of operationalizing the "Tree Fund" which is provided for in the National Forestry and Tree Planting Act, 2003 of Uganda. The farmers envisaged that the fund would promote tree planting and growing at national and local level and support tree planting and growing efforts of a non-commercial nature which are of benefit to the public. If operationalized, it will address the issues of opportunity cost and trade-offs related to use of household labor, hence in the long run, it will lead to the achievement of FLR targets through woodlots. Additionally, a provision for maintaining 23% tree cover on agricultural land in the Land Act, 1998, Physical Planning Act, 2010 and the National Forestry and Tree Planting Act, 2003, of Uganda, could highly contribute towards FLR.

6. Model limitations and proposed extensions and further work.

The model mainly focused on intention and actual human behavior and the perceived control towards forest restoration at farm level. Thus, it lacks social networks and explicit spatial maps that we recommend to be included in model expansion. Nevertheless, WEEM in its current state is robust and provides useful insights in relation to the role of household labor and current cognitive policy understanding of forest Policy laws and regulations in Uganda.

7. Conclusion and highlights

WEEM was developed with the main goal to contribute to forest land restoration through the small-scale tree-based land-use intensification (STLI) pathway, herein woodlot establishment. This is done by capturing mainly two knowledge gaps that have not been highlighted by other ABM models. The gap of understanding a de-facto policy implication on forest land restoration (FLR) through the STLI pathway, and the link between intention and the actual behavior of small farmers towards woodlot establishment. We advocate the use of a holistic approach, combining qualitative and quantitative empirical data and theories (theory of planned behavior and STLI theory) in model building and implementation in solving real-world problems. This approach provided an efficient and effective methodology, indicating that quantitative empirical data sources highly supplements model building and analysis.

Households have a high potential to establish and expand woodlots on their farm, thus a high possibility of woodlots as a pathway to forest transition. This indicates that woodlot establishment can combat wood scarcity and also contribute to the conservation and restoration of forest lands. In summary, WEEM indicates the potential of STLI as a pathway towards forest restoration in agriculture-forest frontiers, especially households that surround protected forest areas, and in highly fragmented landscapes. Given the potential (intended behavior) of woodlot establishment in forest restoration, de-facto policy implementation and awareness of current forest PLRs on land and tree tenure threaten STLI implementation. This is witnessed with the negative trends towards woodlot establishment and expansion with increased awareness of land and tree PLRs. Thus, we confirm the hypothesis that the current situation of de-facto forest PLRs hinders and threatens the observed forest land use restoration potential to fully evolve.

The number of established woodlots decreases with the lack of household labor unless for a household with enough extra savings to hire external labor. This further proves the hypothesis that household labor has a significant effect and importance on the number of established woodlots. Additionally, ignoring the labor requirements and constraints in restoration projects is one channel to failure in achieving restoration targets such as the AFR100 and Bonn Challenge of restoring 350 million hectares of degraded forest and agricultural land by 2030.

Acknowledgment

The authors are grateful to the German Academic Exchange Service (DAAD) for the M.Sc. scholarship, the Chair of Tropical Forestry of the Institute of International Forestry and Forest Products TU Dresden, the Chair of Forest Biometrics and Forest Systems Analysis TU Dresden for academic support and the Thuenen Institute of International Forestry and Forest Economics, including the anonymous reviewers and the Journal editors for the insightful comments and editing.

References

Ahimbisibwe, V., Auch, E., Groeneveld, J., Tumwebaze, S. B., & Berger, U. (2019). Drivers of Household Decision-Making on Land-Use Transformation: An Example of Woodlot Establishment in Masindi District, Uganda. Forests, 10(8), 619. https://doi.org/10.3390/f10080619

Ahimbisibwe, V., Groeneveld, J., Lippe, M., Tumwebaze, S. B., Auch, E., & Berger, U. (2021). “WEEM (Woodlot Establishment and Expansion Model)” (Version version 1.0.0) [Computer software]. CoMSES Computational Model Library. https://www.comses.net/codebases/4faf2984-7b50-4641-9585-d0ffd8b25ca2/releases/1.0.0/

Ajzen, I. (1991). The theory of planned behavior. Organizational Behavior and Human Decision Processes, 50(2), 179–211.

Andersen, L. E., Groom, B., Killick, E., Ledezma, J. C., Palmer, C., & Weinhold, D. (2017). Modelling Land Use, Deforestation, and Policy: A Hybrid Optimisation-Heterogeneous Agent Model with Application to the Bolivian Amazon. Ecological Economics, 135, 76–90. https://doi.org/10.1016/j.ecolecon.2016.12.033

Ashraf, J., Pandey, R., de Jong, W., & Nagar, B. (2015). Factors Influencing Farmers’ Decisions to Plant Trees on Their Farms in Uttar Pradesh, India. Small-Scale Forestry, 14(3), 301–313. https://doi.org/10.1007/s11842-015-9289-7

Balmann, A. (1997). Farm-based modelling of regional structural change: A cellular automata approach. European Review of Agricultural Economics, 24(1), 85–108. https://doi.org/10.1093/erae/24.1.85

Bar Massada, A., & Carmel, Y. (2008). Incorporating output variance in local sensitivity analysis for stochastic models. Ecological Modelling, 213(3-4), 463–467. https://doi.org/10.1016/j.ecolmodel.2008.01.021

Berger, T. (2001). Agent-based spatial models applied to agriculture: a simulation tool for technology diffusion, resource use changes and policy analysis. Agricultural Economics, 25(2-3), 245–260. https://doi.org/10.1111/j.1574-0862.2001.tb00205.x

Broeke, G. ten, van Voorn, G., & Ligtenberg, A. (2016). Which Sensitivity Analysis Method Should I Use for My Agent-Based Model? Journal of Artificial Societies and Social Simulation, 19(1), Article 5. https://doi.org/10.18564/jasss.2857

Cesar, S., & Jessica, C. (2010). Standing tall: Exemplary cases of sustainable forest management in Latin America and the Caribbean. Food and Agriculture Organization of the United Nations (FAO).

Dahlin, A. S., & Rusinamhodzi, L. (2019). Yield and labor relations of sustainable intensification options for smallholder farmers in sub-Saharan Africa. A meta-analysis. Agronomy for Sustainable Development, 39(3). https://doi.org/10.1007/s13593-019-0575-1

Demetriou, D., Stillwell, J., & See, L. (2013). A new methodology for measuring land fragmentation. Computers, Environment and Urban Systems, 39, 71–80. https://doi.org/10.1016/j.compenvurbsys.2013.02.001

Ellis, F. (1993). Peasant economics: Farm households and agrarian development / Frank Ellis (2nd ed.). Wye studies in agricultural and rural development. Cambridge University Press.

Elsawah, S., Filatova, T., Jakeman, A. J., Kettner, A. J., Zellner, M. L., Athanasiadis, I. N., Hamilton, S. H., Axtell, R. L., Brown, D. G., Gilligan, J. M., Janssen, M. A., Robinson, D. T., Rozenberg, J., Ullah, I. I. T., & Lade, S. J. (2019). Eight grand challenges in socio-environmental systems modeling. Socio-Environmental Systems Modelling, 2, 16226. https://doi.org/10.18174/sesmo.2020a16226

FAO. (1989). Forestry and food security. FAO forestry paper: Vol. 90. Food and Agriculture Organization of the United Nations.

Farley, K. A. (2010). Pathways to forest transition: Local case studies from the Ecuadorian Andes. Journal of Latin American Geography, 9, 7–26. https://www.jstor.org/stable/25765305

Foster, K., & Neufeldt, H. (2014). Biocarbon projects in agroforestry: lessons from the past for future development. Current Opinion in Environmental Sustainability, 6, 148–154. https://doi.org/10.1016/j.cosust.2013.12.002

French, J. H. (1995). Farm household decision making and extension framework for understanding farm household-level decision making and design of agroforestry extension strategies. APAN Report (FAO/APAN).

Gebreegziabher, Z., Mekonnen, A., Kassie, M., & Köhlin, G. (2010). Household tree planting in Tigrai, Northern Ethiopia: Tree species, purposes, and determinants. 1403-2465.

Gebreegziabher, Z., Mekonnen, A., Kassie, M., & Köhlin, G. (2020). Household Tree Planting in Tigrai, Northern Ethiopia: Tree Species, Purposes, and Tenure Security. Land Use Policy, 96, 104635. https://doi.org/10.1016/j.landusepol.2020.104635

Gilbert, N., & Troitzsch, K. (2005). Simulation for the social scientist. McGraw-Hill Education (UK).

Grimm, V., Berger, U., Bastiansen, F., Eliassen, S., Ginot, V., Giske, J., Goss-Custard, J., Grand, T., Heinz, S. K., Huse, G., Huth, A., Jepsen, J. U., Jørgensen, C., Mooij, W. M., Müller, B., Pe’er, G., Piou, C., Railsback, S. F., Robbins, A. M., Robbins, M. M., Rossmanith, E., Rüger, N., Strand, E., Souissi, S., Stillman, R. A., Vabø, R., Visser U., & DeAngelis, D. L. (2006).

A standard protocol for describing individual-based and agent-based models. Ecological Modelling, 198(1-2), 115–126. https://doi.org/10.1016/j.ecolmodel.2006.04.023

Grimm, V., Berger, U., DeAngelis, D. L., Polhill, J. G., Giske, J., & Railsback, S. F. (2010). The ODD protocol: A review and first update. Ecological Modelling, 221(23), 2760–2768. https://doi.org/10.1016/j.ecolmodel.2010.08.019

Grimm, V., Revilla, E., Berger, U., Jeltsch, F., Mooij, W. M., Railsback, S. F., Thulke, H.-H., Weiner, J., Wiegand, T., & DeAngelis, D. L. (2005). Pattern-oriented modeling of agent-based complex systems: Lessons from ecology. Science (New York, N.Y.), 310(5750), 987–991. https://doi.org/10.1126/science.1116681

Groeneveld, J., Enright, N. J., Lamont, B. B., & Wissel, C. (2002). A spatial model of coexistence among three Banksia species along a topographic gradient in fire-prone shrublands. Journal of Ecology, 90(5), 762–774. https://doi.org/10.1046/j.1365-2745.2002.00712.x

Groeneveld, J., Müller, B., Buchmann, C. M., Dressler, G., Guo, C., Hase, N., Hoffmann, F., John, F., Klassert, C., Lauf, T., Liebelt, V., Nolzen, H., Pannicke, N., Schulze, J., Weise, H., & Schwarz, N. (2017). Theoretical foundations of human decision-making in agent-based land use models – A review. Environmental Modelling & Software, 87, 39–48. https://doi.org/10.1016/j.envsoft.2016.10.008

Hoch, L., Pokorny, B., & de Jong, W. (2012). Financial attractiveness of smallholder tree plantations in the Amazon: bridging external expectations and local realities. Agroforestry Systems, 84(3), 361–375. https://doi.org/10.1007/s10457-012-9480-1

Holmgren, P., Masakha, E. J., & Sjöholm, H. (1994). Not all African land is being degraded: a recent survey of trees on farms in Kenya reveals rapidly increasing forest resources. Ambio, 23(7), 390–395.

Kimambo, N. E., L'Roe, J., Naughton-Treves, L., & Radeloff, V. C. (2020). The role of smallholder woodlots in global restoration pledges – Lessons from Tanzania. Forest Policy and Economics, 115, 102144. https://doi.org/10.1016/j.forpol.2020.102144

Kiyingi, I., Edriss, A., Phiri, M., Buyinza, M., & Agaba, H. (2016). The Impact of Farm Forestry on Poverty alleviation and Food Security in Uganda. Journal of Sustainable Development, 9(1), 150. https://doi.org/10.5539/jsd.v9n1p150

Koontz, T. M., Gupta, D., Mudliar, P., & Ranjan, P. (2015). Adaptive institutions in social-ecological systems governance: A synthesis framework. Environmental Science & Policy, 53, 139–151. https://doi.org/10.1016/j.envsci.2015.01.003

Kremmydas, D., Athanasiadis, I. N., & Rozakis, S. (2018). A review of Agent Based Modeling for agricultural policy evaluation. Agricultural Systems, 164, 95–106. https://doi.org/10.1016/j.agsy.2018.03.010

Kull, C. A. (1998). Leimavo Revisited: Agrarian Land-Use Change in the Highlands of Madagascar. The Professional Geographer, 50(2), 163–176. https://doi.org/10.1111/0033-0124.00112

Lambin, E. F., & Meyfroidt, P. (2010). Land use transitions: Socio-ecological feedback versus socio-economic change. Land Use Policy, 27(2), 108–118.

Lempert, R. (2002). Agent-based modeling as organizational and public policy simulators. Proceedings of the National Academy of Sciences of the United States of America, 99 Suppl 3, 7195–7196. https://doi.org/10.1073/pnas.072079399

Lienhoop, N., & Brouwer, R. (2015). Agri-environmental policy valuation: Farmers' contract design preferences for afforestation schemes. Land Use Policy, 42, 568–577. https://doi.org/10.1016/j.landusepol.2014.09.017

Lippe, M., Bithell, M., Gotts, N., Natalini, D., Barbrook-Johnson, P., Giupponi, C., Hallier, M., Hofstede, G. J., Le Page, C., Matthews, R. B., Schlüter, M., Smith, P., Teglio, A., & Thellmann, K. (2019). Using agent-based modelling to simulate social-ecological systems across scales. GeoInformatica, 7(2), 161. https://doi.org/10.1007/s10707-018-00337-8

Lupo, C. V. (2015). Adoption of innovation in small-scale forestry: The case of portable-sawmill-based microenterprises. Journal of Social Change, 7(1), 2.

Mather, A. S. (1992). The forest transition. Area, 367–379.

Matthews, R. B., Gilbert, N. G., Roach, A., Polhill, J. G., & Gotts, N. M. (2007). Agent-based land-use models: a review of applications. Landscape Ecology, 22(10), 1447–1459.

McConnell, D. J., & Dillon, J. L. (1997). Farm management for Asia: A systems approach / Douglas J. McConnell, John L. Dillon. FAO farm systems management series, 1020-2080: Vol. 13. Food and Agriculture Organization of the United Nations.

McLain, R., Lawry, S., Guariguata, M. R., & Reed, J. (2018). Toward a tenure-responsive approach to forest landscape restoration: A proposed tenure diagnostic for assessing restoration opportunities. Land Use Policy, 103748. https://doi.org/10.1016/j.landusepol.2018.11.053

Meyfroidt, P [P.], Roy Chowdhury, R., Bremond, A. de, Ellis, E. C., Erb, K.-H., Filatova, T [T.], Garrett, R. D., Grove, J. M., Heinimann, A., Kuemmerle, T., Kull, C. A [C. A.], Lambin, E. F [E. F.], Landon, Y., Le Polain de Waroux, Y., Messerli, P., Müller, D., Nielsen, J., Peterson, G. D., Rodriguez García, V., . . . Verburg, P. H. (2018). Middle-range theories of land system change. Global Environmental Change, 53, 52–67. https://doi.org/10.1016/j.gloenvcha.2018.08.006

Müller, B., Bohn, F., Dreßler, G., Groeneveld, J., Klassert, C., Martin, R., Schlüter, M., Schulze, J., Weise, H., & Schwarz, N. (2013). Describing human decisions in agent-based models – ODD + D, an extension of the ODD protocol. Environmental Modelling & Software, 48, 37–48. https://doi.org/10.1016/j.envsoft.2013.06.003

Nawir, A. A., Kassa, H., Sandewall, M., Dore, D., Campbell, B., Ohlsson, B., & Bekele, M. (2007). Stimulating smallholder tree planting-lessons from Africa and Asia. UNASYLVA-FAO-, 58(3), 53.

Newby, J., Cramb, R., & Sakanphet, S. (2014). Forest Transitions and Rural Livelihoods: Multiple Pathways of Smallholder Teak Expansion in Northern Laos. Land, 3(2), 482–503. https://doi.org/10.3390/land3020482

Newby, J. C., Cramb, R. A., Sakanphet, S., & McNamara, S. (2012). Smallholder Teak and Agrarian Change in Northern Laos. Small-Scale Forestry, 11(1), 27–46. https://doi.org/10.1007/s11842-011-9167-x

Nigussie, Z., Tsunekawa, A., Haregeweyn, N., Adgo, E., Nohmi, M., Tsubo, M., Aklog, D., Meshesha, D. T., & Abele, S. (2017). Factors Affecting Small-Scale Farmers' Land Allocation and Tree Density Decisions in an Acacia decurrens-Based taungya System in Fagita Lekoma District, North-Western Ethiopia. Small-Scale Forestry, 16(2), 219–233. https://doi.org/10.1007/s11842-016-9352-z

Nyberg, Y., Wetterlind, J., Jonsson, M., & Öborn, I. (2020). The role of trees and livestock in ecosystem service provision and farm priorities on smallholder farms in the Rift Valley, Kenya. Agricultural Systems, 181, 102815. https://doi.org/10.1016/j.agsy.2020.102815

Pannell, D. (1997). Sensitivity analysis of normative economic models: theoretical framework and practical strategies. Agricultural Economics, 16(2), 139–152. https://doi.org/10.1016/S0169-5150(96)01217-0

Parker, D. C., Manson, S. M., Janssen, M. A., Hoffmann, M. J., & Deadman, P. (2003). Multi-Agent Systems for the Simulation of Land-Use and Land-Cover Change: A Review. Annals of the Association of American Geographers, 93(2), 314–337. https://doi.org/10.1111/1467-8306.9302004

Rahman, S. A., Sunderland, T., Roshetko, J. M., & Healey, J. R. (2017). Facilitating smallholder tree farming in fragmented tropical landscapes: Challenges and potentials for sustainable land management. Journal of Environmental Management, 198(1), 110–121. https://doi.org/10.1016/j.jenvman.2017.04.047

Rudel, T. K., Bates, D., & Machinguiashi, R. (2002). A Tropical Forest Transition? Agricultural Change, Out-migration, and Secondary Forests in the Ecuadorian Amazon. Annals of the Association of American Geographers, 92(1), 87–102. https://doi.org/10.1111/1467-8306.00281

Rudel, T. K., Meyfroidt, P., Chazdon, R., Bongers, F., Sloan, S., Grau, H. R., van Holt, T., & Schneider, L. (2019). Whither the forest transition? Climate change, policy responses, and redistributed forests in the twenty-first century. Ambio. Advance online publication. https://doi.org/10.1007/s13280-018-01143-0

Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., ... & Tarantola, S. (2008). *Global sensitivity analysis: the primer*. John Wiley & Sons.

Salvini, G., Ligtenberg, A., van Paassen, A., Bregt, A. K., Avitabile, V., & Herold, M. (2016). Redd+ and climate smart agriculture in landscapes: A case study in Vietnam using companion modelling. Journal of Environmental Management, 172, 58–70. https://doi.org/10.1016/j.jenvman.2015.11.060

Schulze, J., Müller, B., Groeneveld, J., & Grimm, V. (2017). Agent-Based Modelling of Social-Ecological Systems: Achievements, Challenges, and a Way Forward. Journal of Artificial Societies and Social Simulation, 20(2). https://doi.org/10.18564/jasss.3423

Squazzoni, F. (2012). Agent-based computational sociology. Wiley & Sons.

Taubert, F., Fischer, R., Groeneveld, J., Lehmann, S., Müller, M. S., Rödig, E., Wiegand, T., & Huth, A. (2018). Global patterns of tropical forest fragmentation. Nature, 554(7693), 519–522. https://doi.org/10.1038/nature25508

Taylor, J. E., & Charlton, D. (2019). Labor in an Agricultural Household. In J. E. Taylor & D. Charlton (Eds.), The farm labor problem: A global perspective (pp. 97–120). Academic Press. https://doi.org/10.1016/B978-0-12-816409-9.00005-7

Tefera, S. A., & Lerra, M. D. (2016). Determinants of Farmers Decision Making for Plant Eucalyptus Trees in Market District, North Willow, Ethiopia, vol.6,, Article No.13.

The Agriculture (Farm Forestry) Rules 193 (2009).

Thiele, J. C., Kurth, W., & Grimm, V. (2014). Facilitating Parameter Estimation and Sensitivity Analysis of Agent-Based Models: A Cookbook Using NetLogo and 'R'. Journal of Artificial Societies and Social Simulation, 17(3), Article 11. https://doi.org/10.18564/jasss.2503

Tiffen, M., Mortimore, M., & Gichuki, F. (1994). More people, less erosion: Environmental recovery in Kenya.

Treue, T. (2001). Politics and economics of tropical high forest management: Case study of Ghana / by Thorsten Treue. Forestry sciences: v. 68. Kluwer Academic Publishers.

Tripathi, B. R., Psychas, P. J., Atta-Krah, K., & Sanginga, N. (1992). The AFNETA alley farming training manual. Alley Farming Network for Tropical Africa.

Twongyirwe, R. (2015). Forests under threat? Changes in land use and forest cover in rural western Uganda [, University of Cambridge]. EndNote Tagged Import Format.

Uganda Bureau of Statistics. (2019). Statistical Abstract 2019.

Veljanoska, S. (2018). Can Land Fragmentation Reduce the Exposure of Rural Households to Weather Variability? Ecological Economics, 154, 42–51. https://doi.org/10.1016/j.ecolecon.2018.06.023

Vicente, V. R., & Pérez, M. F. M. (2008). Assessing the role of the family unit in individual private forestry in northern Spain. Scandinavian Journal of Forest Research, 23(1), 53–77. https://doi.org/10.1080/02827580701672212

Villamor, G. B., van Noordwijk, M., Troitzsch, K. G., & Vlek, P. L. (2012). Human Decision Making In Empirical Agent-Based Models: Pitfalls And Caveats For Land-Use Change Policies. In K. G. Troitzsch, M. Mohring, & U. Lotzmann (Eds.), Proceedings: 26th European Conference on Modelling and Simulation / edited by Klaus G. Troitzsch, Michael Möhring, Ulf Lotzmann (pp. 631–637). European Council for Modelling and Simulation. https://doi.org/10.7148/2012-0631-0637

Wilenski, U. (2016). Netlogo User Manual version 5.3. 1.

Zhang, H., & Vorobeychik, Y. (2019). Empirically grounded agent-based models of innovation diffusion: a critical review. Artificial Intelligence Review, 52(1), 707–741. https://doi.org/10.1007/s10462-017-9577-z